# Votes, Jobs, and Places: The political & economic causes of income inequality, and its impact on well-being

A thesis submitted to the Department of Political Economy of King's College London for the degree of Doctor of Philosophy

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2022

# I ABSTRACT

In this thesis, I examine a political and economic cause of income inequality and its impact on well-being within the United Kingdom.

In Chapter 2, *Mo' Votes, Mo' Money*, I analyse how the electoral importance of groups affects redistribution. I use a static microsimulation model to isolate the impact of redistribution from behavioural and demographic changes. A difference-in-difference method is used to analyse the impact of changes in Relative Electoral Importance. I find that UK governments redistribute more to electorally important groups after changes in power. This led to a rise in inequality and child, but not pensioner, poverty after the Conservative-led government was elected in 2010.

Chapter 3, *No Country for Non-Graduate Men*, examines why non-graduate men are less adept at performing the job tasks that are more highly demanded in the post-industrial economy. I measure the effect of childhood and adolescent skills on adult job tasks and employment outcomes using long-term longitudinal data. I find that cognitive and emotional-health skills (in childhood) help individuals perform high-pay analytical and interactive job tasks. Cognitive and non-cognitive skills positively affect later employment. Gendered differences in skills reduce both the high-pay tasks the least-skilled men perform as well as their employment rates.

Finally, in Chapter 4, *Familiar Faces, Worn Out Places*, I estimate the effect of place-based prosperity at different scales on a range of well-being outcomes such as health, friendships, financial security, and physical safety. I do so using linked individual-area data at both the larger labour market and granular neighbourhood scales. The effect of places does differ between these two spatial scales. Prosperous labour markets, directly and indirectly, improve outcomes associated with greater potential incomes. Better neighbourhoods improve some outcomes associated with social-interactive effects. Policies aimed at improving both labour markets and neighbourhoods are therefore needed to create a *good life* for all citizens.

# II DECLARATION OF AUTHORSHIP

I, Jeevun Sandher, confirm that the research presented here for the examination of a PhD Degree in Political Economy is entirely my own work. The copyright rests with the author. Quotation is permitted provided full acknowledgment is given. This thesis may not be reproduced without my prior written consent. It does not, to the best of my knowledge, infringe any third part's copyright or intellectual property rights.

# III ACKNOWLEDGMENTS

I would like to thank my Indian immigrant parents for helping me, their son, to become a doctor. I'm incredibly grateful to them and the rest of my family and friends for providing a unending well of support throughout the process as well as helpful, consistent reminders to take time off.

My supervisors, David Hope, Brian Bell, and Florian Foos, all gave unfailing support, encouragement, and feedback to me during my PhD. It never took more than 24 hours to get a response to an email, which is exceedingly rare in academia. I appreciate that they always made time in their busy schedules to look over my work and provide feedback at short notice. More than their expertise, I am thankful for their kindness and friendship throughout.

***Everyone*** in the School of Politics and Economics made my PhD more than a bearable experience - they made it a thoroughly enjoyable one. There are too many people in the school to name individually - the list would extend to several pages. I would like to particularly thank the Quantitative Political Economy research group for supporting and promoting its graduate students as well as its invaluable role in creating excellent researchers. I am excited to see what my colleagues achieve in the future. I feel particularly grateful to have been part of a PhD community that was supportive and kind to one another throughout the process.

Finally, I'd like to thank the LISS Doctoral Training partnership for funding me during my doctoral thesis. I am particularly grateful for the way in which they responded during the COVID-19 pandemic, funding both my PhD internship with the Joseph Rowntree Foundation as well as an extension.

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# Chapter 1

# Introduction

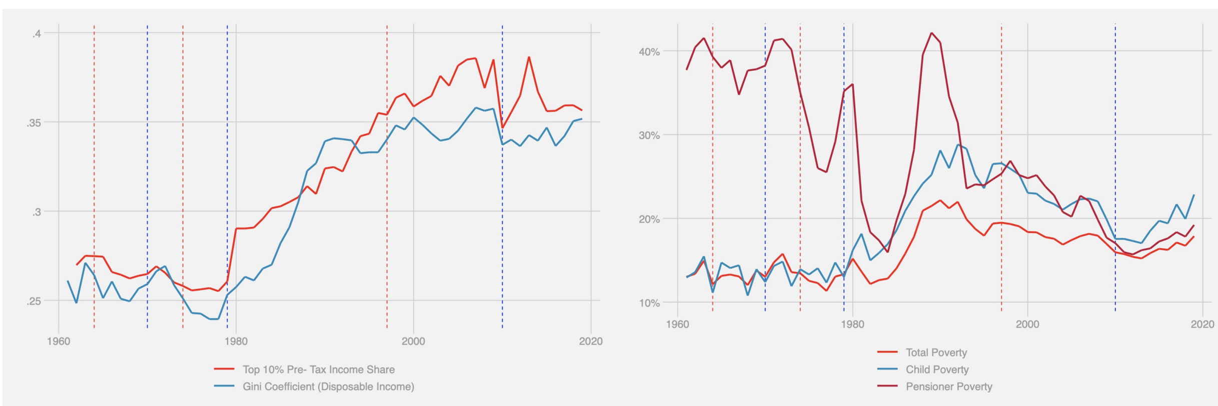
Across advanced economies, the three decades following the Second World War saw people and places share in growing prosperity - it was an era described as the *Les Trente Gloriouses*, the Thirty Glorious years (Crafts and Toniolo 2012). Welfare states expanded dramatically in both size and scope to guarantee incomes for a wider range of people (Scheidel 2017; Obinger 2018). Technological change was labour enhancing and wages grew equally across the distribution (Atkinson 2015; Frey 2019). Relatively deprived areas within these nations converged with more prosperous ones leading to a fall in spatial inequality (Carrascal-Incera et al. 2020). Stable, democratic political systems were the order of the day (Maier 1981; Dunn 2005).

From the 1980's, technological change and globalisation then led to dramatic economic, and subsequently political, changes. People and places would no longer share equally in growing prosperity. Automation and globalisation decimated the manufacturing sector and the mid-pay manufacturing jobs that came with it leading to a divided labour market of high and low-pay jobs with rising earnings inequality as a result (Autor et al. 2003, 2006; OECD 2011; Goos et al. 2014; Hope and Martelli 2019; Nolan and Valenzuela 2019). Unless governments chose to engage in countervailing redistribution, this led to a rise in income inequality and poverty (Figure 1)[1] (Atkinson 2004, 2015; Blundell et al. 2018). Non-graduate men who

[1]The rise in pensioner poverty since 2010 is likely due to a data quality issue rather than reflecting an

used to perform manufacturing jobs found their skills less demanded as job task demands changed in the post-industrial economy, which led to a fall in their employment rates (Figure 2) (Olivetti and Petrongolo 2016; Abraham and Kearney 2020). Manufacturing plants that were located across the country shut down and high-pay jobs were now increasingly located in cities where graduates could work together leading to a rise in spatial inequality (Figure 3) (Moretti 2013; Iversen and Soskice 2019; Rice and Venables 2021). Social security cuts, rising male nonemployment, and increased spatial inequality activated latent ethnocentric sentiments that fuelled a rise in populism (Fetzer 2019; Ford and Sobolewska 2020; Baccini and Weymouth 2021). In the United States, these rising populist forces are endangering democracy itself (Arendt 2017; Levitsky and Ziblatt 2018; Snyder 2021).

**Figure 1.1: Change in Poverty and Inequality in the UK**




(a) Inequality (b) Poverty Rates

Sources: Family Expenditure Survey, Family Resources Survey, World Inequality Database. Blue Dotted Lines indicate change to Conservative Prime Minister. Red Lines indicate change to Labour Prime Minister

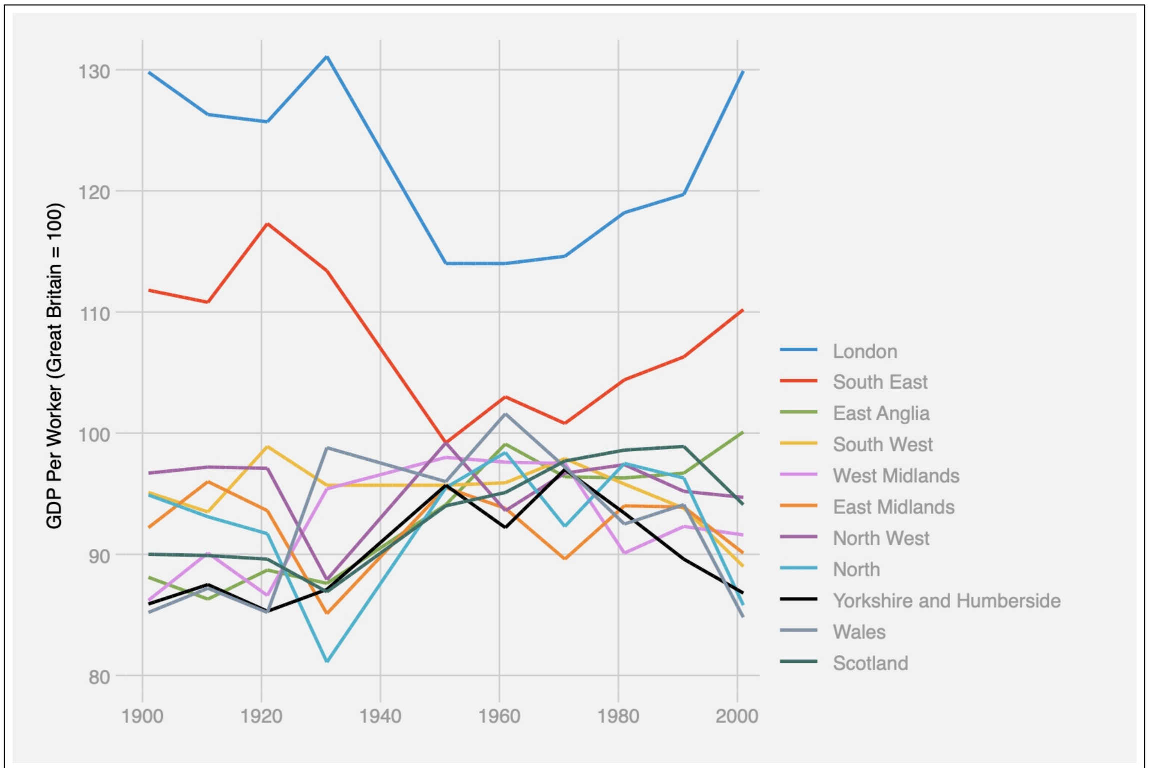
Advanced economies may have continued growing since the 1980s, but citizens did not share equally in this growth. Some saw relative, and others absolute, decline in their well-being. Within the United Kingdom, social security cuts have led to rising poverty, hunger, and mental health problems (Loopstra et al. 2015; Reeves et al. 2021). Falling graduate employment led to non-graduate men turning to, and dying from, drugs, alcohol, and suicide -

actual rise in pensioner poverty (Bourquin et al. 2019a)

**Figure 1.2: Employment Rates for Graduate and Non-Graduate Men and Women**


Source: Labour Force Survey Years: 1979, 1984, 1990, 1995, 2000, 2005, 2007, 2010, 2015, 2019

**Figure 1.3: UK Inter-regional Inequality**




Source:Geary and Stark (2016)

the numbers succumbing to these "deaths of despair" has doubled over the past three decades in the United Kingdom (Joyce and Xu 2019; Case and Deaton 2020). Former manufacturing areas went into decline and saw sharp large numbers of their residents leaving the labour market and then claiming disability related benefits - the numbers claiming these payments increased from 750,000 in 1979 to 3 million in the mid 1980's - it has since declined slightly to around 2.5 million today (Beatty and Fothergill 2017). The places and people negatively impacted by technological change and globalisation were the source of populist support for Trump and Brexit (Becker et al. 2017; Colantone and Stanig 2018; Baccini and Weymouth 2021).

In this thesis, I analyse the causes and consequences of rising inequality within one advanced economy, the United Kingdom. While this thesis addresses important gaps in the academic literature, it also contributes to a deeper question. If the fundamental aim of a political community is, as Aristotle stated, to guarantee a *"good life"* for its citizens, then why do the richest countries in the world not achieve this for all their citizens? (Lloyd 1968; Aristotle 1998). Why are some citizens seeing an absolute decline in their welfare? Why are they killing themselves in greater numbers? Why have they turned away from stable, democratic systems? And how do we address this? Beyond this thesis' academic contribution, I also hope that it will provide policymakers, politicians, and campaigners some answers to these questions.

This is a multidisciplinary, quantitative thesis that draws from economics, political science, psychology, and social policy to fill important gaps in the literature regarding redistribution, job tasks, and well-being in advanced post-industrial economies. Regarding redistribution, it is well known that left-wing governments redistribute to the poor and vice versa (Allan and Scruggs 2004). But why have poor pensioners been far better protected than poor children? Non-graduate men have seen their employment rates fall as they are less adept at performing the job tasks required in the post-industrial economy (Black and Spitz-Oener 2010; Cortes et al. 2017). But why are they less adept at performing these job tasks than women? Within advanced economies, living in a more deprived areas leads to worse health outcomes, fewer friendships, and lower political participation (Layard 2005; Cho and Rudolph 2008; Dolan et al. 2008; Mullainathan 2013; Mood and Jonsson 2016; Victor and Pikhartova 2020; Chyn and Katz 2021). But how do the places people live in affect these outcomes? In this thesis, I provide some answers to these questions by examining one advanced economy in detail, the United Kingdom.

By analysing one advanced economy, I am able to use detailed microdata that is unavailable at the cross-country level to analyse these causes and consequences of rising income inequality. Given that automation and globalisation were common shocks that led to divided political coalitions and increased income and spatial inequality across advanced economies, it is likely that thesis' findings would generalise across them (Lupu and Pontusson 2011; Georgiadis and Manning 2012; Atkinson 2015; Alt and Iversen 2017; Iversen and Soskice 2019; Carrascal-Incera et al. 2020). Confirmation of this will, of course, have to wait for future research and I return to this issue in more detail within Chapter 5. In addition, important measurement and methodological advances are made in this thesis. I now turn to discuss the substantive academic contributions of each chapter.

**Academic Contribution**

In Chapter 2, *Mo' Votes, Mo' Money*, I analyse a political cause of income inequality - redistribution. There is a rich literature that analyses why governments redistribute less (or more) from the rich to the poor (e.g. Meltzer and Richard (1981); Iversen and Soskice (2006); Georgiadis and Manning (2012)). But current explanations focus only on redistribution from rich to poor and miss the more complex redistribution that now takes place - across the OECD, redistribution now favours the old and, consequently, poverty has shifted from pensioners to young adults (Scruggs et al. 2017; Iversen and Goplerud 2018; OECD 2019). Voter coalitions have also become more complex, and are no longer defined solely by income, but also by other dimensions such as age (Dalton 2014; Bell and Gardiner 2019).

The major contribution of this chapter is to provide an explanation for this more complex type of redistribution and then test it. I use the insight from distributive politics literature to provide a link from voter choices to redistribution - that governments will redistribute more to electorally important groups that can help them win the next election (Cox and McCubbins 2010). Electoral Importance here is measured as the proportion of a group that votes for the winning party. Group size makes no difference to Electoral Importance - the marginal impact of a pound per person on voting outcomes is invariant to group size (Dixit and Londregan 1996). Redistributing more to a larger group may get a government more votes but also costs them more money.

This chapter also makes methodological advances to the literature. Using detailed micro-data from a single country, the United Kingdom, allows me to measure Electoral Importance of these more complex, multidimensional groups (such as low-income pensioners).[2] I then use a static microsimulation model that allows me to isolate the impacts of redistribution abstracting demographic and behavioural changes. This is, as far as I am aware, the first time such a model has been used in either political science or political economy (EUROMOD 2021). Finally, this is the first robust empirical test of the distributive politics literature within an advanced economy. Current tests analyse which places governments target for extra expenditure, but they cannot assess which groups are being targeted within a given area (Golden and Min 2013; Albertus 2019).

I find that UK governments between 2005 and 2019 redistribute significantly more to groups that are more electorally important. A standard deviation (between 10 and 17 percentage points) increase in the proportion of a group voting for the winning party leads to between £237 and £458 more a year in redistribution, which represents between 1.3% and 2.6% of average incomes. Generally speaking, low-income groups voted for New Labour in

[2]The current comparative literature, for example, is hamstrung by using a measure of redistribution (the difference between the market and disposable gini coefficients) that can only analyse redistribution between the working-age rich and working-age poor e.g. Iversen and Soskice (2006)

1997 and high-income groups voted for the Conservatives in 2010. After conducting a back-of-the envelope indicative counterfactual calculation, I find both inequality and poverty would been lower if the Labour Government remained in power after 2010.

When, however, we take into account the more complex voter coalitions and redistribution that now take place, a more nuanced picture appears. Low-income parents were far less likely to vote for the Conservatives than they were for New Labour. This led to a substantial rise in child poverty after 2010 - my counterfactual calculation indicates that 260,000 fewer children would be in poverty had New Labour remained in power. However, low-income pensioners were about as likely to vote for the Conservative-led government in 2010 as they were for Labour in 1997. Pensioner poverty would have remained stable. Encouragingly, the results of this counterfactual calculation are consistent with the actual evolution of poverty in the United Kingdom - child poverty is rising while pensioner poverty is broadly stable (Bourquin et al. 2020; DWP 2021).

Chapter 3, *No Country for Non-Graduate Men*, analyses an economic cause of rising income inequality - declining employment rates for non-graduate men. Automation and globalisation have made it harder for non-graduate men to find work as the demand for job tasks changed (Górka et al. 2017; Binder and Bound 2019; Wolcott 2021). There has been a fall in demand for manual tasks that were performed by non-graduate men in the manufacturing sector as well as a rise in demand for analytical and interactive tasks that are complemented by automation and globalisation (Cortes et al. 2017; Deming 2017; Charles et al. 2019).

A growing literature links adult labour market outcomes, such as pay and employment, to the skills people possess as children and adolescents (Heckman et al. 2006; Lindqvist and Vestman 2011; Kautz et al. 2014). A smaller literature also links these childhood and adolescent skills to adult job tasks (Borghans et al. 2014; Weinberger 2014; Górka et al. 2017). However, this literature has been limited to analysing only certain skills and their effect on certain job tasks.

My major contribution to this literature is to analyse the effect of childhood and adolescent cognitive, emotional-health, perseverance, and social skills on the range of adult job tasks set out in Autor et al. (2003) that is used widely in the literature (e.g. Goos et al. (2014)). As expected, cognitive skills have a strong, positive impact on high-pay interactive and analytical tasks. I also find that greater emotional-health skills in childhood (but not adolescence) lead to individuals performing more analytical and interactive job tasks as adults. This may be due to the importance of emotional-health skills for later cognitive and social development (Donati et al. 2021). Happy kids learn more. And kids who learn more, earn more.

I also find, unlike the current literature, that social skills are not related to adult interactive tasks (Borghans et al. 2014; Weinberger 2014). This appears to be because the current literature suffers from an omitted variable bias - they do not properly account for emotional-health and perseverance skills. When I drop measures of emotional-health and perseverance, I then find that social skills do have a positive impact on adult interactive tasks. This demonstrates the importance of accounting for the full range of skills and job tasks as I do in this chapter.

The least-skilled boys have lower cognitive, emotional-health, perseverance, and social skill levels than the least skilled girls in both childhood and adolescence. I conduct illustrative back-of-the-envelope calculations to estimate how job tasks and employment outcomes would change if the least-skilled men had the same skill levels as the least-skilled girls in childhood and adolescence. I find that the least-skilled boys would perform more high-pay analytical and interactive job tasks as well as see their employment rates rise by 2 to 3 percentage points.

Finally, in Chapter 4, *Familiar Faces, Worn Out Places*, I analyse the consequences of rising spatial inequality on well-being outcomes. The major contribution of this chapter is to analyse the effect of place prosperity at different spatial scales on a wide range of well-being outcomes. Specifically, I measure the effect of granular neighbourhoods and larger labour markets on well-being outcomes. The current literature treats place as a homogeneous category that has consistent effects at different spatial scales, usually labelling them (misleadingly) as *place* or *neighbourhood* effects (Cho and Rudolph 2008; Hooghe et al. 2011; Ludwig et al. 2011; Sharkey and Faber 2014; Sørensen 2016; Bernasco et al. 2017; Chetty and Hendren 2018a,b; MacDonald et al. 2020; Petrović et al. 2020).

This is an oversight as places affect individuals through different mechanisms that differ between spatial scales. Larger labour markets improve outcomes through their effect on potential incomes while granular neighbourhoods affect people through social-interactive mechanisms (Galster 2012; Sharkey and Faber 2014; Petrović et al. 2020; Chyn and Katz 2021; Petrović et al. 2022). The small, but growing, literature that does differentiate between different spatial scales tends to only analyse one well-being outcome as well as only focus on differences at granular spatial scales (with populations of less than 10,000) (Propper et al. 2005; Bolster et al. 2007; Brattbakk 2014; Duncan et al. 2014; Graif et al. 2016; Knies et al. 2021; Petrović et al. 2022).

I use Sen's Capability Approach as an organising framework to select a broad range of well-being outcomes that make up a good life. In practice, the list of outcomes selected is similar across multidimensional indices of well-being and it would make little difference which was used (Decancq et al. 2015; Vizard and Speed 2016; Alkire and Kovesdi 2020). The two advantages of using the Capability approach as an organising framework are: 1) that it is designed to incorporate the full breadth of the human experience that makes up a *good life* such as health, happiness, friendship, safety, etc. - rather than arbitrarily equating well-being with a single mental state such as Subjective Well-Being and 2) it requires choosing ends we value rather than means to get them such such as income (Sen 1979, 2001; Aristotle 2004; Robeyns and Byskov 2020).

I analyse the impact of place-based prosperity at both the larger local labour market and granular neighbourhood levels using linked individual-area data. In addition, I use spatial lag measures to account for the prosperity of the surroundings areas, which is often overlooked in the current literature (Fischer and Wang 2011; Grubesic and Rosso 2014; Petrović et al. 2022). I then test the effect of place-based prosperity on well-being outcomes using individual fixed-effect regressions and event studies.

I find that place effects do differ between spatial scales. Labour market prosperity directly improves financial security, physical security and friendship. It also indirectly improves other well-being outcomes by providing better employment prospects and higher potential incomes. More prosperous neighbourhoods lead to greater overall well-being as well as better physical security. Personal income also has a strong effect on well-being outcomes. Place effects can be large - moving to a more prosperous area can have greater effects than having an extra £1,000 in income. Finally, I find that greater personal income, neighbourhood prosperity, being employed before the age of 60, and not losing one's job also increases life expectancy.

## Policy Implications

The policy implications from this thesis for reducing inequality and increasing well-being as well as, more broadly, creating the *good life* for all citizens in advanced economies are as follows.

From Chapter 2, the maximum value that Electoral Importance of any group can take is the proportion who actually vote. In 2010, the turnout gap between high- and low-income voters, as well as between pensioners and under-35s, was over twenty percentage points (Gardiner 2016; Goodwin and Heath 2019). Increasing voting rates for non-pensioners and those on low-incomes should help to increase their Relative Electoral Importance and so the redistribution going toward them. By contrast, measures that make it harder for those on low-incomes to vote, such as compulsory voter ID, is likely to lead to increases in inequality and poverty.

Chapter 3 shows that cognitive and emotional-health skills, in particular, are important for ensuring that adults are able to undertake higher-paying jobs. Children need a warm, nurturing environment with stimulating activities to foster these skills (Putnam 2015). And for parents to provide that warm, stimulating environment that will foster these skills in their children, they need to have enough money (Cooper and Stewart 2021). More money gives parents the material *and* psychological resources to invest in their children - social security transfers to low-income parents do more than alleviate short-term poverty, they also reduce parental stress, giving them more time and energy to invest in their children (Mullainathan 2013; Cooper 2017). Early education and childcare schemes also help to develop childhood skills (Heckman et al. 2013; Stewart 2013). In addition, as these effects show up by age 7, these results indicate interventions should begin from the very earliest ages.

Chapter 4 shows that improving place-based prosperity at different spatial scales is needed to improve a wide range of well-being outcomes. In particular, place-based policies need to be targeted at both labour markets *and* neighbourhoods. Measures that improve personal- and place-based prosperity are also particularly important for less-skilled workers who cannot gain high-pay jobs nor move to more prosperous areas where wages and housing costs are higher (Autor et al. 2006; Moretti 2013; Amior 2015). Measures to stimulate local labour markets will directly improve financial security, friendship, and physical safety as well as indirectly improve other well-being outcomes by raising potential incomes. Increasing neighbourhood prosperity will improve personal safety and overall well-being. Social security transfers that directly increase the personal incomes of those who cannot gain high-skill jobs in the postindustrial labour market will also improve most well-being domains. Finally, as death rates are lower with higher personal incomes and better employment outcomes, this chapter provides indicative evidence that stimulating local labour markets will also reduce deaths of despair (Sullivan and Von Wachter 2009; Dow et al. 2020).

## COVID-19 and the findings in these thesis

I close briefly with a discussion regarding the implications of COVID-19 for redistribution, male employment, and spatial inequality in light of the findings of this thesis. It is worth asking whether the findings of this thesis hold given the huge societal changes wrought by the worst pandemic in a century (Barry 2004).

The COVID-19 pandemic is the most severe shock humankind has experienced since the Second World War. This included large shocks to redistribution, working, and spatial inequality. In advanced economies, governments massively expanded redistribution to those on low-incomes (Kleider and Sandher 2020). Most workers either had to stop working or had to work from home in order to reduce social interaction (Adams-Prassl et al. 2020). As graduates who previously worked in major city centres like London could work from home, this also led to a geographic reallocation of work away from city centres (De Fraja et al. 2021). What implications do these shocks have for the analysis in this thesis?

In short, the findings from this thesis still hold even in the wake of the COVID-19 pandemic and its dramatic societal impacts. The forces described in this chapter remained and have, in some cases, even been strengthened by the impacts of COVID-19. I focus here on the United Kingdom in particular. Firstly, while redistribution did increase to those on low-incomes, it has since been scaled back. It is now only the working poor that benefited, and this increase did not compensate for post-2010 cuts. In addition, non-pensioners on the lowest incomes (i.e. those least likely to vote Conservative) saw the largest cuts (Brewer et al. 2021). Secondly, interactive and analytical job tasks increased in importance as manual tasks could not be performed from home. Non-graduate men were the most likely to lose their jobs during the pandemic because they performed more of these manual job tasks and they were less likely to be Key Workers than non-graduate women (Sandher 2021). Finally, when it comes to spatial inequality, economic activity in city centres did decline but this did not entail a reallocation toward more deprived areas. High-skilled graduates relocated to the suburbs and the vast majority (80%) still want to work in city centre for at least one day a week (De Fraja et al. 2021; Taneja et al. 2021).

## Thesis Outline

The rest of this thesis proceeds as follows. In Chapter 2, I analyse how UK governments redistribute to more complex groups and how this impacts inequality. Chapter 3 analyses the effect of childhood and adolescent skills on adult job tasks and employment. Chapter 4 covers the effects of interpersonal and interspatial inequality on well-being. I finally conclude in Chapter 5, with a brief summary of the main findings in this thesis, its limitations, as well as possible directions for future research.

# Chapter 2

# Mo' Votes, Mo' Money: Relative Electoral Importance, Multidimensional Redistribution and Income Inequality in the United Kingdom (2005 – 2019)

**Abstract**

Governments can use taxation and social security payments to buy votes. I argue that governments redistribute to electorally important groups defined by multiple dimensions (such as age, parental status, and income), and that this multidimensional redistribution helps explain the evolution of income inequality and poverty. I measure Electoral Importance as the proportion of a group that votes for the government and isolate the impact of redistribution from behavioural and demographic changes. Using a difference-in-differences method, I find that governments within the United Kingdom redistribute more to electorally important groups after changes in power, and that this multidimensional redistribution also has a significant impact on income inequality. The multidimensional perspective analysed here also explains patterns of redistribution that the standard unidimensional income perspective, which analyses transfers solely between rich and poor, cannot. It can help explain why child poverty rose after the 2010 election but pensioner poverty did not.

# I INTRODUCTION

Redistribution determines the final income of voters and, subsequently, has a powerful impact on a government's chances of being re-elected (Atkinson 2015; Tilley et al. 2018). Governments do not, however, only redistribute between the rich and poor in order to retain power. I show they engage in more subtle types of redistribution from, for example, low-income non-pensioners to middle-income pensioners. This chapter constitutes the first test of this more precise explanation of redistribution.

The major contribution of this chapter is to test whether the electoral power of politically salient voter groups, which are defined by multiple dimensions beyond income, can explain changes in redistribution within advanced democracies. I find that changes in the electoral importance of multidimensional groups has an economically significant impact on redistribution and, subsequently, the evolution of income inequality and poverty. I also find that multidimensional redistribution explains patterns of redistribution that the standard unidimensional (between rich and poor) perspective cannot.

Current explanations of redistribution focus on explaining unidimensional redistribution between the rich and poor. They range from showing how preferences (Georgiadis and Manning 2012; Margalit 2013; Alt and Iversen 2017), partisanship/ideology (Allan and Scruggs 2004; Hopkin and Alexander Shaw 2016; Bartels 2018), and (changing) electoral coalitions (Iversen and Soskice 2006; Pontusson and Rueda 2008; Lupu and Pontusson 2011; Elkjær and Iversen 2020) have driven political changes to social security and taxation policies.

These explanations do not, however, consider how changes in preferences are translated to changes in policy nor why partisanship/ideology has changed over time. This literature also does not consider multidimensional redistribution between, for example, low-income non-pensioners and low-income pensioners (Iversen and Soskice 2006; Lupu and Pontusson 2011; Bell and Gardiner 2019). Redistribution between multidimensional groups appears to be an increasingly important phenomenon across advanced economies where, *"poverty has* *shifted from the old, who used to have the highest incidence of poverty rates, to young adults"* (OECD 2019, p.188). This shift away from pensioner poverty is not, however, explained by a mechanical ageing of the electorate itself, which has little effect on public pension generosity (Tepe and Vanhuysse 2009; Chrisp and Pearce 2019). Another mechanism appears to be at play.

To explain changes in redistribution that addresses these omissions in the literature, I use the core insight from the distributive politics literature - that governments use redistribution to buy votes and win elections (Dixit and Londregan 1996; Golden and Min 2013). They do so by redistributing more (through social security payments and taxation) to groups from whom a given transfer will buy more votes – what I refer to as Relative Electoral Importance. If political parties within advanced democracies, *"think about electoral mobilisation and conversion in terms of identifiable social groups"* (Bartels 1998, p.56) then it is natural for them to also redistribute more to those groups who will help them win the next election.

Groups can be defined by multiple dimensions, allowing for redistribution between, for example, multidimensional income-age groups (such as from low-income non-pensioners to middle-income pensioners). These dimensions must be both politically salient and feasible to target through the taxation and social security system to have an impact on a government's redistributive choices. Identifying who the politically salient multidimensional groups are and testing whether governments redistribute more to them requires both knowing the stated intentions of leading politicians within a nation as well as microdata that can identify these groups and the amount of redistribution they receive. In this chapter, I analyse multidimensional redistribution within the United Kingdom and the methodology described here can, and I hope will, be extended to other advanced democracies.

Within the United Kingdom, the evidence indicates that groups were constructed along three dimensions - income, age and parental status. The Blair and Brown governments promised to end child and pensioner poverty but not all poverty (Blair 1999; Brown 2002). The existing literature shows that the New Labour government favoured low-income families with children and pensioners for redistribution while subtly raising taxes on those with higher incomes (Phillips and Browne 2010; Hills 2013). Child and pensioner poverty subsequently fell while working-age non-parent poverty actually rose. In the face of rising earnings inequality, this led to income inequality remaining stable (Belfield et al. 2016). The New Labour Government did not aim to redistribute to all of those on low-incomes as a unidimensional account of redistribution would suggest.

The post-2010 Conservative-led governments favoured a different set of groups for redistribution: higher income families and pensioners (Snowdon and Seldon 2016; Laws 2017) This led to a rise in child and working-age poverty but pensioners saw their poverty rates remain stable (Browne and Elming 2015; De Agostini et al. 2018; Bourquin et al. 2019b). A key contribution of this chapter is to explain these patterns of redistribution that unidimensional accounts, which focus only on rich to poor, miss.

Using data from the British Household Panel Survey/UK Household Longitudinal Study, I measure the Relative Electoral Importance of a group as the proportion who votes for the winning party/parties relative to all other groups when a new government comes to power. Redistribution is measured using the UKMOD tax and benefit static microsimulation model, which allows for the identification of the direct policy impact of changes to redistribution without confounding changes in behaviour or the underlying population (Sutherland and Figari 2013). This is the first time such a model has been used to evaluate questions in either political economy or political science.

Using a difference-in-differences method, I find that changes in Relative Electoral Importance had an economically and statistically significant impact on redistribution directed toward multidimensional groups after the change in government at the 2010 election. There is indicative evidence that this result also extends to the 1997 election. A one standard deviation increase in Relative Electoral Importance for a group led to an increase of between £237 and £458 per person per year in redistribution after 2010, which is equivalent to between 1.3% and 2.6% of mean disposable income.

As poorer multidimensional groups saw their Relative Electoral Importance fall at the 2010 election, this also led to a subsequent rise in disposable income inequality and poverty. Indicative back-of-the envelope calculations indicate that the Gini coefficient would have been between 0.7 and 1.2 points lower and between 784,000 and 1.223 million fewer people would be in poverty had there been no change in government in 2010.

I also test whether governments engage in multidimensional, rather than solely unidimensional, redistribution. I find that differences between uni- and multidimensional Relative Electoral Importance are associated with significant differences in subsequent redistribution between uni- and multidimensional groups. This multidimensional perspective explains why some low-income groups (i.e. pensioners), saw no rise in poverty rates after 2010 while others (i.e. children) did. Accounting for multidimensinonal redistribution, I find that child poverty rates would have been around 2 percentage points lower (equivalent to 260,000 children) while pensioner poverty rates would be 0.2 percentage points lower had Labour remained in power after 2010. Encouragingly, this counterfactual exercise is consistent with the evolution in actual poverty rates - child poverty rose while pensioner poverty remained largely stable (Bourquin et al. 2019a; DWP 2021).

The remainder of this chapter proceeds as follows. The literature review sets out the gap in current explanations of redistribution as well as its importance for understanding income inequality, how governments use redistribution to retain power, and which multidimensional groups governments in the United Kingdom redistributed to. Following this, I describe the data to be used and the measurement of the key variables – Relative Electoral Importance and Relative Redistribution. I then move on to the empirical analysis and close with a discussion of the main results and their implications for future research.

# II REDISTRIBUTION AND INCOME INEQUALITY

Current explanations of redistribution in the literature are extensive but incomplete. The canonical Meltzer-Richard model of redistribution shows how the median-income voter chooses a level of unidimensional redistribution from rich to poor that rises with income inequality. This canonical model cannot, however, explain why governments of different partisan hues choose different levels of redistribution and the empirical support for it is, at best, mixed (Meltzer and Richard 1981; McCarty and Pontusson 2011; Foerster and Tóth 2015; Iversen and Goplerud 2018).

More recent explanations point to declining support for redistribution due to secular economic changes (Georgiadis and Manning 2012; Margalit 2013; Beramendi and Rehm 2016; Alt and Iversen 2017). These explanations do not, however, show how, when or to what extent these individual preferences are transmitted to policy decisions. Other explanations fall into the "black box" category showing that phenomena such as partisanship (Allan and Scruggs 2004; Bartels 2018) or ideology (Hopkin and Alexander Shaw 2016) could be responsible for changes in redistribution. These explanations, however, require a further explanation of why governments of a particular party/ideology redistribute more to certain individuals and why their redistributive strategies have changed over time.

The comparative literature that seeks to explain why political parties choose different redistributive strategies (over time) provides a more complete mechanism by connecting voter preferences to electoral coalitions and government decisions. This literature finds that factors such as electoral rules (Iversen and Soskice 2006, 2015), low-income turnout (Pontusson and Rueda 2008), and the skew in wage inequality (Lupu and Pontusson 2011) has an effect on redistribution through their impact on the groups of voters who elect governments of different partisan hues. This comparative literature is, however, limited as the the dependent variable used (the difference between the market and net Gini coefficients) only allows the examination of unidimensional, progressive redistribution from the working-age rich to the working-age poor.

This type of redistribution is less relevant today when voter coalitions are not defined solely by the single dimension of income but also include others such as age (Dalton 2014). This is an increasingly important feature of redistribution across advanced economies. Between 1990/1991 and 2010/2011, minimum public pension payments became relatively more generous than unemployment payments in 15 out of 20 OECD nations (Scruggs et al. 2017) and *"poverty has tended to shift from people aged over 65 to people aged 18 to 25"* (OECD 2019, p.186) across advanced economies. Within the United Kingdom the, *"emergence of age-based divisions has eroded, and partially replaced ....class"* (Bell and Gardiner 2019, p.3). The word, *"partially,"* is key here - there is still an income gradient for voting patterns and redistribution within age groups, and this multidimensional perspective is omitted from current accounts that focus only on the single dimension of age or income (Tepe and Vanhuysse 2010; Chrisp and Pearce 2019). Governments can redistribute to any group that can be targeted using the taxation and social security system and there is no *a priori* reason these groups need be defined solely by income or age (or any other dimension).

Understanding these changes in multidimensional redistribution is also crucial for understanding the evolution of income inequality and poverty in advanced democracies. Disposable income, and therefore disposable income inequality, is made of up two components: market income (earnings and investment income), and redistribution (social security payments minus taxation payments). Market income inequality had been rising across advanced economies in the two decades leading up to the Great Recession, largely due to the secular economic forces of technological change & globalisation (mediated by labour market institutions) (Autor et al. 2006; OECD 2011; Goos et al. 2014; Atkinson 2015; Hope and Martelli 2019; Nolan and Valenzuela 2019).

Redistribution either exacerbated or ameliorated these secular economic forces and, in most advanced economies, income inequality rose as redistribution did not fully offset the secular rise in market income inequality (Atkinson 2004; OECD 2011; Nolan and Valenzuela

2019).

Within the United Kingdom, for example, Thatcher's changes to redistribution were responsible for most of the dramatic rise in inequality during the 1980's, exacerbating the existing trend of rising earnings inequality (Johnson and Webb 1993; Atkinson 2004). The redistributive policies of New Labour ameliorated the trend of rising market income inequality so that disposable income inequality remained stable between 1997 and the Great Recession (Brewer and Wren-Lewis 2016; Belfield et al. 2017). By contrast, declining market income inequality in the wake of the Great Recession did not lead to falls in disposable income inequality because of changes to redistribution implemented by the post-2010 Conservative-led governments (Hood and Waters 2017).

In order to understand these changes in redistribution and income inequality, we need to go, *"beyond purely economic explanations and look for an explanation in the theory of public choice or political economy"* (Atkinson 1997, p.315). This chapter tests such an explanation from distributive politics.

# III WHY DO GOVERNMENTS REDISTRIBUTE MORE TO CERTAIN GROUPS?

In formal models of distributive politics, political parties unambiguously redistribute more (or promise more redistribution) to groups where a given transfer "buys" more votes – what I define as Relative Electoral Importance (Cox and McCubbins 2010; Golden and Min 2013). This literature is ambiguous, however, regarding how Relative Electoral Importance should be evaluated – some models predict that core groups receive the most (Cox and McCubbins 1986), others that swing groups will be favoured (Lindbeck and Weibull 1987; Dixit and Londregan 1996), while further models also incorporate turnout (Bartels 1998; Cox and McCubbins 2010).

The empirical distributive politics literature tends to analyse how governments use area-based public expenditure to buy votes. A consistent finding in this literature is that governments target expenditure at places that are electorally important to them in a form of "pork-barrel" politics (Golden and Min 2013). The UK-based literature finds that British governments tend to direct this area-based expenditure to marginal areas, with some evidence that governments direct more funding to swing seats where they are in power in an attempt to hold on to them (Ward and John 1999; John and Ward 2001; Golden and Min 2013; Bertelli et al. 2014; Fouirnaies and Mutlu-Eren 2015; Hanretty 2021). Governments can and do direct area-based expenditure toward places that will help them win the next election and this should be viewed as one of the tools they can use to win votes (Kramon and Posner 2013). It is likely that governments also direct individual-based redistribution to groups that are more electorally important for them, something that this chapter aims to assess. Area-based expenditure and individual-based redistribution should be seen as complementary rather than competing explanations of vote buying behaviour. This is covered further in this section below as well as in the Discussion and Conclusion of this chapter

Current empirical tests of the distributive politics literature that purport to assess who rather than where governments redistribute to are, however, flawed. To my knowledge, every empirical test of distributive politics within advanced democracies suffers from the ecological fallacy – they try to make inferences about whether governments target "core" or "swing" voters by testing which areas, rather than which people, are targeted for extra redistribution (Ward and John 1999; John and Ward 2001; Bertelli and John 2010; Cox and McCubbins 2010; Golden and Min 2013; Bertelli et al. 2014; Fouirnaies and Mutlu-Eren 2015; Albertus 2019). This leads to incorrect inferences as political parties could be targeting core voters within marginal constituencies in order to gain votes. Where individual data has been used to test theories of distributive politics, it has been in developing nations where it is easier to monitor individual votes and/or clientelist rewards given to individual voters (Stokes 2005; Guardado and Wantchekon 2018; Albertus 2019).

Governments may not differentiate between core and swing voters when evaluating Relative Electoral Importance given the rise in voter volatility. In the UK, for example, volatility in partisan identification and vote choice is high and rising - between 1998 and 2008, around a 1/3 of those who identified with a party stopped supporting them and there has been a fourfold increase (5% to 20%) who did not identify with any party between 1964 and 2015 (Dalton et al. 2011; Kuhn 2013; Sanders 2017). Core voters are better viewed as latent swing voters who stop supporting parties when they stop catering to their economic interests (Clarke et al. 2004; Kuhn 2013; Whiteley et al. 2013). By 2010, around a 1/3 of voters switched parties between elections and this figure has since risen (Mellon 2016; Ford and Sobolewska 2020). Given the weakness and volatility of partisanship & vote choice, governments in the United Kingdom may simply evaluate Relative Electoral Importance through voting behaviour and reward the electoral coalition that brought them to office in order to retain power.

The Relative Electoral Importance of different groups is likely to have a significant impact on redistribution because taxation and social security policies are the most powerful distributive policy tools that a government can use to buy votes. Voters are only more likely to vote for the incumbent when their income rises *if* this growth can reasonably be attributed to government decisions - the traditional finding in the literature that sociotropic assessments of economic performance have a much larger impact than egotropic ones should be reinterpreted with this in mind (Anderson 2007; Healy and Malhotra 2013; Lewis-Beck and Stegmaier 2013). Sociotropic assessments have a greater impact on vote choice because voters are aware the government bears more responsibility for the state of the economy as a whole whereas idiosyncratic factors and personal decisions can affect their own income growth. Taxation and social security policy decisions, which have a direct impact on income growth and are solely attributable to government decisions have, therefore, a much greater impact on vote choice than income growth from other sources including area-based expenditure (Manacorda et al. 2011; Tilley et al. 2018; Harris and Posner 2019).

Area-based expenditure is likely to be far less effective than individual-level expenditure in vote buying as voters are less likely to directly benefit from it. Such expenditure leaks - it benefits a large group within a geographic area, irrespective of whether they will vote for the governing party/parties. The evidence for area-based expenditure having an effect on vote choices is at best mixed, and where positive effects are found, they are small in magnitude (Evans 2006; Golden and Min 2013; Larcinese et al. 2013; Klingensmith 2019). Area-based expenditure is also less effective in larger municipalities where voters are less likely to be directly benefit or notice such expenditure (Spáč 2021). While governments can, and the evidence indicates that they do, use area-based expenditure to buy votes, this type of redistribution is less effective than the individual based redistribution examined in this chapter.

When it comes to individual-based redistribution, poorer households always receive more than the richer ones in advanced democracies, and so it is changes, rather than levels, of Relative Electoral Importance that are important for understanding differences in redistribution (Pontusson and Rueda 2008; Dalton et al. 2011; Falkenbach et al. 2020). And governments do change redistributive policies to favour groups who are part of their electoral coalitions. Leftist governments redistribute more to the to the working-age poor, rightist governments redistribute more to the working-age rich, while middle income voters are consistently rewarded as they are part of the electoral coalitions for both (Iversen and Soskice 2006; Pontusson and Rueda 2008; Dalton et al. 2011; McCarty and Pontusson 2011; Lupu and Pontusson 2011; Elkjær and Iversen 2020; Falkenbach et al. 2020). This comparative literature does not, however, consider how governments redistribute between multidimensional groups.

A separate comparative literature on redistribution considers how ageing populations across the OECD, or increasing "grey power" may impact redistribution. It finds that societal ageing itself, however, has little effect on the generosity of individual pension payments although it does lead to an increase in the proportion of GDP devoted to pensioners in a mechanical fashion (Tepe and Vanhuysse 2009, 2010; Casamatta and Batté 2016; Vlandas et al. 2021). (Tepe and Vanhuysse 2009, p.23) note their, *"findings also point to the need* *to pry open further black boxes regarding ... the coalitions involved"*. The explanation put forward in this chapter provides a possible explanation for how voter coalitions influence redistribution toward high- & low-income pensioners & non-pensioners.

Firstly, pensioner power in the electorate may not come from their greater size, but their voting behaviour. Larger groups may have more potential votes, but they are also more expensive to buy votes from (Dixit and Londregan 1996; Vlandas et al. 2021). Redistributing the same total amount to a larger group will lead to smaller individual payments than giving that same total amount to a smaller group. In that case, how a group votes rather than its size will influence individual payment generosity.

Secondly, pensioners are not a homogeneous group. While all pensioners support higher pension payments, left-wing pensioners (who also tend to have lower incomes) are more strongly in favour of them (Busemeyer et al. 2009; Sørensen 2013; Chrisp and Pearce 2019). There are *"important social class differences amongst older voters in their welfare state preferences"* (Chrisp and Pearce 2019, p.753).

Thirdly, and relatedly, right- and left-wing parties provide different offers to high- and low-income pensioners (Kweon and Suzuki 2021). Left-wing parties are more likely to provide higher individual pension payments than right-wing parties. Individual pension generosity depends upon government partisanship, and they in turn may be responding to their own voter coalitions when deciding on the level of individual pension payments.

The grey power literature does not examine this type of multidimensional redistribution in detail - namely, how voter coalitions made up of groups defined by both income *and* age affect individual redistribution payments. That is the gap this chapter aims to fill.

## IV DOES RELATIVE ELECTORAL IMPORTANCE MEASURE GOVERNMENT PROMISES OR VOTING PATTERNS?

The discussion above indicates that governments redistribute more to salient and feasible groups that vote for them in greater numbers. These groups are electorally important and redistributing to them helps the government win the next election.

It is exceedingly difficult to disentangle the extent to which governments are delivering on the promises they made prior to an election or are responding to their voter coalitions. Governments are likely to be doing a mixture of both. Parties make promises to voters, voters respond to those promises by voting for them, and then governments make decisions on who to redistribute to based both upon their promises and who makes up their electoral coalition (Dalton et al. 2011).

Whether governments deliver on their promises and/or reward their voters is also less important than it may first appear. Voters will not vote for a government that will not serve their interests, and wanting to being materially better off is (one of) a voter's most important interests (Lewis-Beck and Stegmaier 2013). Low-income voters support left-wing parties that redistribute to them, while high-income voters support right-wing parties that cut taxes for them (Iversen and Soskice 2006; Elkjær and Iversen 2020). Similarly, governments redistribute to the groups that they made promises to and who subsequently voted for them. In the UK, governments keep over 85% of the manifesto promises they make (Thomson et al. 2017). Parties do not leapfrog each other in the ideological space when they get into office and redistribute to a wholly different set of groups they did not make promises to and who did not vote for them (Ware 1996; Dalton et al. 2011).

A group that votes in greater numbers for a government on the basis of their promises/ideology is still electorally important and the government must still deliver on their promises and redistribute to them in order to maintain power. If the government does not deliver on those promises, they will lose votes. Voters punish left-wing (but not right-wing) parties that cut welfare, suggesting that not following through with promises for an electoral coalition costs votes (Schumacher et al. 2013). Voters will also stop supporting a government when it stops making them better off, and redistribution has a particularly strong effect on voting (Manacorda et al. 2011; Tilley et al. 2018). Keeping promises to a voter coalition and ensuring their incomes grows through redistribution is also more important in today's era of declining partisanship and rising voter volatility (Dalton et al. 2011; Sanders 2017; Horn and Jensen 2017).

On this reading, Relative Electoral Importance serves as an imperfect measure of promises made prior to an election. The canonical theoretical literature on distributive politics involve prospective voting (who parties make promises to) rather than retrospective voting (them delivering to a political coalition) (Cox and McCubbins 1986; Lindbeck and Weibull 1987; Dixit and Londregan 1996). These promises then have an effect on voter behaviour, and can therefore be viewed through the prism of how they affect the voting patterns, and so Relative Electoral Importance, of different groups.

Manifestos and ideologies are also sufficiently vague to allow Governments considerable scope when choosing how to implement them, and which groups to favour, once they are elected (Bara 2005; Kang and Powell Jr 2010). And Governments do appear to pay at least some attention to the groups that vote for them beyond just their own policy promises. When it comes to low-income voters with lower turnout rates, they redistribute less than these voters would like and deliver less welfare to them than they promise (Horn and Jensen 2017; Rosset and Stecker 2019). The amount of redistribution left-wing parties promise and deliver also rises with the turnout rates of low-income voters (i.e. when their electoral importance rises) (Pontusson and Rueda 2010; Fenzl 2018). There still, however, a symbiotic link between promises and voting behaviour that is difficult to disentangle. Governments may promise and deliver less because they believe low-income voters will turn out less and/or low-income voters may not vote due to a lack of promises.

The extent to which Relative Electoral Importance serves as an imperfect measure of promises and the voter coalition to be rewarded is less important than whether governments redistribute more to groups who vote for them in greater numbers. The central focus of this chapter is whether governments redistribute more to the multidimensional groups who vote for them, and uses these voting rates as a measure of Electoral Importance. The extent to which this Electoral Importance derives from government promises or voter behaviour is less important than whether they do, in fact, redistribute more to them. The main contribution of this chapter to analyse whether governments redistribute more to electorally important multidimensional groups, irrespective of where this Electoral Importance ultimately derives from. This is missing in current accounts of redistribution, which only examine unidimensional redistribution. It is to this which I turn.

## V DISTRIBUTIVE POLITICS AND MULTIDIMENSIONAL REDISTRIBUTION WITHIN THE UNITED KINGDOM

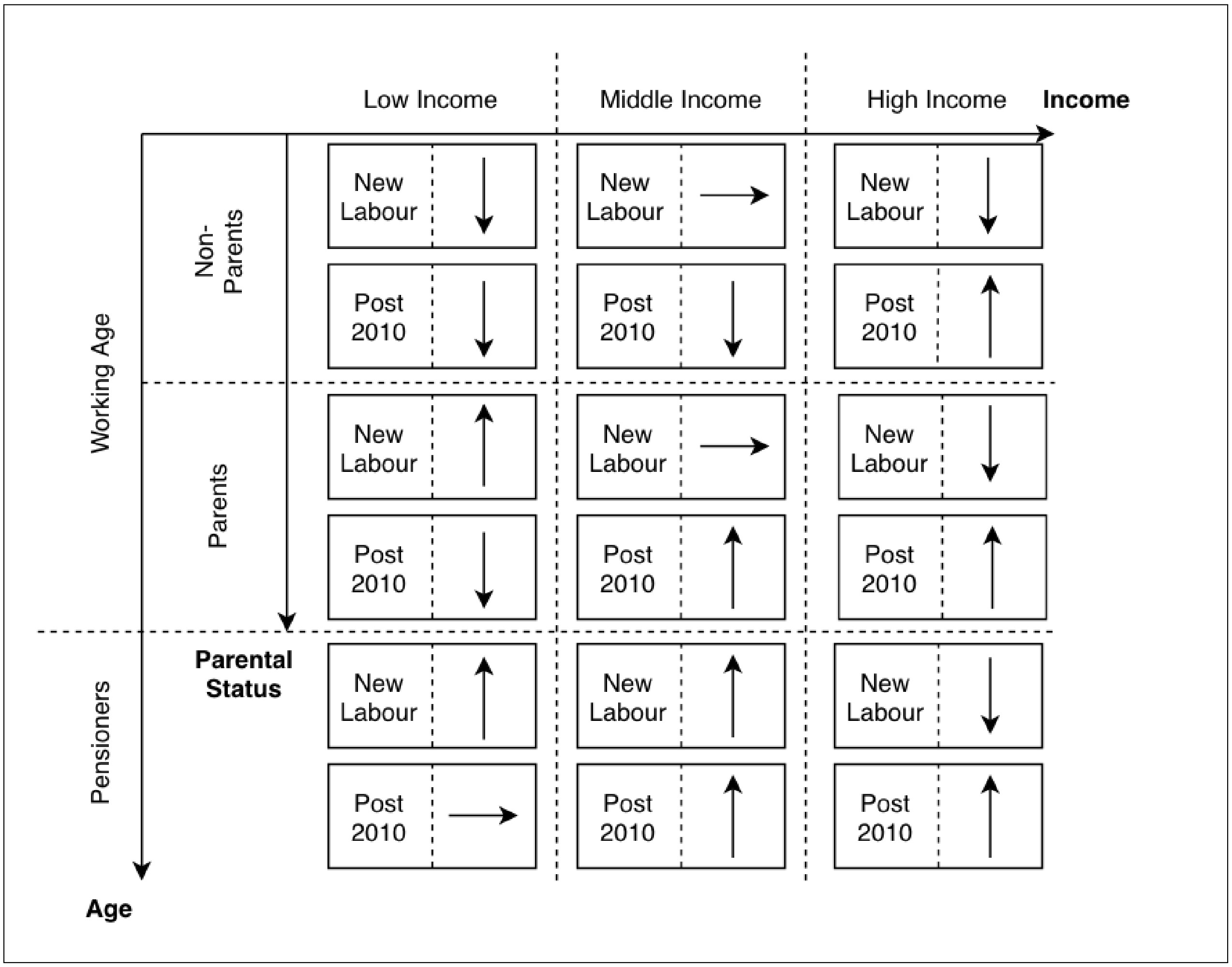
Testing how changes in Relative Electoral Importance affect multidimensional redistribution requires understanding which dimensions governing parties use to construct groups for redistribution. There are two conditions that a characteristic must meet for it to be used as a dimension for redistributive group construction: 1) feasibility and, 2) salience. The feasibility condition states that groups can only be targeted if they are defined by a characteristic used within the taxation and social security system so while income can be used to construct groups, ethnicity cannot. The salience condition is that groups must have been identified, privately or publicly, by leading government politicians as politically salient.

Within the United Kingdom, redistributive patterns as well as the expressed (private and public) intentions of leading politicians suggest the New Labour Governments of 1997 to 2010 used at least three dimensions to construct groups for redistribution - income, age and parental status; the post-2010 government then changed the redistributive transfers going to these groups. While these three dimensions appear to have been used for multidimensional redistribution within the United Kingdom, I do not claim these dimensions are exhaustive. For this chapter, the post-2010 Coalition and Conservative administrations are also viewed as being effectively one government reflecting both the power of the Conservatives in Coalition and their ability to implement policy changes over their coalition partners' wishes (Snowdon and Seldon 2016; Laws 2017).

A simplified schematic of how these three dimensions were used to construct groups, and which were favoured under both governments can be found in Figure 2.1 below, where arrows indicate whether governments increased, kept stable or reduced the relative redistribution going to each group. While the dimension of income was always used to construct groups, it was interacted with other dimensions to create multidimensional groups for redistribution. The dimensions used to construct groups and those rewarded by each party were different in preceding decades, which forces us to look further than partisanship/ideology to explain changes in redistribution (Johnson and Webb 1993; Timmins 2001; Hills et al. 2004).

As soon as the New Labour government was freed from its commitment to stick to Conservative spending plans for their first two years, they immediately began to redistribute more to low-income working age families with children (through e.g. tax credits) and pensioners (through e.g. the minimum income guarantee) while subtly increasing taxes on higher income households (through fiscal drag) (Phillips and Browne 2010; Hills 2013; Belfield et al. 2017). This was in line with their stated intentions. Tony Blair promised to, *"end child poverty,"* in his 1998 Beveridge Lecture while Gordon Brown made a similar promise regarding pensioners at his 2002 conference speech (Blair 1999; Brown 2002). Poverty subsequently fell for both groups – but actually rose for working-age families without children because their aim was to end *child* and *pensioner* poverty, not *all* poverty. Income inequality remained

**Figure 2.1: Multidimensional Redistribution under the New Labour & Post-2010 Governments**




Upward arrows indicate s group received more relative redistribution, sideward arrows that they received similar levels of relative redistribution, and downward arrows that relative redistribution fell. Sources: Hills (2013); Belfield et al. (2017); De Agostini et al. (2018), & Author's calculations using UKMOD 2005 - 2019 largely stable as this redistribution offset rising earnings inequality.

From their first budget, the post-2010 Governments redistributed more to high-income working-age people and pensioners while cutting social security payments for low-income non-pensioners (Browne and Elming 2015; De Agostini et al. 2018; Bourquin et al. 2019b). The immediate changes that took effect in 2011 were to increase the personal allowance (benefit higher income individuals), bringing in the Triple Lock for pensions (benefiting pensioners), and uprating social security payments with CPI rather than RPI (hitting those on lower incomes). These had the immediate effect of reducing relative redistribution going to those on low-incomes and increasing to those on high incomes as well as pensioners. From April 2012, tax thresholds would increase in line with CPI rather than RPI, representing a relative rise in redistribution for higher income individuals in that year and beyond (Joyce and Levell 2011).

Other more substantial change took effect in 2013 with the reduction of the top income tax rate (benefiting higher income individuals), the introduction of the benefit cap (hitting lower income individuals), and uprating social security payments below inflation. Even more extreme measures were brought in after 2015 with the nominal freeze of social security payments (Hills 2015; De Agostini et al. 2018; McEnhill and Taylor-Gooby 2018)

This was despite the Liberal Democrats aim being to, *"ensure that the burdens of austerity did not fall on those . . . with the lowest incomes"* (Laws 2017, p.36), indicating that the Conservatives were the dominant party in this coalition. Nick Clegg, the Deputy Liberal Democrat Deputy Prime Minister, stated that David Cameron, the Conservative Prime Minister, *"had very little sympathy [for] people on very low incomes, and [wrote] them off politically as 'not our voters'"* (Laws 2017, p.98). The Conservative Chancellor of the Exchequer (Finance Minister), George Osborne, had a clear and stated aim to move the UK from a *"high tax, high welfare economy; to . . . [a] lower tax, lower welfare country"* – a measure that usually benefits those on high incomes while harming those on low incomes (Korpi and Palme 1998; Marx et al. 2015; Osborne 2015).

However, the Conservatives did not intend to hit everyone on low incomes with their redistributive changes. The Conservatives made it clear to civil servants, *"that they will not touch pensioners"* (Snowdon and Seldon 2016, p.39) because they *"regarded the older population, with its high propensity to vote, as a key electoral target"* (Laws 2017, p.100). They brought in the Triple Lock for pensions that ensured the state pension rises by the highest of prices, earnings, or 2.5 %. This stands in stark contrast to working age social-security payments that were cut or frozen in real terms (Gardiner and Rahman 2018). They did, however, cut pension credit in real terms, a social security payment that goes only to the poorest pensioners, which were also the only group of retirees were less likely to vote for them New Labour in 1997. Overall, this led to rising child poverty but stable pensioner poverty. Income inequality, however, remained broadly stable after 2010 due to the fall in earnings inequality (Hood and Waters 2017; Bourquin et al. 2019b, 2020; DWP 2021).

Strikingly, the groups targeted differed between the Thatcher/Major governments and the post-2010 Conservative-led governments. The Thatcher government engaged in uni-dimensional redistribution, reducing redistribution for all those on low incomes including pensioners. Taxes were cut and social security payments were frozen (or cut) in real terms (Timmins 2001). This is unsurprising given that Thatcher clearly stated when she came to office that she did not believe that the government should , *"take money in taxes from those who work hard and pay it out to those who don't"* (Thatcher 1980). The pattern of income growth mirrored her intention. Both child and pensioner poverty grew while inequality also dramatically increased (Johnson and Webb 1993; Hills et al. 2004; Sandher 2019). Pension payments were cut after a decade in which the old-age dependency ratio had increased by 15%, which is consistent with the evidence on grey power presented above. Societal ageing itself is not the cause of more generous pension payments to the old.

The preceding discussion shows that groups were constructed along at least three dimensions in the UK following the 1997 general election - age, income and parental status – and I construct groups using these dimensions in the empirical analysis below. It also shows how these dimensions could differ through time. I do not claim these dimensions are exhaustive, merely that they are that are easily identifiable. The preceding discussion also shows that UK Governments have set the direction of redistribution when they first came to office rather than dramatically adjusting the groups to be rewarded after each general election.

I now turn to the hypotheses to be tested.

# VI HYPOTHESES

There are two hypotheses to be tested in this chapter. The first hypothesis tests whether changes in Relative Electoral Importance have an impact on subsequent redistribution and the evolution of income inequality. The second hypothesis tests whether governments engage in multidimensional, as opposed to solely unidimensional, redistribution.

**Hypothesis 1**: For a group that is both feasibly targetable and politically salient, an increase in Relative Electoral Importance after a change in government will lead to an increase in Relative Redistribution (social security payments – taxation)

**Hypothesis 2**: After a transfer of power, changes in multidimensional Relative Electoral Importance will explain more of the subsequent differences in Relative Redistribution than changes in unidimensional Relative Electoral Importance

# VII DATA

I measure Relative Electoral Importance using the British Household Panel Survey (BHPS) and its successor, the UK Household Longitudinal Study (UKHLS) for general election years between 1992 and 2010. This dataset has a large sample size as well as rich socioeconomic, voting and demographic information (Whiteley 2015). I restrict the sample to adults who are eligible to answer questions on voting and the sample rises from 9,119 adults in 1992 to 19,830 in 2010. To measure redistribution, I use the UKMOD tax and benefit microsimulation model, which has information on distributive systems between 2005 and 2019 and use the 2009 Family Resources Survey as the base dataset. This contains information on 57,830 people in 25,200 households. Women between the ages of 60 to 64 are excluded because the post-2010 rise in the State Pension Age means their inclusion is equivalent to assuming that the new government withdrew the state pension from those already in receipt of it. They are included in the New Labour counterfactual robustness check in Appendix F, where the results are qualitatively identical.

# VIII GROUP CONSTRUCTION

Multidimensional groups are constructed by interacting the dimensions of income (20 original income groups), age (18-24, 25-65 and 65+ year groups) and parental status (1 parent and 1 non-parent group). As any income threshold can be targeted by the taxation and social security system, I have chosen 20 income groups in order to maximise the number of non-empty cells. Robustness checks using 5 and 10 income groups were tested and the results still hold (Appendix G). Age groups are constructed as above because 25 and 65 are key age thresholds for social security payments (such as Housing Benefit and the State Pension), and parental status is used within the social security system to target payments e.g. Child Benefit. Groups are constructed in 2010 and individuals followed through time to ensure that changes in redistribution do not impact group assignment.

Constructing a group across dimensions involves the interaction of each group within a dimension with all groups from another. For example, there are 20 income groups and three age groups. Interacting them gives 60 income-age groups – one group contains those who are in Income Group 1 aged 18-24, another with individuals in Income Group 1 aged 26-64 etc. The number of groups that could be used in the empirical analysis for each construction are described below in Table 2.1 - the actual number differs in some empirical specifications due to empty cells.

**Table 2.1: Uni/Multidimensional Group Construction**

| Group Dimensions | Number of Groups |
|---|---|
| Income | 20 |
| Income by Age | 60 |
| Income by Parental Status | 40 |
| Income by Age by Parental Status | 120 |

# IX MEASURING CHANGES IN RELATIVE ELECTORAL IMPORTANCE

Electoral importance is measured as the proportion of a group that votes for the winning party multiplied by 100 (for a percentage point interpretation), and it indicates the number of votes that will be "bought" from a given redistributive transfer to a group. Turnout is incorporated into the above measure - if only 80 percent of a vote groups, then the maximum value this measure can take is 80. Partisanship is incorporated insofar as it is reflected by an individual's vote choice. Group size does not have an impact - a given per person transfer to a larger group gains more votes but also costs more (Dixit and Londregan 1996). The electoral importance of any group does not come from their size but in their uniformity in voting for the winning party.

$$\text{Group } j\text{'s Electoral Importance} = \left(\frac{\text{Number in Group } j \text{ Voting for Winning Party}}{\text{Total Number of Individuals in Group } j}\right) \times 100 \tag{2.1}$$

I adjust measures of Electoral Importance in 2010 in line with the proportion of seats won by each coalition partner at the 2010 election (84% Conservatives 16% for the Liberal Democrats), which was the same formula used to allocate ministerial positions to each party (Laws 2017).

Governments maximise votes by redistributing more to groups from whom a given transfer buys more votes. Governments redistribute more to groups who are relatively more important than other groups. Relative Electoral Importance for any group, $j$, is measured as its Electoral Importance minus the average Electoral Importance of all groups.

$$\text{Relative Electoral Importance}_j = \text{Electoral Importance}_j - \text{Average Electoral Importance of All Groups} \tag{2.2}$$

The change in Relative Electoral Importance (REI) at the 2010 Election for any group is measured as the difference in electoral importance for that group in 2010 and 1997 when New Labour came to power. Differences in Electoral Importance are ideally measured when there is a change in government. At this point, the new government gains information on the electoral coalition they want to reward in order to retain power. Robustness checks show that these results also hold when using Electoral Importance in 2005 for this measure (Appendix G).

$$\text{Change in Relative Electoral Importance (REI) at 2010 election}_j = \text{REI at 2010 Election}_j - \text{REI at 1997 Election}_j \tag{2.3}$$

As the BHPS/Understanding Society only includes information going back to the 1992 election, the Change in Relative Electoral Importance in 1997 is measured as:

$$\text{Change in Relative Electoral Importance (REI) at 1997 election}_j = \text{REI at 1997 Election}_j - \text{REI at 1992 Election}_j \tag{2.4}$$

The summary statistics for both measures are given in Appendix A. For both the 2010 and 1997 elections, the average Change in Relative Electoral Importance is close to zero. The possible range also increases with the number of dimensions, indicating that these extra dimensions provide information on Electoral Importance that is lost when only considering unidimensional income groups.

# X MEASURING CHANGES IN RELATIVE REDISTRIBUTION

I measure changes in redistribution using the UKMOD static tax and benefit microsimulation model, which simulates how much taxation households pay and the social security payments they receive under different redistributive policy systems (Sutherland and Figari 2013). The modelling here covers personal taxation (41% of forecasted revenue in 2018/19) and social security expenditure (30% of forecasted expenditure in 2018/19). I assume full take up of social security payments as do the IFS (e.g. Bourquin et al. (2019a)), and all income variables, including redistribution, are measured at the household level, and then divided by the number of adults because households share income and only adults can vote.

In this static microsimulation model, market income grows through time by a common value for all individuals, but all other factors remain constant so that changes to redistribution are applied to the same population through time. The key advantage of using this model over survey datasets is that it allows for a clean identification of the pure policy effects of changes to the redistributive system, while keeping fixed factors that can affect the definitions of groups or household income such as employment status, lifecycle & family formation effects, and behavioural responses (Bargain 2012; Sutherland and Figari 2013).

The modelling in the main section does not include Universal Credit, the UK's major welfare reform program which combines six means tested working-age social security payments into one, because numerous delays as well as repeated changes in its design mean it is unclear when, how, or even if, it will apply to all who are eligible (Buchanan 2018; Finn 2018). I do report results using the full rollout of Universal Credit as designed prior to the COVID-19 pandemic in Appendix C, where the results are qualitatively identical.

Remembering that redistribution is social security payments minus taxation payments, Relative Redistribution is measured as:

$$\text{Relative Redistribution}_{i,t} = \text{Redistribution}_{i,t} - \text{Average Redistribution}_t \tag{2.5}$$

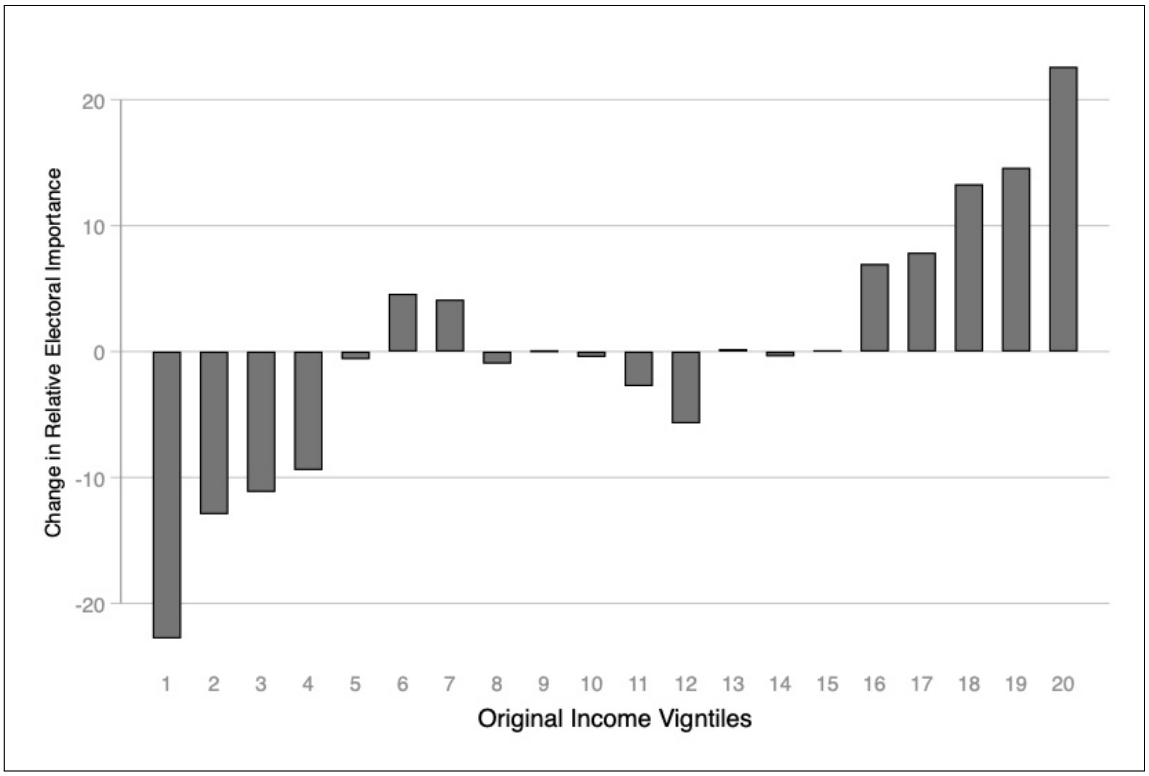
# XI THE MULTIDIMENSIONALITY OF RELATIVE ELECTORAL IMPORTANCE AND REDISTRIBUTION IN THE UNITED KINGDOM

Descriptive statistics indicate that changes in Relative Electoral Importance for the 2010 election are positively associated with subsequent changes in Relative Redistribution for multidimensional groups.

## XI.1 Income Groups

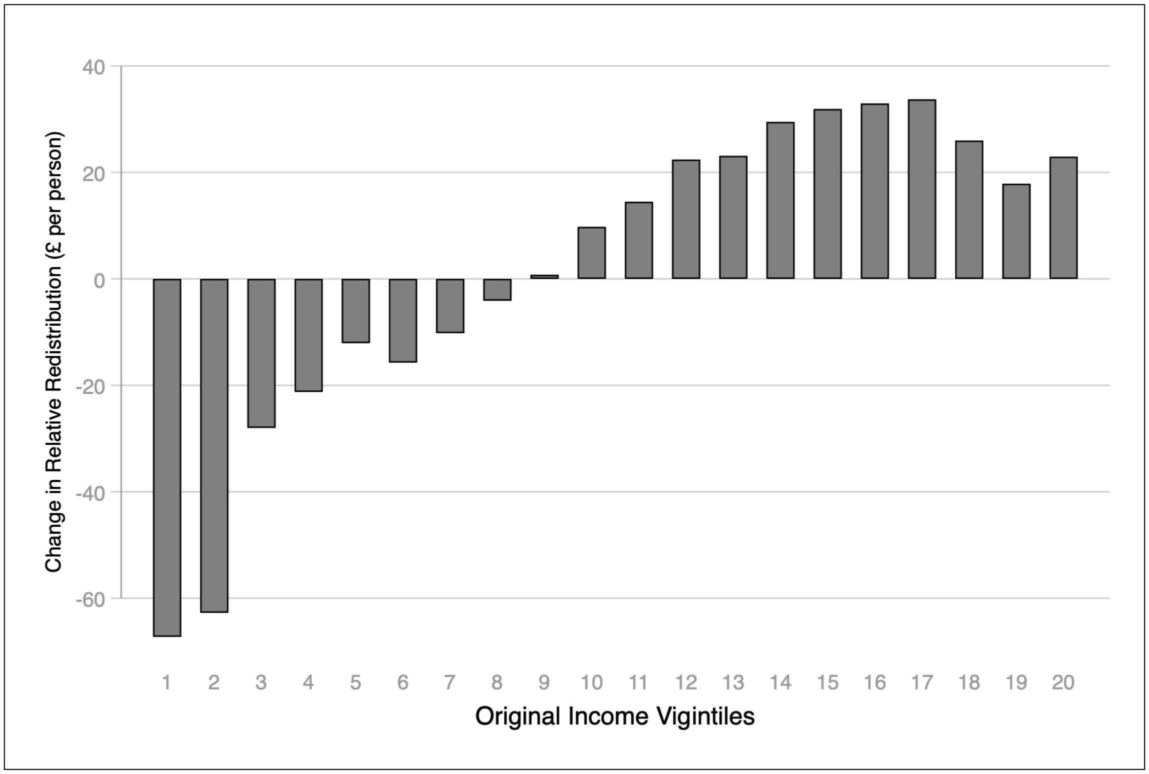
Changes in Relative Electoral Importance and redistribution between unidimensional income groups follows the expected regressive pattern after 2010 – both increase with income (Figures 2.2 and 2.3). Low-income groups were less likely to vote for the Conservative-led government in 2010 than 1997 and, subsequently, saw their redistribution cut between 2010 and 2019. There was very little change in either Relative Electoral Importance or Redistribution for middle income groups who are able to secure income growth by being part of electoral coalitions for both right- and left-wing governments (Iversen and Soskice 2006; Elkjær and Iversen 2020).

**Figure 2.2: Change in Relative Electoral Importance at 2010 Election (Income Groups)**




Source: BHPS/Understanding Society UKMOD Microsimulation Model

**Figure 2.3: Change in Relative Redistribution (Income Groups)**



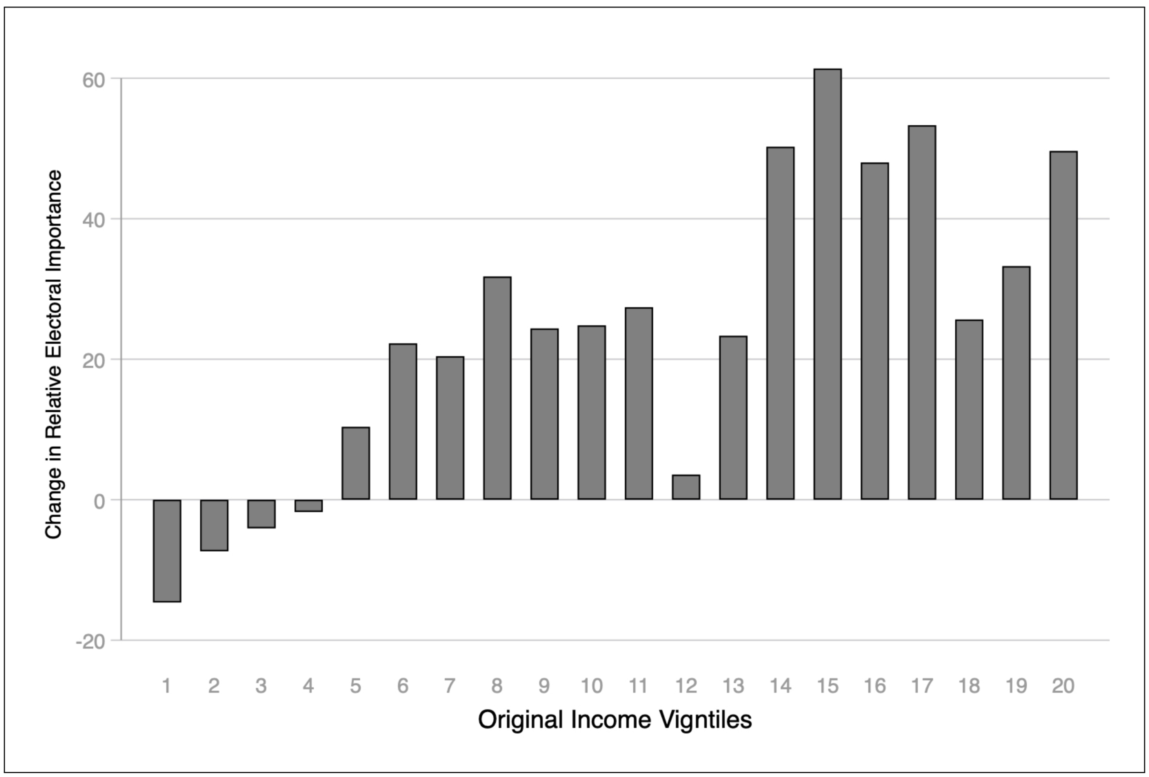

Source: UKMOD Microsimulation Model

### Income-Age Groups

The importance of multidimensional redistribution is apparent when reviewing changes in Relative Electoral Importance and redistribution for income-age groups. The relationship between income, changes in Relative Electoral Importance and redistribution, while still positive, differs across age categories. For any income group, young (18-24) and middle age (26-64) individuals have more negative changes in both Relative Electoral Importance and redistribution than pensioners (65+).

The changes in Relative Electoral Importance and Relative Redistribution for old income-age groups are shown below (results for young and middle-age groups are shown in Appendix B). Changes in both Relative Electoral Importance and Relative Redistribution show a distinctly different pattern for old income-age groups compared to income groups (Figure 2.4 below) and younger income-age groups (Appendix B). Across the income distribution, pensioners were more likely to vote for the Conservative-led government in 2010 than for Labour in 1997 and almost all saw increases in redistribution. Only the very poorest pensioner income-age groups saw falls in Relative Electoral Importance and redistribution. By contrast, almost all young and middle-age income-age groups saw falls in Relative Electoral Importance and their falls in redistribution were also much larger in the subsequent period. In addition, increases in both Relative Electoral Importance (47 points) and Relative Redistribution (£118) for the six richest old income-age groups dwarfs those of the six richest unidimensional income (11 points, £31) groups as well those of six richest young (8 points, £35) and middle-age income-age groups (10 points, £26).

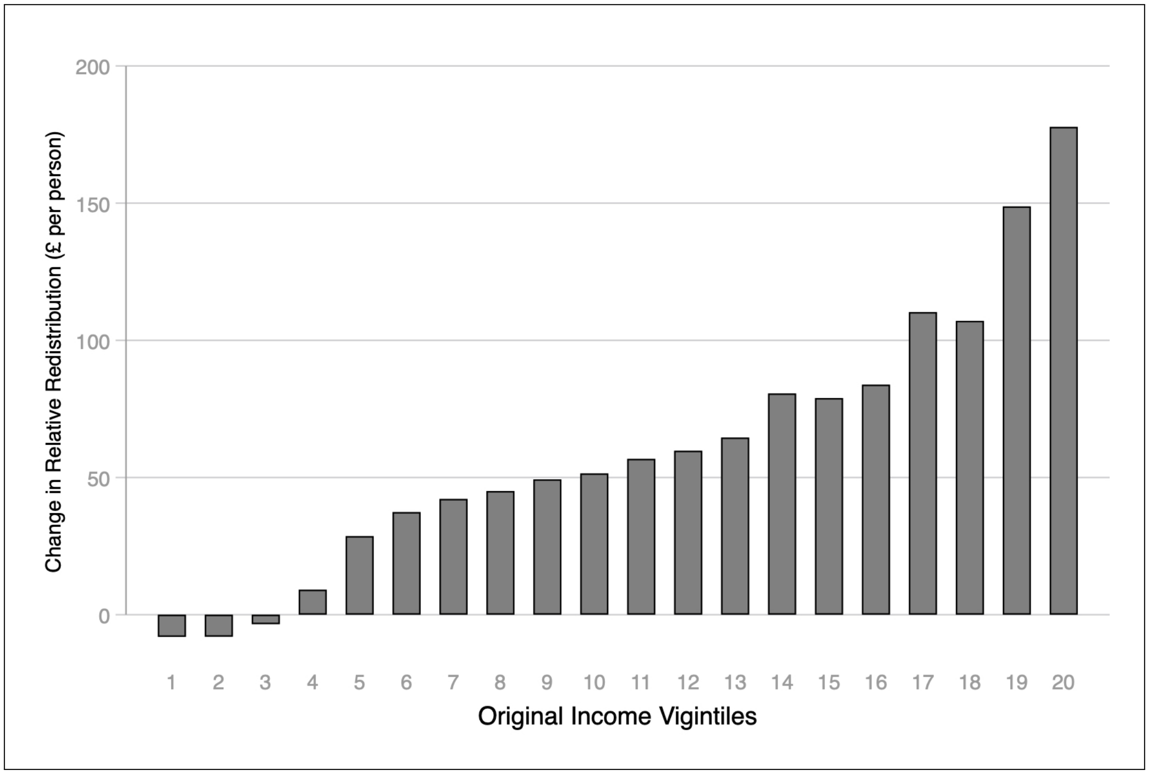
**Figure 2.4: Change in Relative Electoral Importance at 2010 Election (Pensioner Income-Age Groups)**




Source: UKMOD Microsimulation Model

The patterns of both REI and redistribution do not favour a unidimensional grey power explanation of rising ageing leading to more generous redistribution either. The poorest pensioners see small cuts in redistribution, largely due to changes to pensioner credit. Under

**Figure 2.5: Change in Relative Redistribution (Pensioner Income-Age Groups)**




Source: UKMOD Microsimulation Model

New Labour, this same group saw rises in relative redistribution.

This provides *prima facie* support for changes in Relative Electoral Importance having a subsequent impact on redistribution as well as the importance of multidimensional redistribution. Not all rich/middle-income/poor people are of equal electoral worth to governments nor are they treated equally in terms of redistribution. This distinction is missed in accounts that only consider unidimensional redistribution from the rich to the poor.

# XII DO CHANGES IN RELATIVE ELECTORAL IMPORTANCE LEAD TO CHANGES IN RELATIVE REDISTRIBUTION?

I formally analyse the relationship between changes in Relative Electoral Importance and redistribution using a difference-in-differences methodology. Analogous to the difference-in-differences methodology used in Duflo (2001), the implicit control group are those groups for whom the dependent variable remains stable after a change in government i.e. where the change in Relative Electoral Importance was close to zero. However, while these analyses clearly identify the impact of changes in government policy on redistribution, as well as their association with preceding changes in Relative Electoral Importance, they do not allow a robust causal claim to be made. This is because I cannot exclude other factors, such as ideology, having an impact on both Relative Electoral Importance and subsequent redistribution. Instead, I show that it is plausible that changes in Relative Electoral Importance led to changes in multidimensional redistribution.

Identification relies upon a common trends assumption – that had there been no change in government in 2010, then redistribution would have grown at a constant rate for each individual *conditional* on earnings growth. Individual specific earnings trends are, therefore, included to control for the heterogeneous effects of the economic cycle on redistribution (Angrist and Pischke 2009; Lechner 2011). The UKMOD microsimulation model allows for the identification of policy effects on redistribution by excluding the impact of confounding effects. The common trends assumption is discussed and formally analysed in Appendix D using a placebo time test as well as in Appendix F through the construction of a New Labour Counterfactual. Both tests indicate that the common trends assumption holds.

## XII.1 Empirical Specification and Results

To analyse the impact of Relative Electoral Importance on subsequent redistribution, I estimate a standard difference-in-differences specification with an OLS fixed effects estimator and Hubert-White standard errors clustered at the group level (Lechner 2011; Angrist and Pischke 2015; Cunningham 2021).

The estimating equation is given below for the 2010 election:

$$\begin{aligned}\text{Relative Redistribution}_{i,t} = a_j + c_t + \rho(\text{post 2010 Election})_j + \\ \delta(\text{Change in Relative Electoral Importance 2010 Election} \times \text{post 2010})_{j,t} \\ + \varrho(\text{Original Income} \times \text{Year})_{i,t} + \epsilon_{i,j,t}\end{aligned} \tag{2.6}$$

Where *Relative Redistribution*$_{i,t}$ are social security payments received minus taxation payments paid per person in year $t$ relative to all others, $a_j$ are group fixed effects controlling for time-invariant group characteristics, $c_t$ are time fixed effects, $\varrho(OriginalIncome_i \times Year)$ are individual-specific earnings trends and $\epsilon_{i,j,t}$ is the error term.

The key independent variable, *Change in Relative Electoral Importance 2010 Election* is interacted with a $post2010_(j,t)$ dummy that takes a value of 1 after the 2010 election. The coefficient on this variable, $\delta$, is approximately equivalent to the amount an individual receives from a 1 percentage point increase in the proportion of their group voting for the winning party between 2010 and 1997.

As individuals remain constant through time, and there are no demographic, employment or behavioural changes within the model, I do not need to control for additional covariates through time. The only things that change are the amount they receive in redistribution as well as earnings (that grow by a common parameter).

The results are shown in Table 2.2 below. Each column represents the estimation for different uni/multidimensional group constructions – Column 1 for Income groups, Column

2 for Income x Age groups, Column 3 for Income x Child groups and column 4 for Income x Age x Child groups.

An increase in Relative Electoral Importance at the 2010 election led to a statistically and economically significant increase in relative redistribution after the 2010 election across all group constructions, which provides support for Hypothesis 1. A one percentage point increase in the relative proportion of a group voting for the winner led to between £1.17 and £3.60 per person per month. This rise is large – a one standard deviation increase in Relative Electoral Importance (Table 2A.1) led to an increase in redistribution of between £20 to £38 per adult per month, in 2005 prices, which represents between 1.3% and 2.6% of mean disposable income.

**Table 2.2: Standard DiD, Impact of Change in Relative Electoral Importance (2010) on Relative Redistribution (2005-2019)**

| | Uni/Multidimensional Group Type | | | |
|---|---|---|---|---|
| | Income Groups | Income x Age | Income x Child | Income x Age x Child |
| | (1) | (2) | (3) | (4) |
| $\rho$(Post-2010 Election) | 42.08** | 28.52* | 34.42** | 27.58* |
| | (15.68) | (16.35) | (15.03) | (14.29) |
| $\delta$ (Change in Relative Electoral Importance 2010 Election x Post-2010 Election) | 3.604*** | 1.375*** | 2.266*** | 1.171*** |
| | (0.647) | (0.473) | (0.603) | (0.356) |
| Constant | 451.7*** | 449.0*** | 451.6*** | 449.6*** |
| | (33.92) | (30.10) | (25.31) | (23.49) |
| Group Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Individual Earnings-Specific Trends | Yes | Yes | Yes | Yes |
| No. of Groups | 20 | 60 | 40 | 111 |
| No. of Individuals | 41826 | 41826 | 41826 | 41786 |
| No. of Observations | 627390 | 627390 | 627390 | 626790 |
| Overall $R^2$ | .91 | .91 | .91 | .91 |

Robust standard errors, clustered by Groups, calculated. Standard Errors in parentheses
Empty cells in calculation of REI for income-age-child groups leads to 111 groups & fewer observations.
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

With almost identical levels of statistical significance and $R^2$s, there is little information here that allows us to choose between the uni- and multidimensional constructions of REI. The coefficient for unidimensional income groups (3.60) is greater than those for multidimensional groups (at 1.17 to 2.27) but the larger number of groups in the multidimensional constructions may indicate that, for individuals and sub-groups, the multidimensional constructions give a better prediction of subsequent changes in redistribution - this is tested formally for Hypothesis 2 below. Overall, the range of effects (found by multiplying the coefficients in Table 2.2 by the range in REI from Appendix Table 2A.1) is greatest for multidimensional income-age-child groups at £199 per month compared to £163 per month for unidimensional income groups. The range of effects is greater for multidimensional groups because the range in REI is greater for these groups (-82 to 64 for income-age-child groups compared to -28 to 29 for income groups).

# XIII ARE THESE FINDINGS GENERALISABLE IN THE UNITED KINGDOM?

The results above provide support for Hypothesis 1 but considers only one change in government. Using the available data from redistribution in 2005 to 2010, I conduct an indicative test of whether this holds in the UK for the 1997 change in power. As UKMOD does not currently allow for examination of redistribution prior to 2005, I implement a fixed effects regression, with a pre-2011 dummy, that takes the value of 1 in the years 2005 through 2010, and 0 thereafter and restrict the sample to 2005-2011 to limit the impact of post-2010 policy changes. The estimating equation and results are given below:

$$\begin{aligned}\text{Relative Redistribution}_{i,t} = a_j + c_t + \rho(\text{pre 2011 })_j + \\ &\delta(\text{Change in Relative Electoral Importance 1997 Election} \times \text{pre 2011})_{j,t} + \\ &\varrho(\text{Original Income} \times \text{Year})_{i,t} + \epsilon_{i,j,t}\end{aligned} \tag{2.7}$$

There is plausible evidence that changes in Relative Electoral Importance had an impact on multidimensional redistribution prior to 2011 and, therefore, that the results above are generalisable. The impact of changes in Relative Electoral Importance in 1997 is both statistically and economically significant across different group types – a one standard deviation increase led to a rise in redistribution worth between 1.5% and 2.8% of mean disposable income between 2005 and 2010. This provides further support for Hypothesis 1.

**Table 2.3: Standard DiD, Impact of Change in Relative Electoral Importance (1997) on Relative Redistribution (2005-2011)**

| | Uni/Multidimensional Group Type | | | |
|---|---|---|---|---|
| | Income Groups | Income x Age | Income x Child | Income x Age x Child |
| | (1) | (2) | (3) | (4) |
| $\rho$(Pre-2011) | -71.16*** | -56.68*** | -64.41*** | 0 |
| | (23.43) | (19.46) | (22.90) | (.) |
| $\delta$ (Change in Relative Electoral | 3.046** | 1.265* | 2.110** | 1.111** |
| Importance 1997 Election x Pre-2011) | (1.337) | (0.635) | (1.014) | (0.510) |
| Constant | 536.1*** | 463.4*** | 529.6*** | 466.0*** |
| | (50.78) | (25.60) | (40.14) | (19.59) |
| Group Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Individual Earnings-Specific Trends | Yes | Yes | Yes | Yes |
| No. of Groups | 20 | 60 | 40 | 109 |
| No. of Individuals | 41826 | 41826 | 41826 | 41759 |
| No. of Observations | 292782 | 292782 | 292782 | 292313 |
| Overall $R^2$ | .91 | .91 | .91 | .90 |

Robust standard errors, clustered by Groups, calculated. Standard Errors in parentheses
Empty cells in calculation of REI for income-age-child groups leads to 109 groups
& fewer observations.
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

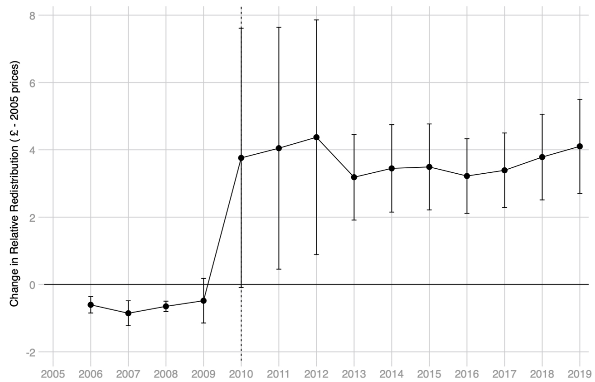
# XIV DOES THE IMPACT OF RELATIVE ELECTORAL IMPORTANCE CHANGE OVER TIME?

I analyse how the impact of Relative Electoral Importance changes over time, by interacting Changes in Relative Electoral Importance with year dummies. The added advantage of this specification is that it allows for a further test of the common trends assumption (Autor 2003; Angrist and Pischke 2009; Cunningham 2021).

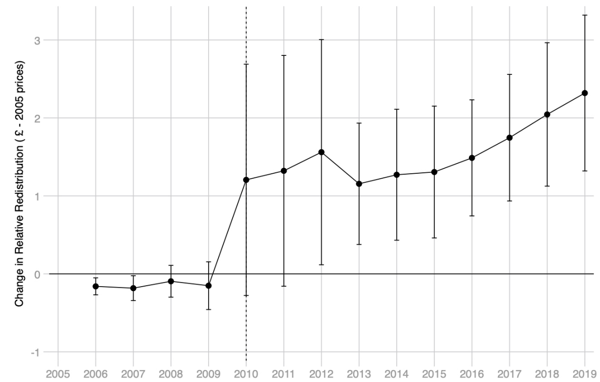
$$\begin{aligned}\text{Relative Redistribution}_{i,t} = a_j + c_t + &\\ &\delta(\text{Change in Relative Electoral Importance 2010 Election} \times \text{Year})_{j,t} + \\ &\varrho(\text{Original Income} \times \text{Year})_{i,t} + \epsilon_{i,j,t}\end{aligned} \tag{2.8}$$

Changes in Relative Electoral Importance have a statistically and economically significant impact on redistribution that builds after the election in 2010. Figures 2.6a-6d below show the $\delta(\text{Change in Relative Electoral Importance 2010 Election} \times \text{Year})_{j,t}$ coefficient for each year between 2005 and 2019 (tables in Appendix E). Please note that years in the below refer to years in which policies take effect - for example, 2010 refers to policies that are operational in the tax year 2010/11. Relative Electoral Importance has an impact on redistribution a year before the post-2010 government's policies could be implemented (in 2010) but this is likely due to an uprating quirk that is discussed in more detail below. A one percentage point increase in the relative proportion voting for the winning parties (i.e. in REI) led to an increase of between an (imprecisely estimated) £1.07 and £4.05 more per person per month in redistribution in 2011 rising to a precisely estimated rise of between £2.02 and £4.10 in 2019. A one standard deviation increase in REI led an increase in redistribution worth between 2.1% and 2.7% of mean disposable income in 2019.The possible range of effects is also greatest for the multidimensional income-age-child groups at £343 compared to £186 for unidimensional income groups in 2019. The results of this specification, as well as the New Labour counterfactual set out in Appendix F, are consistent with Hypothesis 1.

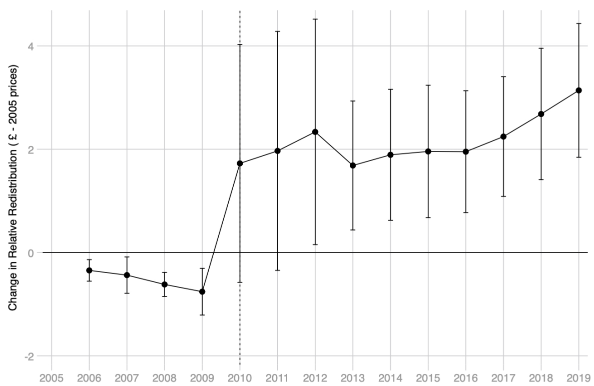
**Figure 2.6: Impact of One Unit Increase in Relative Electoral Importance (2010) on Relative Redistribution**



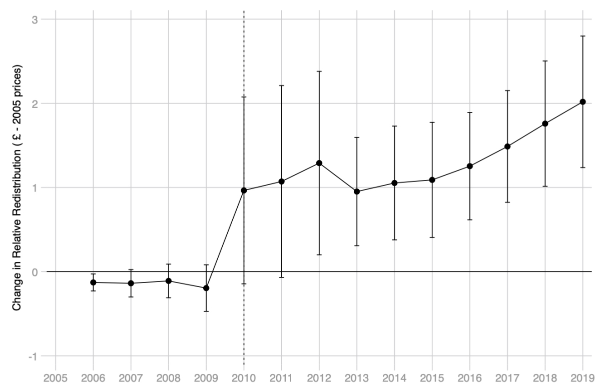

(a) Unidimensional Income Groups




(b) Multidimensional Income-Age Groups




(c) Multidimensional Income-Child Groups




(d) Multidimensional Income-Age-Child Groups

It does, at first, appear surprising that changes in Relative Electoral Importance have a large impact in 2010, the year before the Conservative-led government takes office and then continues to have an effect throughout their term. This is explained by an uprating quirk in 2010 and subsequent policy changes in 2011 and beyond. Both the uprating quirk and subsequent policy changes tended to lead a fall in relative redistribution for those on low incomes. The standard errors of the coefficients become more precise in 2013 when changes to major social security payments that significantly reduce relative redistribution for low-income individuals take effect.

I explain the uprating quirk in more detail here before describing the other policy measures below. A quirk of policy led to a fall in *relative* redistribution for low income groups in the last year of the New Labour Government, 2010. This occurred because uprating of social security payment and tax thresholds is generally made by using inflation (or earnings) in the year prior to the payment levels and thresholds taking effect. As RPI inflation was negative in 2009, the uprating decisions taken were to freeze most taxation thresholds and raise social security payments by 1.5% for 2010 (HMT 2010). CPI Inflation (the deflator used in this chapter) was then 3.5% in 2010 leading to a fall in real redistribution for those on the low incomes. Crucially, this uprating quirk had a greater impact on low-income households as most (or even all) of their income was affected by it. By contrast, only some of the income of middle- and higher-income households were affected by this uprating quirk i.e. only the portion of their income pulled into higher tax brackets (albeit taxed at a much higher rate).

To show that the evolution of coefficients above is not due to quirks of UKMOD itself, I display the change in relative redistribution and original income for three income groups (low, middle, and higher) from 2005. These descriptive statistics are shown in Figures 2.7 to 2.9 below.

Figure 2.7 below shows the change in redistribution for income group 1, the low-income group. Redistribution for this group rises until 2009. It then falls slightly in 2010 and continues to fall steadily until 2012, when a sudden dramatic fall takes place in 2013. Redistribution then stabilises until 2017, when it again starts to fall dramatically.

Redistribution falls in 2010 due to the uprating quirk discussed above. Social security payments were uprated by 1.5% while inflation was 3.5% in that year leading to a real fall in social security payments for almost all low-income households. This was not retrospectively changed by the incoming Conservative-led government.

In 2011, the Conservative-led government's policy changes begin to take effect. The largest of these was changing uprating rules from RPI to CPI, which led to a general fall in redistribution for those on low incomes from 2011 onwards - social security payments were between 1.5 and 1.7 percentage points lower in 2012 as a result of this uprating changes and this shortfall continued to go through time (Joyce and Levell 2011). Other social security cuts also took effect in 2011 including a freeze in working tax credit payments, an increase in the marginal tax rate that tax credits claimants face (known as the "withdrawal rate"), a child benefit freeze, and a decrease in housing benefit (Hills 2015). These all led to (relative) falls in redistribution for low-income families in 2011.

Large changes in redistribution that hit low-income voters took effect in 2013. Social security payments were only uprated by 1%, while the benefit cap limited the amount of redistribution low-income families could receive (Hills 2015). The large fall can be seen in Figure 2.7. From 2010 to 2012, low-income households face steady falls in redistribution and then see a large fall in 2013 due to these drastic policy changes. The standard errors from equation 2.8 become far more precise in 2013 when these changes take place.

Between 2014 and 2016, a combination of low inflation and rising pension payments led to a slight rise in real redistribution for low-income households. Non-pensioner social security payments were frozen in nominal terms from 2016, and these led to a large fall in redistribution from 2017 when inflation began to rise (Corlett 2019).

For those on middle and higher incomes, it is more difficult to discern the effects of policies from a simple descriptive graph. This is because falls in earnings leads to a rise in redistribution as tax payments fall. This is why I control for original income in all specifications. Figures 2.8 and 2.9 show the evolution of redistribution and original income for the 10th and 19th income groups. I do not show the 20th income group here for presentational reasons as large changes make it difficult to assess the evolution of redistribution and earnings on a simple bar graph. The income changes for group 20 can be seen in Appendix Figures 2A.5 and 2A.6 if of interest, where changes in both relative redistribution and original income can be seen for all income groups in a line graph presentation.

In 2010, there is a small fall in redistribution for some middle and higher income households as tax rates remain frozen while earnings rise in nominal terms. The very highest

**Figure 2.7: Change in Real Redistribution from 2005 for 1st Income Decile**


Source: UKMOD Microsimulation Model

income households also saw a fall in redistribution with the imposition of the 50% tax rate on those with incomes over £150,000 but this only affected the top 1% of the distribution and so the effect is small (Browne and Phillips 2010).

The effect of policy changes on redistribution then serves to increase relative redistribution middle and higher income households from 2011. As can be seen in Figures 2.8 to 2.9, redistribution *rises* for middle-and high income households in 2011 but *falls* for low-income households (Figure 2.7). The personal allowance rises from 2011 onwards (although those on high-incomes have this steadily withdrawn) and those on the highest incomes also see a rise in redistribution with the reduction in the top tax rate from 50% to 45% from 2013. Further, while uprating rule changes are implemented immediately for social security payments in 2011, they are delayed for income tax and national insurance thresholds to only take effect in 2013 and 2012 respectively, effectively increasing relative redistribution for those on middle to higher income households and this compounds through time (Joyce and Levell

**Figure 2.8: Change in Real Redistribution from 2005 for 10th Income Decile**

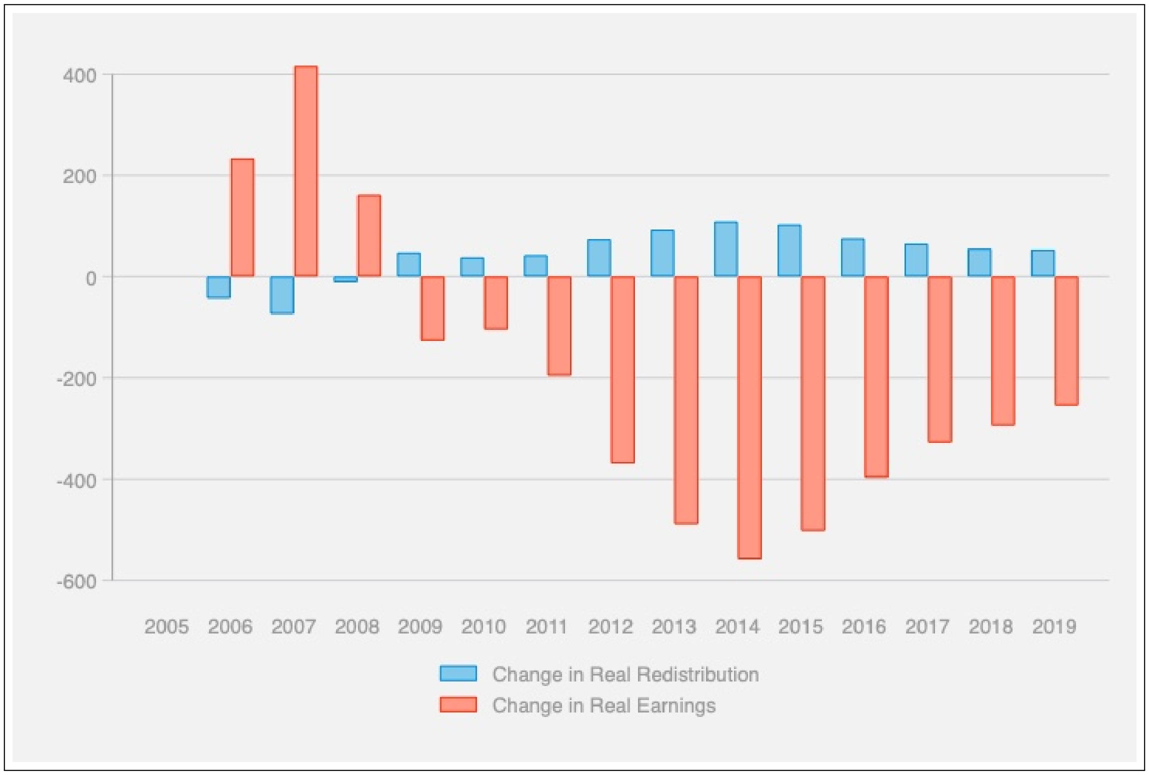

Source: UKMOD Microsimulation Model

2011; Browne and Elming 2015; Hills 2015).

Another way to show that these effects are not being driven by any strange modelling decisions is to graphically display the results from the New Labour Counterfactual in Appendix Table 2A.8 in Figure 2.10 below. The New Labour counterfactual uses, as the dependent variable, the difference between modelled relative redistribution under the post-2010 conservative government and a New Labour counterfactual. The New Labour counterfactual shows what each household would have received in redistribution had New Labour won the 2010 election and remained in power. It is constructed using the uprating rules, policies, and promises that New Labour had in place when they left office. This iteration is not, therefore, affected by the uprating quirk in 2010 as policies are the same in that year. Differences only take place in 2011 and the years following. Full details of the constructed counterfactual are given in Appendix F.

The equation that is estimated in this New Labour counterfactual is shown below:

**Figure 2.9: Change in Real Redistribution from 2005 for 19th Income Decile**



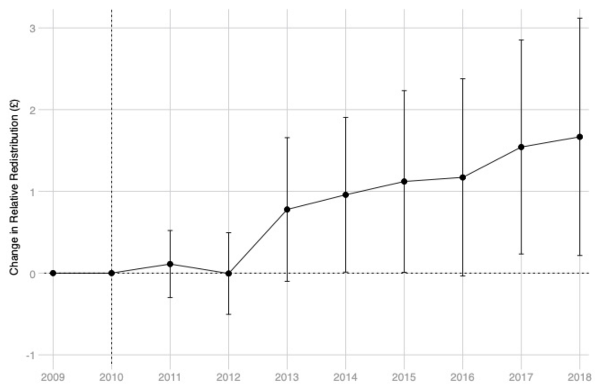

Source: UKMOD Microsimulation Model

$$\text{Difference in Relative Redistribution under Conservative-led \& New Labour Governments}_{i,t} = a_j + c_t + \delta(\text{Change in Relative Electoral Importance 2010 Election} \times \text{Year})_{j,t} + \epsilon_{i,j,t} \quad (2.9)$$

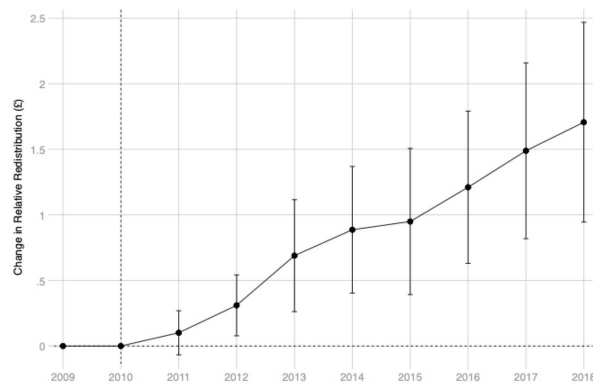
Graphical results are shown below. From 2011, we see a general pattern of the rising effect of Relative Electoral Importance, with a marked increase in 2013 as large social security policy changes take place. Full regression tables are shown in Appendix F.

In summation, the figures used here show that the UKMOD microsimulation model, which is used widely in both policy and academic work (Immervoll et al. 2007; Atkinson 2017; De Agostini et al. 2018) is consistent with other studies that simulate the effect of taxes and benefits within the United Kingdom (Joyce and Levell 2011; Browne and Elming

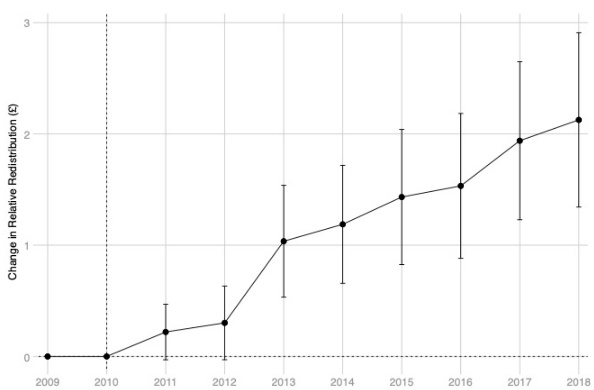
**Figure 2.10: Impact of One Unit Increase in Relative Electoral Importance (2010) on Relative Redistribution in the New Labour Counterfactual**



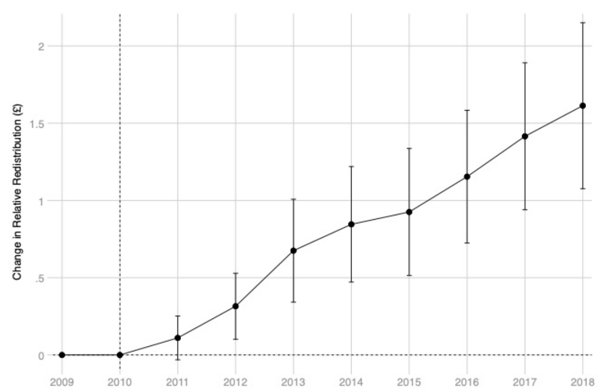

(a) Unidimensional Income Groups




(b) Multidimensional Income-Age Groups




(c) Multidimensional Income-Child Groups




(d) Multidimensional Income-Age-Child Groups

2015; Hills 2015). The large rise in the coefficient in 2010 is due to an uprating quirk that disproportionately favoured middle- and higher-income households. Subsequent policy changes then continue to relatively favour people whose Relative Electoral Importance rose in 2010, with a particularly large change in 2013. Descriptive statistics show that the modelling itself is not responsible for the quirk while the New Labour counterfactual, unaffected by the uprating quirk, show the expected coefficient values over time.

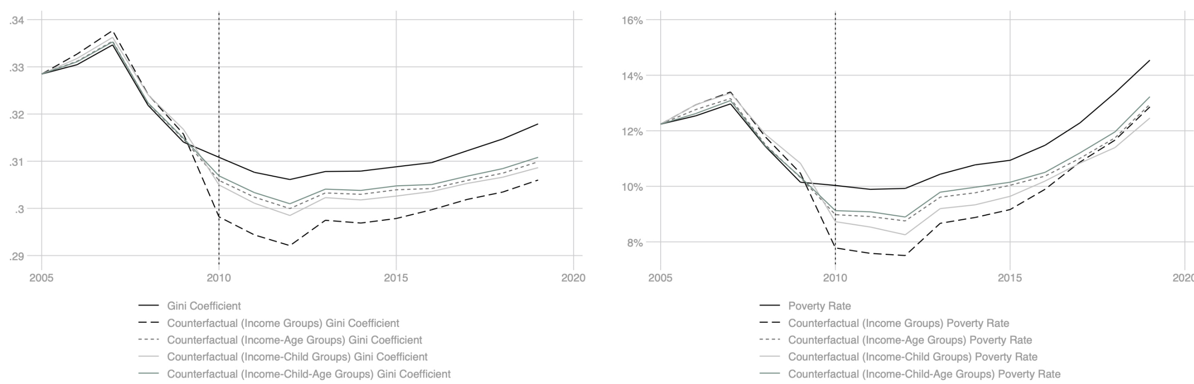
# XV HOW DID CHANGES IN RELATIVE ELECTORAL IMPORTANCE AFFECT INCOME INEQUALITY AND POVERTY?

Across different empirical specifications, changes in Relative Electoral Importance are positively associated with subsequent changes in multidimensional redistribution. I now show the impact this had on income inequality and poverty rates through an indicative, back-of-the envelope calculation.

I do so by constructing counterfactual distributions of disposable income. I then calculate the counterfactual Gini coefficients and poverty rates, and then compare these distributions to the original UKMOD output.

I construct these counterfactual distributions by multiplying the change in Relative Electoral Importance at the 2010 election by its coefficient from the results of Equation 8 (Appendix E, Table A7) in any given year for each uni/multidimensional group construction. For example, an individual in the lowest unidimensional income group saw their Relative Electoral Importance fall in 2010 by -23 percentage points. To calculate their counterfactual disposable income in 2019, I multiply this by the 2019 coefficient from Appendix Table 2A.7, which was 4.10, and add this to their actual income. I then calculate counterfactual Gini coefficient and poverty rates for all uni/multidimensional group constructions. Market income is identical across the actual and counterfactual specifications and so differences in Gini coefficients and poverty rates are driven solely by differences in redistribution

The results are shown in Figures 2.11a & 2.11b below. Falling Relative Electoral Importance for poorer groups led to a significant rise in income inequality and poverty after 2010. The Gini coefficients are permanently lower by between 0.7 and 1.2 points in these counterfactual specifications by 2019 while the market Gini coefficient was almost entirely stable. Poverty is measured using the relative poverty rate - the proportion of households falling below 60% of actual median disposable household income. Poverty rates are between 1.3 and 2.1 percentage points lower in 2019, representing between 784,000 and 1.223 million people. The New Labour Counterfactual in Appendix F also leads to lower rates of income inequality (1.4 points) and numbers in poverty (880,000). Crucially, the calculations that incorporate multidimensional redistribution lead to higher counterfactual poverty and inequality rates. It is to this which I now turn.




(a) Counterfactual Gini Coefficients

(b) Counterfactual Poverty Rates

**Figure 2.11: Counterfactual Uni/Multidimensional Gini Coefficient and Poverty Rates**

# XVI DO GOVERNMENTS USE MULTIPLE DIMENSIONS TO TARGET REDISTRIBUTION?

The results above provide some evidence that governments engage in multidimensional redistribution. The range of effects are greater when considering multidimensional redistribution and the counterfactual multidimensional income inequality & poverty rates were subtly, but notably, different from the unidimensional counterfactual rates.

Here, I directly test Hypothesis 2 and the importance of multidimensional redistribution by analysing whether using multiple dimensions to calculate Relative Electoral Importance explains more of the subsequent changes in redistribution than using the the single dimension of income alone. I do so by analysing whether differences in uni- and multidimensional REI at the 2010 election are associated with subsequent differences in the amount of redistribution going to uni- and multidimensional groups between 2011 and 2019.

If Governments do undertake multidimensional redistribution, then individuals whose multidimensional Relative Electoral Importance (e.g. of their income-age group) rose higher than the unidimensional REI (of their income group), should see greater growth in redistribution than their income group as a whole. For example, low-income pensioners saw their unidimensional Relative Electoral Importance fall at the 2010 election because low-income people *overall* were less likely to vote for the Conservatives/Liberal Democrats than they were for New Labour in 1997. These low-income pensioners would also, however, see their multidimensional income-age Relative Electoral Importance remain stable because low-income pensioners were about as likely to vote for the Conservatives/Liberal Democrats in 2010 as they were to vote for Labour in 1997. If governments use the dimensions of both income *and* age to target groups for redistribution, then low-income pensioners should see greater growth in Relative Redistribution after 2010 than low-income individuals as a whole. In this case, using the extra dimension of age gives us more information about whether an individual is part of an electorally important group. This information would not be reflected in the unidimensional income measure, which indicates that *all* low-income people, including low-income pensioners, would be less favoured for redistribution.

If Governments do not, however, undertake multidimensional redistribution, then there should be no systematic relationship between differences in uni/multidimensional Relative Electoral Importance and uni/multidimensional redistribution. There would be no extra information gained from considering age as a dimension - a low-income pensioner's electoral importance would derive solely from their income level and they would be no more or less likely to see more/less redistribution than any other low-income individual.

## XVI.1 Measuring Differences in Unidimensional and Multidimensional REI and Redistribution

I measure the difference in Uni/Multidimensional Relative Electoral Importance as:

$$\text{Uni/Multidimensional Relative Electoral Importance Difference}_i = \text{Multidimensional REI}_i - \text{Unidimensional REI (Income Group)}_j \quad (2.10)$$

For example, a low-income pensioner in income group 4 (i.e. the fourth poorest) saw their unidimensional Relative Electoral Importance fall by 9.40 percentage points whereas their multidimensional Relative Electoral Importance of their Income-Age Group fell by 1.74 points. Their uni/multidimensional REI Difference is then 7.66.

I measure the difference in unidimensional and multidimensional redistribution in 2019 as:

$$\text{Uni/Multidimensional Redistribution Difference (2011 - 2019)}_i = \text{Relative Redistribution Growth}_i - \text{Unidimensional Relative Redistribution Growth (Income Group Average: 2019-2011)}_j \quad (2.11)$$

The uni/multdimensional redistribution difference for a low-income pensioner in income group 4, for example, would be their own growth in Relative Redistribution between 2011 and 2019 minus the average growth in Relative Redistribution of everyone in income group 4 (-£20.80).

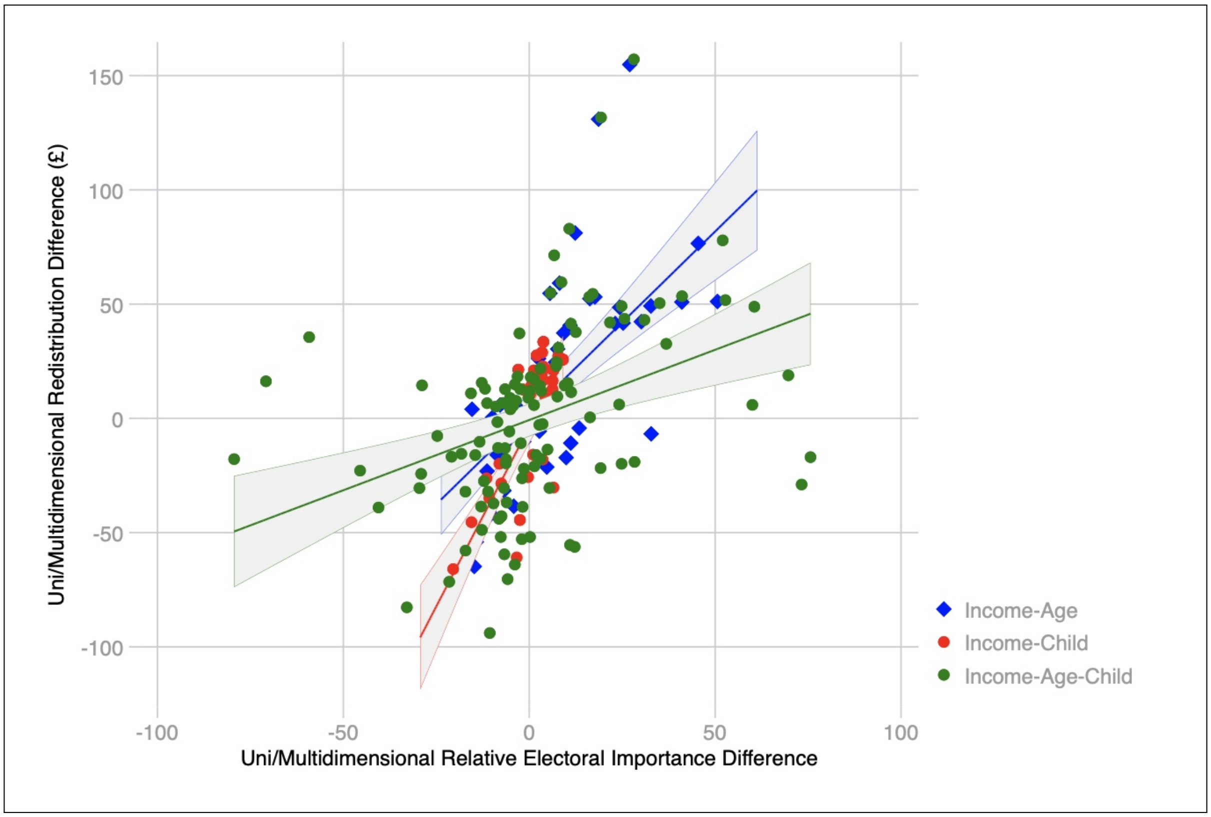
Figure 8 below shows, at the group level, the relationship between Uni/Multidimensional Relative Electoral Importance and the average Uni/Multidimensional Redistribution Difference (2011-2019). Specifically, I estimate a simple first-differenced regression of the form:

$$\text{Average Uni/Multidimensional Redistribution Difference (2011-2019)}_{j,t} = \alpha + \delta(\text{Uni/Multidimensional Relative Electoral Importance Difference (2011-2019)}_{j,t} + \epsilon_{j,t} \quad (2.12)$$

Note that all variables are measured at the $j$ group level. I do so to provide a simple graphical representation of the relationship between Uni/Multidimensional Relative Electoral Importance and Uni/Multidimensional Redistribution. If there is a positive relationship, it indicates that governments engage in multidimensional redistribution. A positive relationship indicates that a group whose multidimensional REI is greater than their unidimensional REI receives more in redistribution than their unidimensional group as a whole. It indicates that, for example, low-income pensioners who have a greater REI than low-income people overall, will receive more in redistribution than low-income people do on average. If the relationship is flat, or negative, it indicates that accounting for multidimensional Relative Electoral Importance does not give further information about a government's redistributive decisions.

As shown in Figure 2.12, this relationship is positive for all multidimensional constructions. Where a group's multidimensional REI is greater than their unidimensional REI, then that group's average growth in redistribution between 2011 and 2019 is also likely to be greater than for the equivalent income group. For example, low-income pensioners in income group 4 saw an average increase in relative redistribution of £8.89 per month between 2011 and 2019, compared to -£20.80 for income group 4 as a whole, leading to a Uni/Multidimensional Redistribution Difference of £29.69 for that multidimensional group. As above, their uni/multidimensional REI difference is 7.66. This positive relationship provides indicative evidence in support of Hypothesis 2.

**Figure 2.12: Relationship between Uni/Multidimensional REI and Relative Redistribution (2011-2019)**




Linear First-Difference Regression of average changes in redistribution for multidimensional groups (2011-2019) and changes in REI at the 2010 election. 41,787 observations. Standard errors clustered at group level. Shaded 95% confidence intervals. Source: UKMOD Microsimulation Model.

## XVI.2 Empirical Specification and Results

In order to analyse multidimensional redistribution more completely, I estimate a standard first-differenced OLS specification to test whether multidimensional measures of Relative Electoral Importance explain more of the subsequent differences in redistribution than unidimensional measures do. The difference between this specification and that in equation 2.12 is that I measure differences in redistribution at the individual level and include a control for original income growth. The equation to be estimated is shown below:

$$\begin{aligned}&\text{Uni/Multidimensional Redistribution Difference (2011-2019)}_{i,t} = \alpha + \\ &\delta(\text{Uni/Multidimensional Relative Electoral Importance Difference (2011-2019)}_{j,t} + \\ &\varrho(\text{Original Income (2011-2019)})_{i,t} + \epsilon_{i,j,t} \qquad (2.13)\end{aligned}$$

Multidimensional redistribution has an economically and statistically significant impact on redistribution beyond that explained by unidimensional redistribution. Results are shown in Table 2.4 below. On average, a one percentage point difference between unidimensional and multidimensional Relative Electoral Importance is associated with £1.17 and £2.80 increase in redistribution between 2011 and 2019. This is a significant amount - a one standard deviation difference in Uni/Multidimensional REI leads to between £15.56 and £19.65 per person per month in redistribution. These results provide support for Hypothesis 2.

**Table 2.4: Linear First-Difference Regression, Impact of Differences in Uni/Multidimensional REI in 2010 on Uni/Multidimensional Relative Redistribution Difference (2011-2019)**

| | Multidimensional Group Difference | | |
|---|---|---|---|
| | Income x Age | Income x Child | Income x Age x Child |
| | (1) | (2) | (3) |
| $\delta$ (Uni/Multidimensional REI Difference) | 1.333*** | 2.799*** | 1.172*** |
| | (0.285) | (0.286) | (0.221) |
| $\rho$(Earnings Growth(2011-2019)) | -0.383*** | -0.396*** | -0.385*** |
| | (0.0464) | (0.0457) | (0.0482) |
| Constant | -4.500 | -3.800 | -4.328 |
| | (3.254) | (3.247) | (3.634) |
| No. of Groups | 60 | 40 | 111 |
| No. of Individuals | 41826 | 41826 | 41787 |
| No. of Observations | 41826 | 41826 | 41786 |
| Overall $R^2$ | .35 | .37 | .35 |

Robust standard errors, clustered by Groups, calculated. Standard Errors in parentheses
Empty cells in calculation of REI for income-age-child groups leads to 111 groups
& fewer observations.
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

# XVII CAN MULTIDIMENSIONAL REDISTRIBUTION EXPLAIN DIFFERENCES IN POVERTY RATES?

Multidimensional redistribution helps explain why governments have different redistributive policies for different groups with the same income. Here I demonstrate this by showing how poverty rates differ for Pensioners, Working-Age Adults, and Children under the different uni/multidimensional counterfactual income distributions used to construct Figures 2.11a & 2.11b.

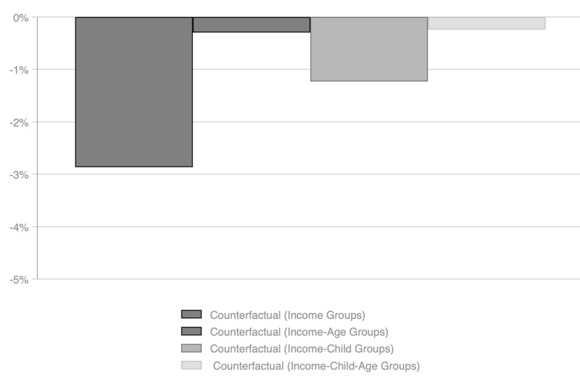
In table 5 below, I show the average change in uni/multidimensional REI for Pensioners, Working Age Adults, and Parents in the bottom third of the income distribution. Crucially, pensioners see negative falls in unidimensional REI but little difference in multidimensional REI constructions that incorporate age.

**Table 2.5: Uni/Multidimensional REI (2010) for Pensioners, Working Age Adults, & Parents in the Bottom Third of the Income Distribution**

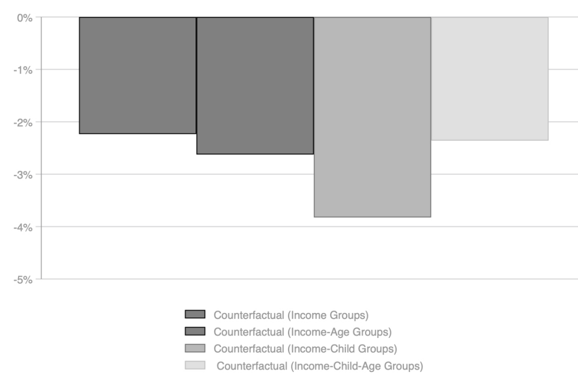
| | Change in Relative Electoral Importance by Group Construction | | | |
|---|---|---|---|---|
| | Income (Unidimensional) | Income-Age (Multidimensional) | Income-Child (Multidimensional) | Income-Age-Child (Multidimensional) |
| Pensioners | -9.11 | 0.37 | -5.78 | 0.30 |
| Working Age | -12.05 | -20.56 | -9.18 | -20.12 |
| Parents | -11.14 | -19.07 | -21.54 | -21.00 |

This differences in Relative Electoral Importance is reflected in the poverty rates constructed under different uni/multidimensional counterfactuals in 2019 as shown in Figures 2.13a - 2.13c below.

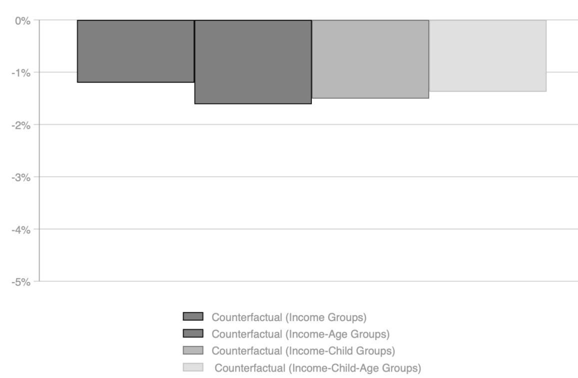
**Figure 2.13: Difference between Actual and Counterfactual Uni/Multidimensional Poverty Rates in 2019**




(a) Counterfactual Pensioner Poverty Rates




(b) Counterfactual Child Poverty Rates




(c) Working Age Poverty Rate

For pensioners, the counterfactual poverty rate is dramatically lower if we use only the results from the unidimensional income group specification (Figure 2.13a). But including age as a dimension incorporates the fact that low-income pensioners saw very small falls in Relative Electoral Importance at the 2010 election and leads to practically no difference in poverty rates. There is considerably less variation in counterfactual child and working age poverty rates reflecting the uniform falls they saw in both uni- and multidimensional Relative Electoral Importance at the 2010 election (Figures 2.13b & c).[1]

When using multidimensional income-age-child groups to calculate counterfactual poverty rates (i.e. the multiple dimensions that incorporates the most information) I find that child poverty rates would be around 2 percentage points lower (representing 260,000 fewer children in poverty) while pensioner poverty rates remain unchanged.

These results are, encouragingly, consistent with the evolution of actual relative poverty rates within the United Kingdom since 2010. Pensioners[2]have seen little change in poverty rates while children have seen a substantial rise (Bourquin et al. 2019b, 2020; DWP 2021). Similarly, the New Labour counterfactual in Appendix F (Figure 2.A8) also shows that, had they remained in power, child and working age poverty rates would be significantly lower while pensioner poverty rates would be slightly higher. This provides further support for the account of multidimensional redistribution described in this chapter.

# XVIII DISCUSSION & CONCLUSION

Governments in the United Kingdom redistributed more towards multidimensional groups whose Relative Electoral Importance increased after a change in government. The changes in redistribution were economically significant and, as poorer groups saw their Relative Electoral Importance fall at the 2010 election, led to a subsequent increase in income inequality and poverty. There were also significant differences between changes in Relative Electoral Importance for uni- and multidimensional groups with similar incomes and, subsequently,

[1] The impact that Relative Electoral Importance has on poverty rates depends on both their interaction with the coefficients from Appendix Table 2A.7 as well as the proportion of income they receive from redistribution. We should not, therefore, expect Child and Working Age poverty to fall by similar amounts despite similar falls in Parental and Working Age Relative Electoral Importance.

[2] The small rise in pensioner poverty rates is likely due to a statistical quirk (Bourquin et al. 2019b)

significant differences in the amount of redistribution they received.

The most important implication of these results is that they provide support for an explanation of redistribution between multidimensional groups that has not been tested in the current literature. These results explain why, after the 2010 election, low-income pensioners saw redistribution toward them remain stable while low-income non-pensioners saw large falls. An attractive feature of this explanation is that it can be used to explain redistribution in other advanced economies where non-income dimensions, such as age and place, are important for voter behaviour and subsequent redistributive policy choices (Sanderson and Scherbov 2007; OECD 2019; Pierson and Schickler 2020). This explanation also provides a mechanism that links the preferences of voters (who are more likely to vote for the incumbent when government decisions directly increase their income (Healy and Malhotra 2013)), to electoral coalitions (who have shown they are willing to vote for the incumbent (Kayser and Wlezien 2011)), to the partisan policy choices of governments (who redistribute to the multidimensional groups that voted for them in order to retain their support).

The clear policy implication from this chapter is that increasing the electoral incentives for governments to redistribute toward those on low-incomes is crucial for reducing income inequality and poverty (for certain groups). In particular, increasing the voting rates of non-pensioners and those on low-incomes is likely to lead to greater redistribution toward them. This is because their voting rates are much lower than pensioner and high-income citizens and so their maximum electoral importance is also correspondingly lower. [3] At the 2010 election the gap between pensioners and under-35s rate was over 20 percentage points as was the gap between high and low-income voter turnout (Gardiner 2016; Goodwin and Heath 2019). As a non-zero number of new low-income and non-pensioner voters will vote for each major party, increasing the voting rates of these groups will increase their Relative Electoral Importance and shift more redistribution toward them (compared to a scenario in which these citizens do not cast a ballot). More broadly, while current efforts to alleviate

[3] The maximum value a group's electoral importance can take is their turnout rate.

poverty focus on technical solutions, the results here indicate that these will not be successful unless governments have an electoral incentive to redistribute to low-income groups.

A possible limitation of these results is that they may be biased because they do not account for all taxation and government expenditure. It is theoretically possible that governments cut taxes and/or directed expenditure not considered here to groups whose Relative Electoral Importance fell when they came to power. This is, however, unlikely. The taxation changes not included in this modelling, such as corporation tax cuts, are likely to represent a relative increase for higher income groups (Miller 2017; Roantree et al. 2019). Similarly, changes in service expenditure also shows pensioners being relatively protected. In real terms, current expenditure on health (that is disproportionately used by older voters) was protected while non-health public service expenditure fell by 20% in real terms between 2009/10 to 2019/20, which is likely to reflect a cut for low-income groups (Marx et al. 2015; Farquharson 2019). Future research could consider how changes in Relative Electoral Importance affect public service expenditure.

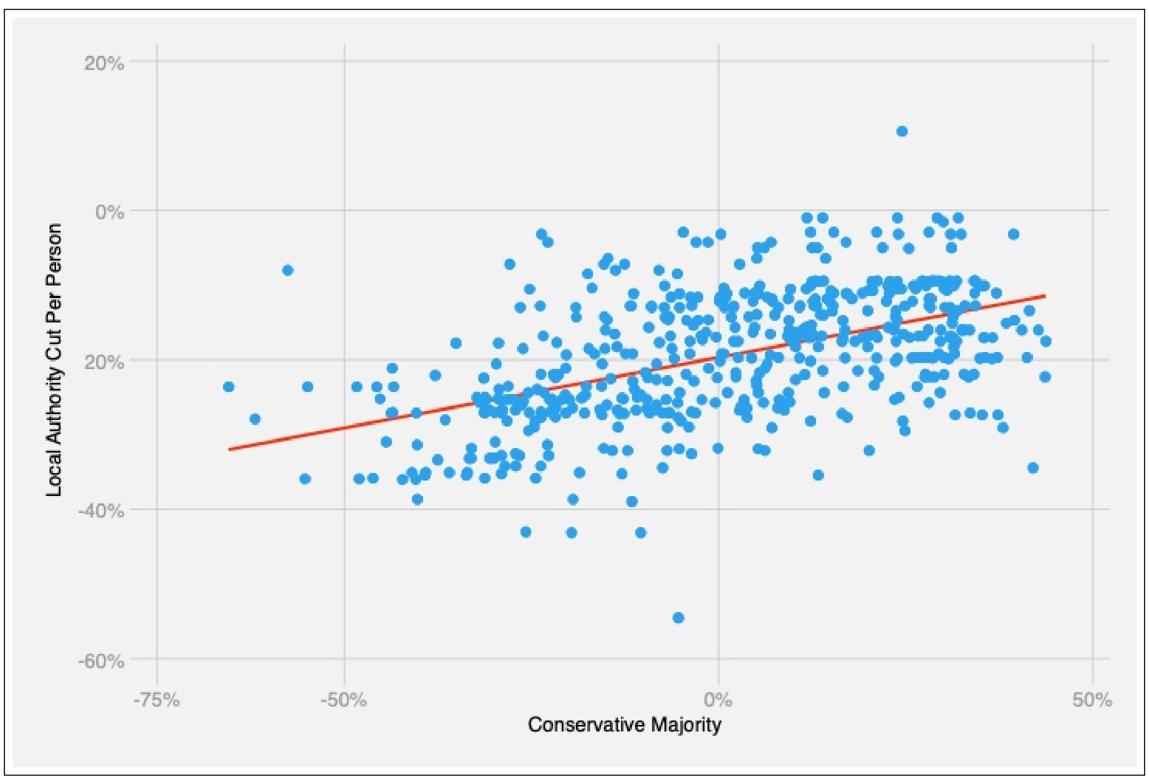
An objection to these results may be that governments, in a majoritarian system, use area-based rather than individual-based redistribution to buy votes. As is discussed above, while individual-based redistribution is likely to be more efficient at buying votes, governments can also engage in area-based redistribution as a complementary strategy (rather than a competing one).

Below, I assess whether governments do also engage in area-based expenditure. I do so analysing the change in local authority expenditure per person between 2010 and 2019 and its correlation with the Conservative margin of victory within constituencies in the 2010 election. This method is necessarily rough as there is no perfect fit between constituencies and local authorities. Constituencies often sit in more than one local authority, and local authorities often contain more than one than one constituency. While this makes assigning area-based expenditure somewhat complex, governments also face this same problem. They do not have easy mechanisms to target area-based expenditure directly to constituencies.

Most work on pork-barrel politics in the UK analyses local authorities because of this reason (Ward and John 1999; John and Ward 2001; Fouirnaies and Mutlu-Eren 2015). Even where expenditure is not assigned by local authority, such as the Towns Fund that was recently shown to be assigned for political purposes, governments faced a similar problem with funding often split between constituencies (Hanretty 2021). For this analysis, where constituencies sit in more than one local authority, they are assigned to the local authority where most wards exist.

The evidence from my indicative analysis indicates that UK governments after 2010 were engaged in both area-based expenditure and individual-based redistribution (as shown by the results in the main text). As can be seen in Figure 2.14 below, there is a negative relationship between the Conservative share of victory and the cut per person.

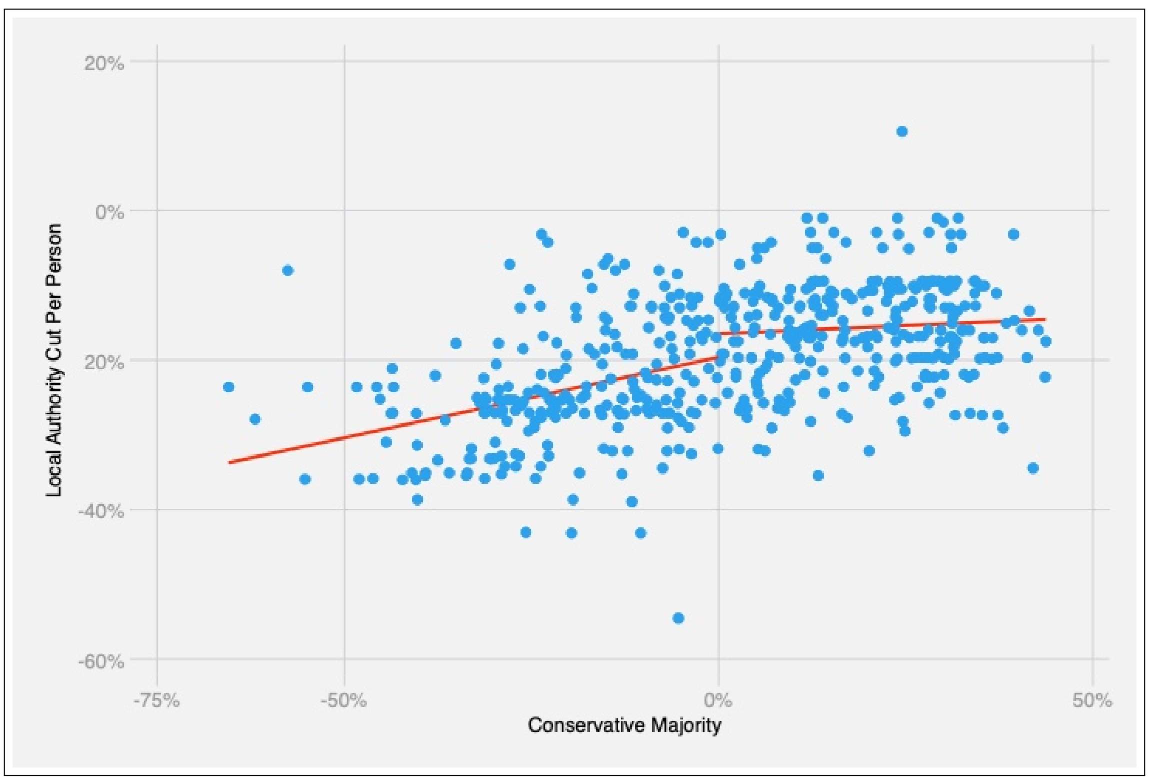
**Figure 2.14: Local Authority Cuts (2011-2019) and Conservative Majority in Parliamentary Constituencies (2010)**




Source: Harris et al. (2019)

This indicative analysis also provides little evidence here governments exploit the unique characteristics of majoritarian systems by targeting more expenditure at marginal constituencies. In Figure 2.15, I construct separate regression lines for constituencies where the Conservatives are and are not in power. The regression line for Conservative held constituencies is flat. This line should slope upwards toward the 0% x-axis line if more expenditure is targeted at marginal constituencies. However, this indicative result should be interpreted with caution as the literature generally finds that UK governments do target marginal areas with greater area-based expenditure (Ward and John 1999; Fouirnaies and Mutlu-Eren 2015; Hanretty 2021). More concretely, this analysis suggests that UK governments since 2010 have used area-based expenditure to target more funding to constituencies that voted for them in greater numbers as a complementary strategy to the individual-based redistribution targeted at groups that voted for them in greater numbers, which is analysed in the main text.

**Figure 2.15: Local Authority Cuts (2011-2019) and Conservative Majority in Parliamentary Constituencies (2010)**




Source: Harris et al. (2019), Regression Line Break at 0%

Another possible limitation concerns the identification assumption used in the difference-in-differences specification. Specifically, would New Labour have continued to redistribute *relatively* more to the same groups after 2010 given their fiscal plans to halve the deficit? While I cannot, of course, be completely certain, the available evidence indicates that the answer is yes. New Labour protected low-income parents and pensioners from cuts and increased taxes on the rich after the financial crisis struck in 2008 (Phillips and Browne 2010). They committed to doing so after 2010 as well. New Labour broke a manifesto commitment to introduce a new 50% top tax rate (reduced to 45% by the post-2010 government in 2012) (Seely 2018), passed the Child Poverty Act of 2010 that enshrined in law their commitment to practically end child poverty by 2020 (abolished by the Conservatives in 2016) (Roberts and Stewart 2015), and planned to freeze tax thresholds that would have led to the richest paying more (the post-2010 government increased these thresholds) (Joyce and Levell 2011). New Labour's planned measures for the 2010 to 2014 period would have seen the bottom 10 % lose around 0.3% of their income while the richest 10% would have lost 3.2% of their income (Adam et al. 2010). As seen above, this stood in marked contrast to the actual evolution in relative redistribution after 2010.

The evidence presented here did not evaluate Relative Electoral Importance in terms of partisanship as is standard in the distributive politics literature due to increasing partisan volatility in the UK electorate (Dixit and Londregan 1996; Kuhn 2013; Golden and Min 2013). Future research could include measures of partisanship. A methodological contribution this chapter does make is that it constitutes, to my knowledge, the first robust empirical test of distributive politics within an advanced economy, which has thus far only tested which areas, rather than which people, are targeted for distributive rewards (Golden and Min 2013; Albertus 2019).

Similarly, future research could consider where Relative Electoral Importance ultimately derives from. As is discussed in more detail above, it is very difficult to disentangle the extent to which it reflects promises or rewarding electoral coalitions but it makes little difference to the main analysis. Parties still do redistribute to multidimensional groups who vote for them in greater numbers, and these groups are likely to vote for someone else if they are not rewarded with redistribution (Dalton 2014; Lewis-Beck and Stegmaier 2013; Sanders 2017; Tilley et al. 2018). It is also clear that the Relative Electoral Importance measure used here contains information that current measures of ideology and manifestos do not. These measures only evaluate redistribution from a unidimensional perspective placing governments on a left to right scale or assessing whether they plan to increase or reduce taxation/expenditure without considering which specific groups are being targeted by these policies (Herwartz and Theilen 2017; Volkens et al. 2019).

Manifestos and ideologies are also sufficiently vague to allow governments considerable scope when choosing which policies to implement, and so which groups to favour, once elected (Bara 2005). The 1997 New Labour manifesto did not contain policy commitments regarding their major social security reforms while their tax policies were sufficiently flexible as to allow for tacit rises for those on high incomes through fiscal drag (The Labour Party 1996; Phillips and Browne 2010). Neither the Conservative nor the Liberal Democrat manifestos of 2010 included their largest social security cut, changes to uprating, nor their largest give away to high-income voters, the cut in the top rate of income tax (Conservative Party 2010; Liberal Democrats 2010). Protecting pensioners was originally a Liberal Democrat policy, which was then absorbed and enhanced by the Conservatives when they saw the electoral benefits of doing so (Snowdon and Seldon 2016; Laws 2017).

How generalisable these results are remains an open question. This chapter largely focuses on one change in government (from New Labour to Coalition/Conservative) in one country (the United Kingdom), with an indication that these results also hold for the 1997 transfer of power. However, this chapter does provide a methodology to evaluate multidimensional redistribution across advanced democracies and other time periods. The EUROMOD microsimulation model, available alongside the UKMOD microsimulation model, has information on the distributive systems of each of the EU-27 nations, which, when combined with microdata on voting patterns as well as the salience and feasibility of characteristics used to create political coalitions, can be used to test multidimensional redistribution across advanced democracies. This could be a fruitful avenue for future research.

# XIX APPENDIX A: CHANGE IN RELATIVE ELECTORAL IMPORTANCE 2010 AND 1997 ELECTIONS

**Table 2A.1: Descriptive Statistics for Change in Relative Electoral Importance (2010) of Uni/Multidimensional Groups**

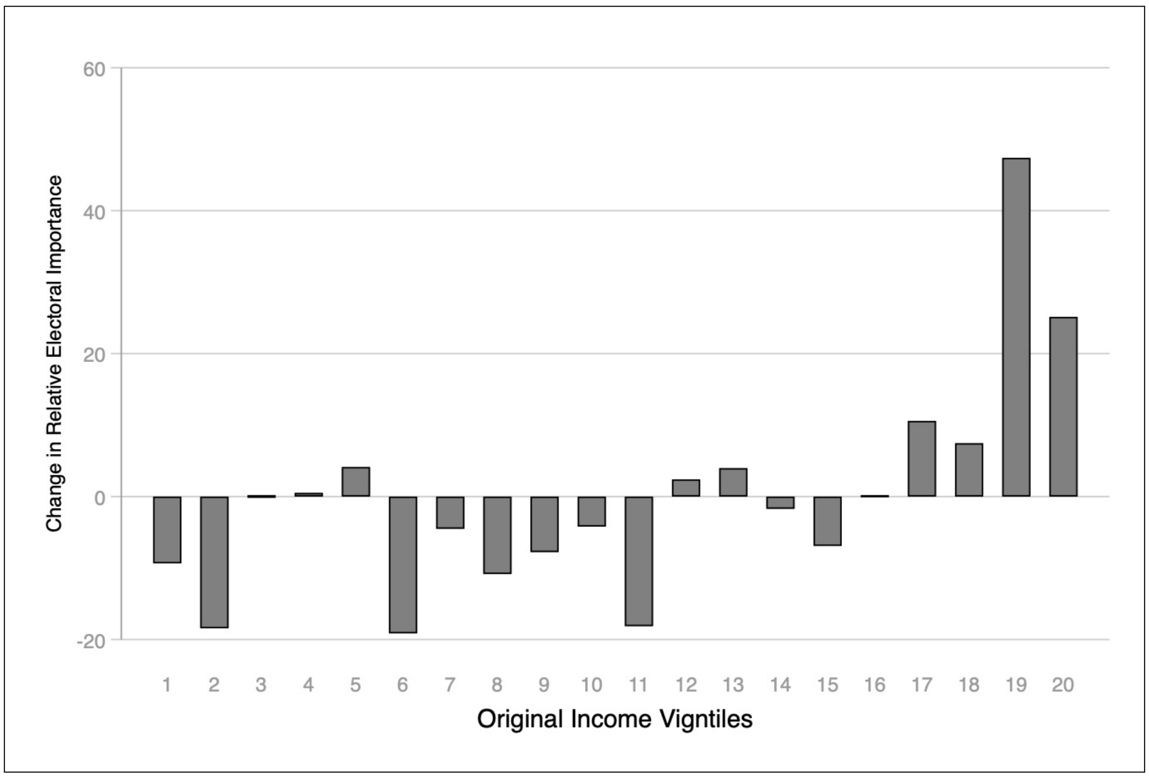
| | Change in Relative Electoral Importance at 2010 election | | | | |
|---|---|---|---|---|---|
| | Groups | Mean | Standard Deviation | Min | Max |
| Income Groups | 20 | -.003 | 10.61 | -22.78 | 22.61 |
| Income-Age Groups | 60 | .065 | 15.52 | -30.46 | 61.38 |
| Income-Parent Groups | 40 | .028 | 12.70 | -31.61 | 26.43 |
| Income-Age-Parent Groups | 111 | .026 | 16.90 | -81.96 | 87.85 |

**Table 2A.2: Descriptive Statistics for Change in Relative Electoral Importance (1997) of Uni/Multidimensional Groups**

| | Change in Relative Electoral Importance at 1997 election | | | | |
|---|---|---|---|---|---|
| | Groups | Mean | Standard Deviation | Min | Max |
| Income Groups | 20 | .334 | 13.73 | -27.66 | 29.25 |
| Income-Age Groups | 60 | -.399 | 18.97 | -79.73 | 38.98 |
| Income-Parent Groups | 40 | .376 | 15.02 | -31.61 | 31.13 |
| Income-Age-Parent Groups | 109 | -.336 | 20.03 | -81.96 | 63.70 |

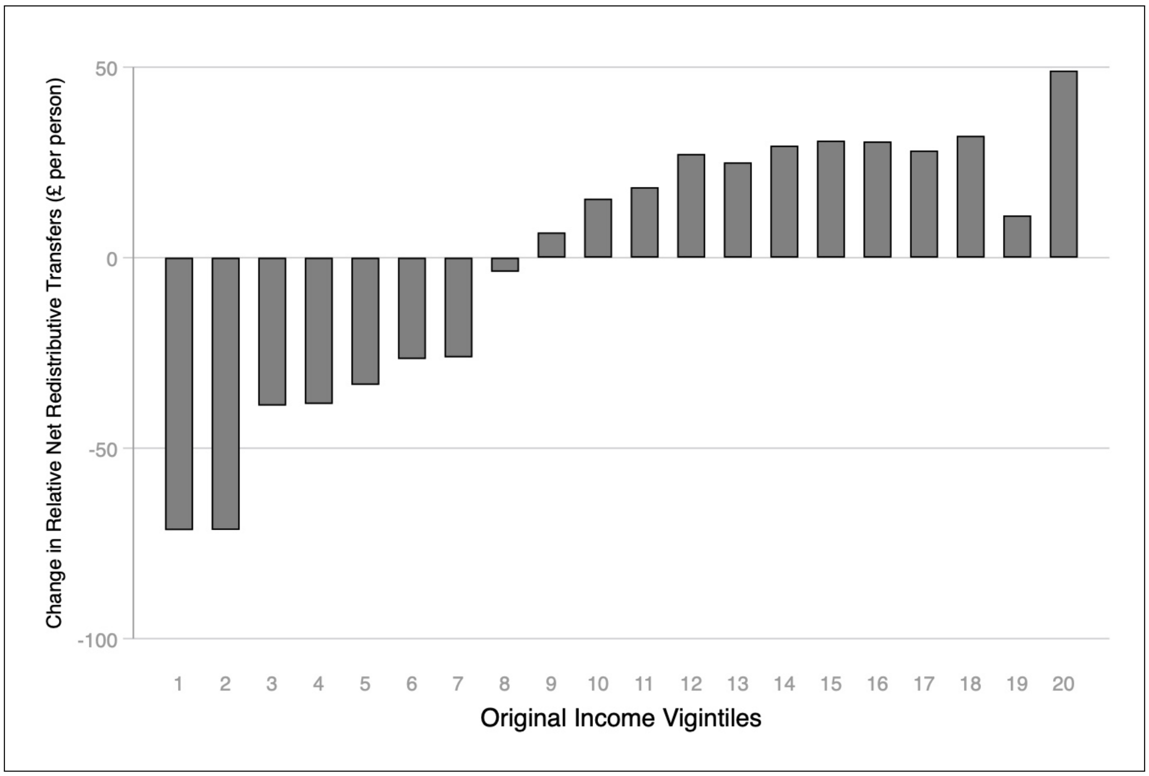
# XX APPENDIX B: CHANGE IN RELATIVE ELECTORAL IMPORTANCE AND RELATIVE REDISTRIBUTION FOR YOUNG & MIDDLE-AGE INCOME-AGE GROUP

**Figure 2A.1: Change in Relative Electoral Importance at 2010 Election (Young Income-Age Groups)**



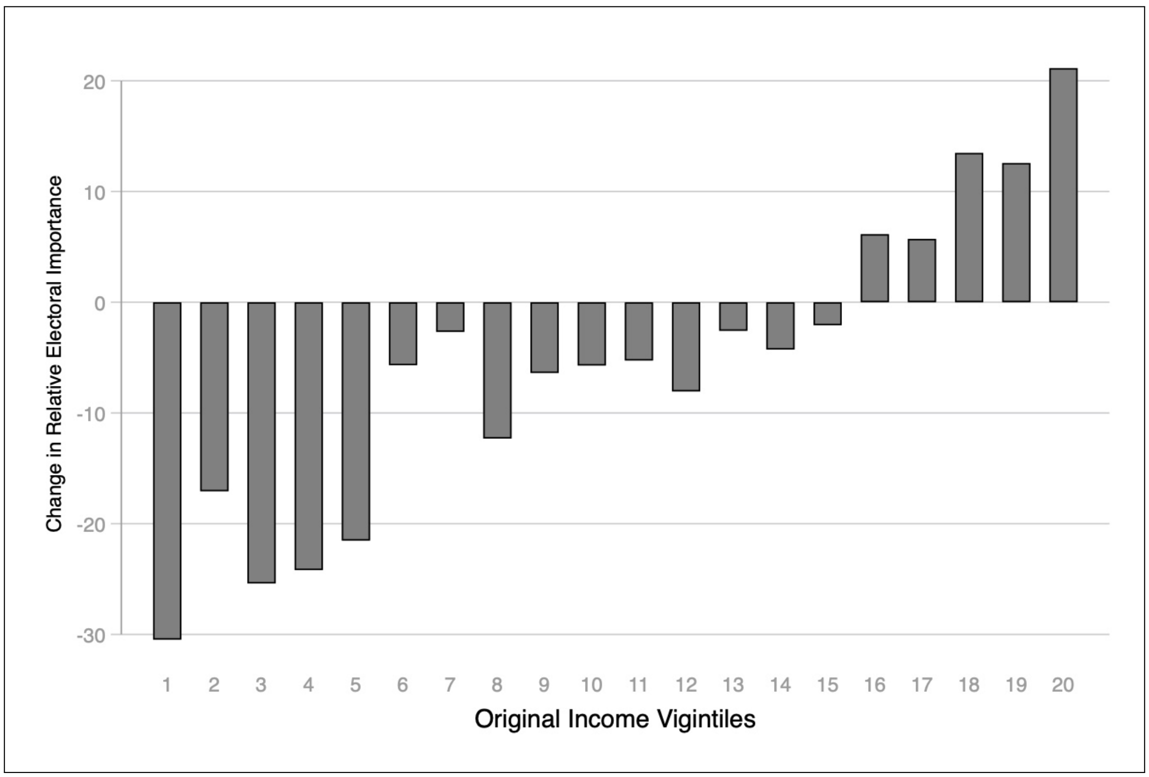

Source: BHPS/Understanding Society and UKMOD Microsimulation Model

**Figure 2A.2: Change in Relative Redistribution (Young Income-Age Groups)**



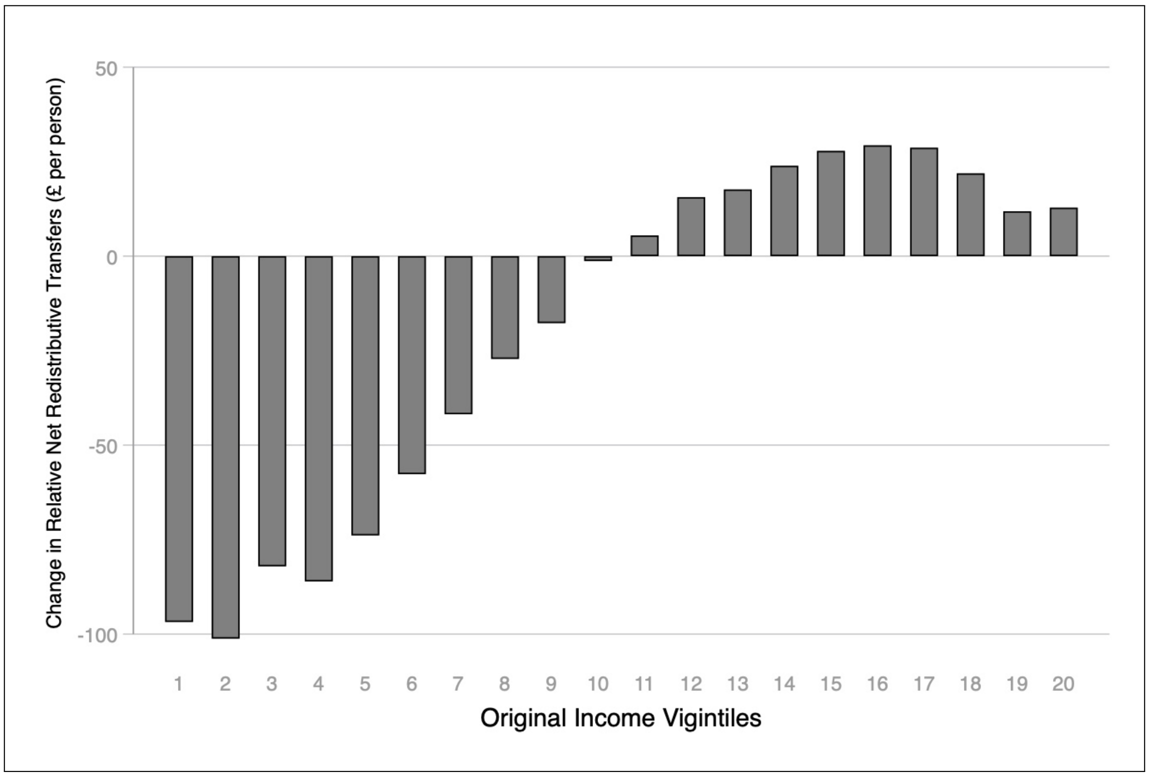

Source: UKMOD Microsimulation Model

**Figure 2A.3: Change in Relative Electoral Importance at 2010 Election (Middle-Age Income-Age Groups)**




Source: BHPS/Understanding Society and UKMOD Microsimulation Model

**Figure 2A.4: Change in Relative Redistribution (Middle-Age Income-Age Groups)**




Source: UKMOD Microsimulation Model

# XXI APPENDIX C: RESULTS FOR FULL UNIVERSAL CREDIT ROLLOUT

**Table 2A.3: Standard DiD, Impact of Change in Relative Electoral Importance (2010) on Relative Redistribution (2005-10 & full UC Rollout)**

| | Uni/Multidimensional Group Type | | | |
|---|---|---|---|---|
| | Income Groups | Income x Age | Income x Child | Income x Age x Child |
| | (1) | (2) | (3) | (4) |
| $\rho$(Post-2010 Election) | 0 | 0 | 0 | 0 |
| | (.) | (.) | (.) | (.) |
| $\delta$ (Change in Relative Electoral Importance 2010 Election x Post-2010 Election) | 4.103*** | 2.060*** | 3.399*** | 1.852*** |
| | (0.630) | (0.459) | (0.556) | (0.348) |
| Constant | 460.4*** | 457.0*** | 459.4*** | 457.2*** |
| | (31.77) | (28.49) | (25.31) | (21.96) |
| Group Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Individual Earnings-Specific Trends | Yes | Yes | Yes | Yes |
| No. of Groups | 20 | 60 | 40 | 111 |
| No. of Individuals | 41826 | 41826 | 41826 | 41786 |
| No. of Observations | 292782 | 292782 | 292782 | 292502 |
| Overall $R^2$ | .90 | .90 | .90 | .90 |

Robust standard errors, clustered by Groups, calculated. Standard Errors in parentheses
Empty cells in calculation of REI for income-age-child groups leads to 111 groups
& fewer observations.
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 2A.4: Linear First-Difference Regression, Impact of Differences in Uni/Multidimensional REI in 2010 on Uni/Multidimensional Relative Redistribution Difference (2011-2019) with full UC Rollout**

| | Multidimensional Group Difference | | |
|---|---|---|---|
| | Income x Age | Income x Child | Income x Age x Child |
| | (1) | (2) | (3) |
| $\delta$ (Uni/Multidimensional REI Difference) | 1.237*** | 3.141*** | 1.163*** |
| | (0.266) | (0.341) | (0.231) |
| $\rho$(Earnings Growth(2011-2019)) | -0.383*** | -0.393*** | -0.383*** |
| | (0.0465) | (0.0468) | (0.0488) |
| Constant | -4.444 | -3.761 | -4.288 |
| | (2.912) | (3.708) | (3.842) |
| No. of Groups | 60 | 40 | 111 |
| No. of Individuals | 41826 | 41826 | 41787 |
| No. of Observations | 41826 | 41826 | 41786 |
| Overall $R^2$ | .27 | .29 | .27 |

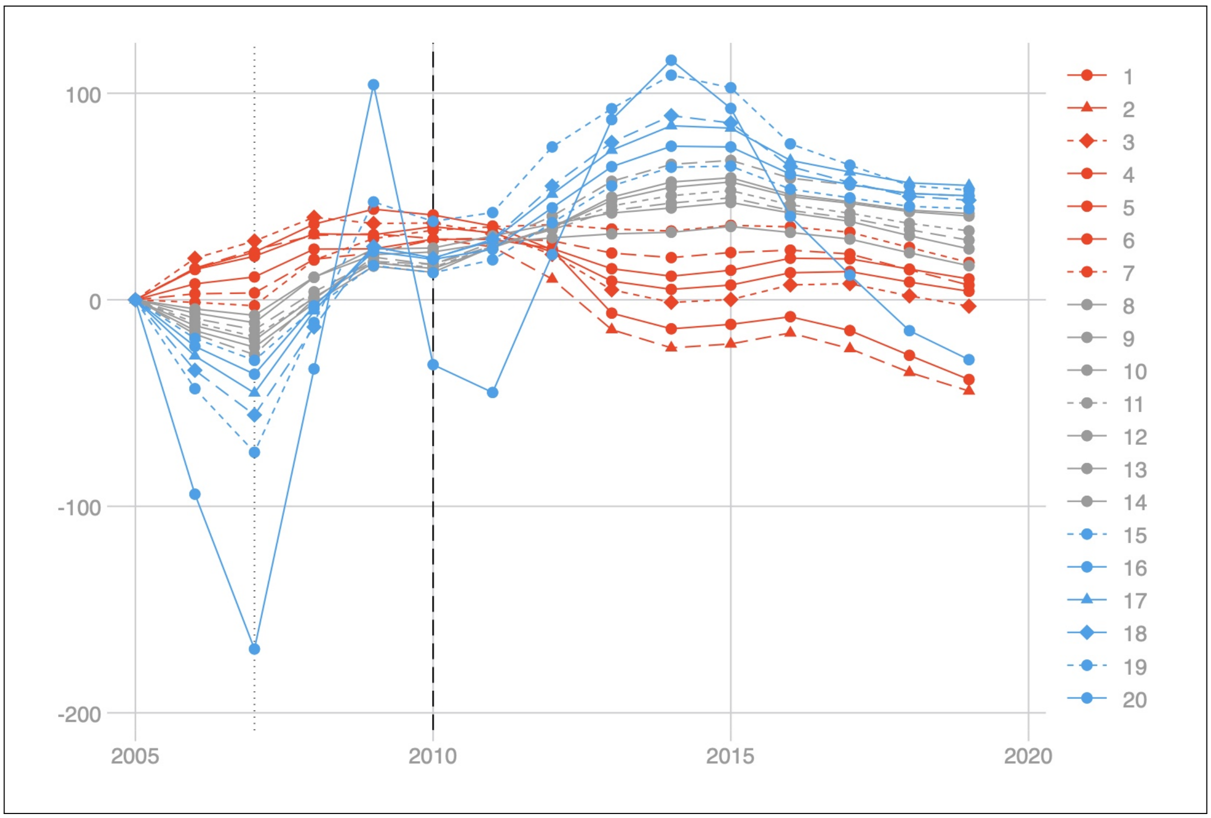
Robust standard errors, clustered by Groups, calculated. Standard Errors in parentheses
Empty cells in calculation of REI for income-age-child groups leads to 111 groups & fewer observations.
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

# XXII APPENDIX D: IDENTIFICATION ASSUMPTION TESTS

I graphically examine the common trends assumption below. The identification assumption is that, *conditional* on earnings growth, redistribution would have remained constant for each group without a change in government in 2010. Until the onset of the Great Recession in 2008 there were constant trends in redistribution for each income group (Figure 2A.5). Had there not been a large fall in earnings, then group-specific trends could have controlled for differential growth rates in redistribution (Angrist and Pischke 2009, 2015). However, the large fall in earnings caused by the financial crisis (Figure 2A.6) then led to a large fall in taxation payments, and thus a rise in redistribution, for higher income groups. Individual specific earnings trends are, therefore, included to control for differential time trends in redistribution. Specifically, they control for the heterogeneous effects of the economic cycle on redistribution (Lechner 2011). This time-varying covariate is an appropriate control as it is exogenous within the microsimulation model, which abstracts from behavioural and demographic changes. Earnings are not affected by changes in Relative Electoral Importance as individuals do not change their behaviour in response to the coming election (Wing et al. 2018).

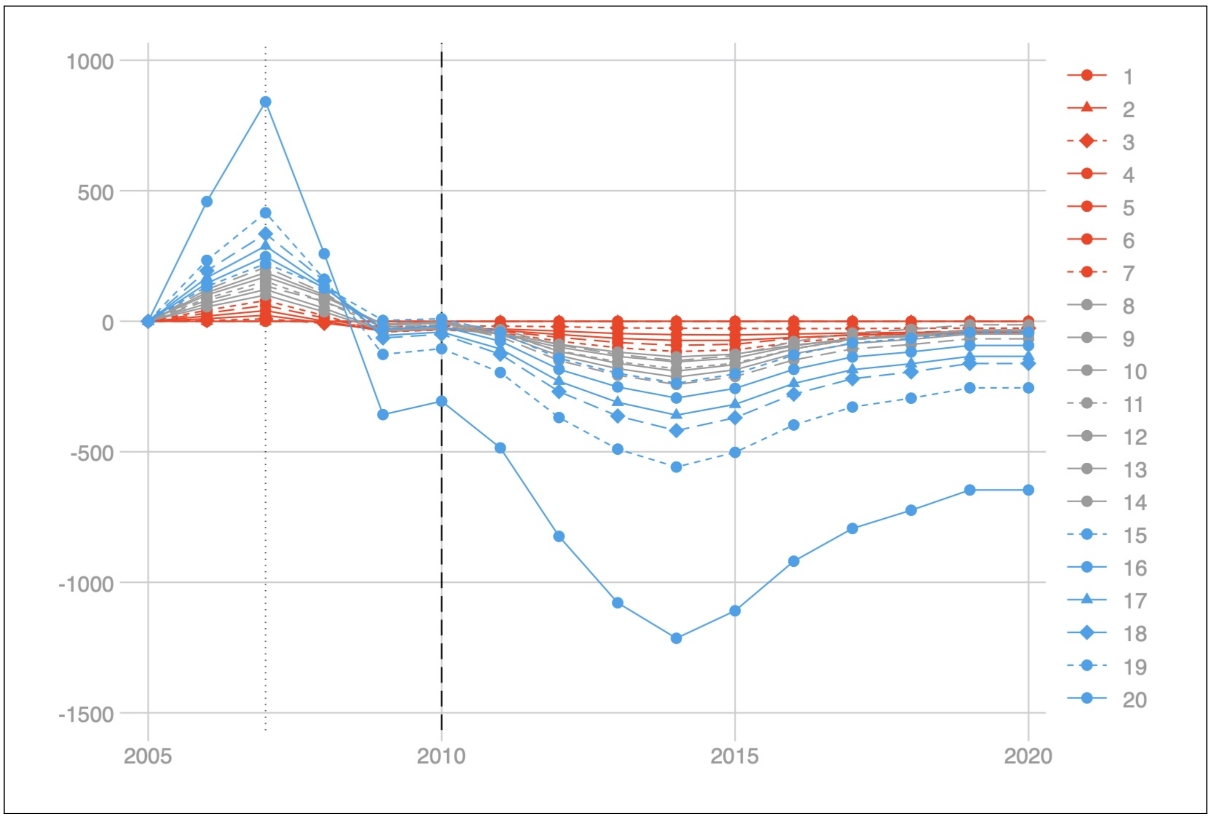
I formally test the pre-treatment common trends assumption using placebo time tests. I do not, however, expect these placebo tests to be precisely zero but instead for them to be slightly negative. This is because groups see their Change in Relative Electoral Importance change after every change in power, including in the period prior to 2010. For some groups, there is a negative correlation between the Change in Relative Electoral Importance in 2010 and the Change in Relative Electoral Importance in 1997. The bottom income group, for example, saw their Relative Electoral Importance rise dramatically in 1997 and fall dramatically in 2010. Descriptively, the bottom income group saw large rises in redistribution prior to 2010 (conditional on earnings growth) and so the coefficient on the leads for this

**Figure 2A.5: Cumulative Change in Relative Redistribution for Income Groups**




Dotted line indicates start of Great Recession. Dashed line indicates change in power at 2010 election. Source: UKMOD Microsimulation Model

**Figure 2A.6: Cumulative Change in Market Income for Income Groups**




Dotted line indicates start of Great Recession. Dashed line indicates change in power at 2010 election. Source: UKMOD Microsimulation Model group alone would be strongly negative. The leads are not, however, likely to be strongly negative overall because some groups would have seen their Relative Electoral Importance remain stable at the 1997 election and then increase or decrease after at the 2010 election

Tables 2A.5 and 2A.6 show placebo time tests restricting the pre-treatment samples to 2005-2010 and 2005 – 2009 data respectively. As discussed above, I expected the leads to be slightly negative due to the negative, but not perfectly negative, correlation between Relative Electoral Importance at the 2010 and 1997 elections. The results of these placebo tests are consistent with the common trends assumption. The effect of REI is slightly negative between 2005 and 2009. Due to the uprating quirk in 2010, including 2010 data into the sample drives up the coefficient estimates to 0.

**Table 2A.5: Standard DiD, Impact of Change in Relative Electoral Importance (2010) on Relative Redistribution (2005-2009)**

| | Uni/Multidimensional Group Type | | | |
|---|---|---|---|---|
| | Income Groups | Income x Age | Income x Child | Income x Age x Child |
| | (1) | (2) | (3) | (4) |
| $\rho$(Post-2007 | -19.27*** | -18.40*** | -20.82*** | -18.46*** |
| | (1.310) | (1.254) | (2.022) | (1.804) |
| $\delta$ (Change in Relative Electoral Importance | -0.442* | -0.318*** | -0.715*** | -0.323*** |
| 2010 Election x Post-2007) | (0.208) | (0.0603) | (0.156) | (0.0894) |
| Constant | 451.7*** | 487.0*** | 485.8*** | 487.1*** |
| | (33.92) | (21.19) | (18.77) | (16.35) |
| Group Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Individual Earnings-Specific Trends | Yes | Yes | Yes | Yes |
| No. of Groups | 20 | 60 | 40 | 111 |
| No. of Individuals | 41826 | 41826 | 41826 | 41786 |
| No. of Observations | 209130 | 209130 | 209130 | 208930 |
| Overall $R^2$ | .90 | .90 | .90 | .90 |

Robust standard errors, clustered by Groups, calculated. Standard Errors in parentheses
Empty cells in calculation of REI for income-age-child groups leads to 111 groups
& fewer observations.
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 2A.6: Standard DiD, Impact of Change in Relative Electoral Importance (2010) on Relative Redistribution (2005-2010)**

| | Uni/Multidimensional Group Type | | | |
|---|---|---|---|---|
| | Income Groups | Income x Age | Income x Child | Income x Age x Child |
| | (1) | (2) | (3) | (4) |
| $\rho$(Post-2007) | 5.369 | -0.752 | -0.595 | -1.253 |
| | (8.159) | (6.810) | (8.624) | (6.637) |
| $\delta$ (Change in Relative Electoral Importance | 1.288 | 0.232 | 0.237 | 0.134 |
| 2010 Election x Post-2007) | (0.894) | (0.295) | (0.515) | (0.231) |
| Constant | 486.8*** | 485.3*** | 486.2*** | 485.6*** |
| | (28.35) | (22.58) | (20.01) | (16.91) |
| Group Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Individual Earnings-Specific Trends | Yes | Yes | Yes | Yes |
| No. of Groups | 20 | 60 | 40 | 111 |
| No. of Individuals | 41826 | 41826 | 41826 | 41786 |
| No. of Observations | 250956 | 250956 | 250956 | 250716 |
| Overall $R^2$ | .90 | .90 | .90 | .90 |

Robust standard errors, clustered by Groups, calculated. Standard Errors in parentheses
Empty cells in calculation of REI for income-age-child groups leads to 111 groups
& fewer observations.
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

# XXIII APPENDIX E: CHANGE IN IMPACT OF RELATIVE ELECTORAL IMPORTANCE OVER TIME

**Table 2A.7: Dynamic DiD, Impact of Change in Relative Electoral Importance (2010) on Relative Redistribution (2005-2019)**

| | Uni/Multidimensional Group Type | | | |
|---|---|---|---|---|
| | Income Groups | Income x Age | Income x Child | Income x Age x Child |
| | (1) | (2) | (3) | (4) |
| Change in Relative Electoral Importance (2010 Election) x : | | | | |
| 2006 | -0.604*** | -0.160*** | -0.346*** | -0.128** |
| | (0.124) | (0.0557) | (0.106) | (0.0515) |
| 2007 | -0.854*** | -0.184** | -0.437** | -0.138* |
| | (0.189) | (0.0811) | (0.179) | (0.0830) |
| 2008 | -0.649*** | -0.0953 | -0.618*** | -0.110 |
| | (0.0786) | (0.104) | (0.119) | (0.102) |
| 2009 | -0.482 | -0.152 | -0.758*** | -0.195 |
| | (0.338) | (0.156) | (0.231) | (0.141) |
| 2010 (Election Year) | 3.760* | 1.206 | 1.726 | 0.965* |
| | (1.965) | (0.757) | (1.175) | (0.566) |
| 2011 | 4.048** | 1.321* | 1.967 | 1.071* |
| | (1.833) | (0.755) | (1.180) | (0.582) |
| 2012 | 4.374** | 1.561** | 2.336** | 1.290** |
| | (1.778) | (0.737) | (1.114) | (0.556) |
| 2013 | 3.186*** | 1.155*** | 1.685** | 0.952*** |
| | (0.649) | (0.397) | (0.637) | (0.328) |
| 2014 | 3.449*** | 1.271*** | 1.892*** | 1.054*** |
| | (0.663) | (0.429) | (0.647) | (0.345) |
| 2015 | 3.492*** | 1.306*** | 1.957*** | 1.090*** |
| | (0.651) | (0.431) | (0.654) | (0.349) |
| 2016 | 3.222*** | 1.488*** | 1.953*** | 1.254*** |
| | (0.564) | (0.380) | (0.602) | (0.325) |
| 2017 | 3.391*** | 1.746*** | 2.245*** | 1.487*** |
| | (0.565) | (0.414) | (0.591) | (0.339) |
| 2018 | 3.784*** | 2.045*** | 2.682*** | 1.759*** |
| | (0.649) | (0.469) | (0.649) | (0.380) |
| 2019 | 4.104*** | 2.319*** | 3.140*** | 2.018*** |
| | (0.713) | (0.510) | (0.661) | ((0.399) |
| Constant | 459.7*** | 454.3*** | 458.9*** | 454.9*** |
| | (49.68) | (41.18) | (37.13) | (31.21) |
| Group Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Individual Earnings-Specific Trends | Yes | Yes | Yes | Yes |
| No. of Groups | 20 | 60 | 40 | 111 |
| No. of Individuals | 41826 | 41826 | 41826 | 41786 |
| No. of Observations | 627390 | 627390 | 627390 | 626790 |
| Overall $R^2$ | .81 | .82 | .81 | .82 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# XXIV APPENDIX F: NEW LABOUR COUNTERFACTUAL

As a robustness check for the common trends assumption used in the main text, I construct a counterfactual of how much redistribution each individual would have received if the New Labour Government had remained in power between 2011 and 2019. I then compare the amount each individual received under the post-2010 Conservative led Government and the New Labour counterfactual. This counterfactual is constructed using the policies and legislation New Labour had in office in 2010 as well as their manifestos. This tends to involve uprating[4] means-tested benefits in line with RPIX inflation[5] , non-means tested social security payments in line with RPI inflation, tax thresholds in line with RPI inflation and pensions in line with earnings (as set out in the Pensions Act 2007), but where thresholds and amounts were frozen in nominal terms under New Labour (e.g. the family element of Child Tax), then I also keep them frozen (Joyce and Levell 2011; Kennedy et al. 2013; Thurley 2018). Both the IFS and HM Treasury construct counterfactuals using a similar methodology set out here whereas other distributional analyses uprate all taxation and social security thresholds in line with either prices or earnings (Hills 2013; De Agostini et al. 2018)

In addition, I uprate the Minimum Wage as the Conservative government did up to 2015 (as both tended to follow the advice of the Low Pay Commission when setting minimum wages (Rutter 2016)) and then linearly uprate it from £6.70 in 2015 to £8 in 2020 (as in 2015 Labour Manifesto (The Labour Party 2015)), as well as increase the State Pension Age in line with path set out in the Pensions Act 1995 (Thurley and Keen 2018).

I estimate the following dynamic specification, where I compare the differences in redistribution under the post-2010 and New Labour counterfactual governments. There is no

[4]Uprating involves increasing a social security/tax threshold in year t, with the prevailing uprating factor in year t-1 – for example, social security payment thresholds in 2006 were uprated in line with 2005 inflation.

[5]The New Labour Government, and previous governments, actually used the Rossi Index but as this is no longer being produced in 2017, I use the RPIX as a substitute – the differences between the two are miniscule

common trends assumption required because the counterfactual is constructed rather than assumed, nor a need to control for earnings growth, as they evolve almost identically for individuals in both distributive systems.

$$\text{Difference in Relative Redistribution under Conservative-led \& New Labour Governments}_{i,t} = a_j + c_t + \delta(\text{Change in Relative Electoral Importance 2010 Election} \times \text{Year})_{j,t} + \epsilon_{i,j,t} \quad (2.14)$$

The results in Table 2A.8 provide further support for Hypothesis 1. These results also provide further support for the common trends assumption. In this specification, the counterfactual amount each individual receives without a change in government is constructed and is consistent with the results of specifications that assumes that redistribution would have grown at a constant rate, conditional on earnings.

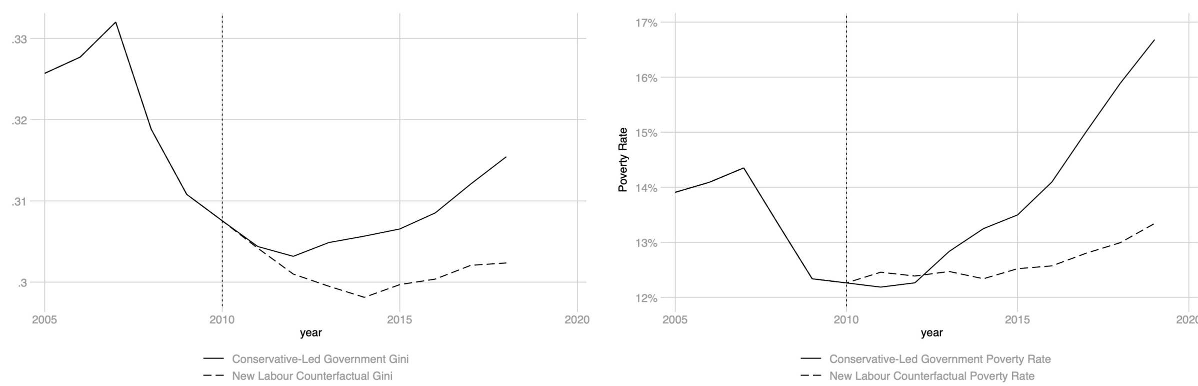
**Table 2A.8: Dynamic DiD, Impact of Change in Relative Electoral Importance (2010) on Relative Redistribution (2009-2019)**

| | Uni/Multidimensional Group Type | | | |
|---|---|---|---|---|
| | Income Groups | Income x Age | Income x Child | Income x Age x Child |
| | (1) | (2) | (3) | (4) |
| Change in Relative Electoral Importance (2010 Election) x : | | | | |
| 2009 | 0 | 0 | 0 | 0 |
| | (.) | (.) | (.) | (.) |
| 2010 (Election Year) | 0 | 0 | 0 | 0 |
| | (0) | (0) | (0) | (.) |
| 2011 | 0.111 | 0.101 | 0.220* | 0.110 |
| | (0.209) | (0.0858) | (0.127) | (0.0722) |
| 2012 | -0.00516 | 0.310** | 0.302* | 0.315*** |
| | (0.255) | (0.119) | (0.169) | (0.109) |
| 2013 | 0.778* | 0.689*** | 1.035*** | 0.675*** |
| | (0.448) | (0.218) | (0.256) | (0.170) |
| 2014 | 0.958* | 0.887*** | 1.188*** | 0.846*** |
| | (0.663) | (0.246) | (0.271) | (0.191) |
| 2015 | 1.121* | 0.949*** | 1.433*** | 0.925*** |
| | (0.567) | (0.284) | (0.310) | (0.210) |
| 2016 | 1.171* | 1.211*** | 1.533*** | 1.154*** |
| | (0.615) | (0.296) | (0.332) | (0.219) |
| 2017 | 1.543** | 1.489*** | 1.939*** | 1.415*** |
| | (0.668) | (0.342) | (0.362) | (0.243) |
| 2018 | 1.667** | 1.706*** | 2.126*** | 1.614*** |
| | (0.741) | (0.389) | (0.400) | (0.274) |
| 2019 | 1.847** | 1.888*** | 2.520*** | 1.815*** |
| | (0.869) | (0.439) | (0.488) | (0.305) |
| Constant | 0 | 0 | 0 | 0 |
| | (3.057) | (2.607) | (2.708) | (2.502) |
| Group Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Individual Earnings-Specific Trends | Yes | Yes | Yes | Yes |
| No. of Groups | 20 | 60 | 40 | 109 |
| No. of Individuals | 43852 | 43852 | 41826 | 41786 |
| No. of Observations | 482372 | 482372 | 482372 | 481822 |
| Overall $R^2$ | .03 | .05 | .05 | .05 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Inequality and poverty are also significantly lower in the New Labour counterfactual (Figure 2A.7 below)

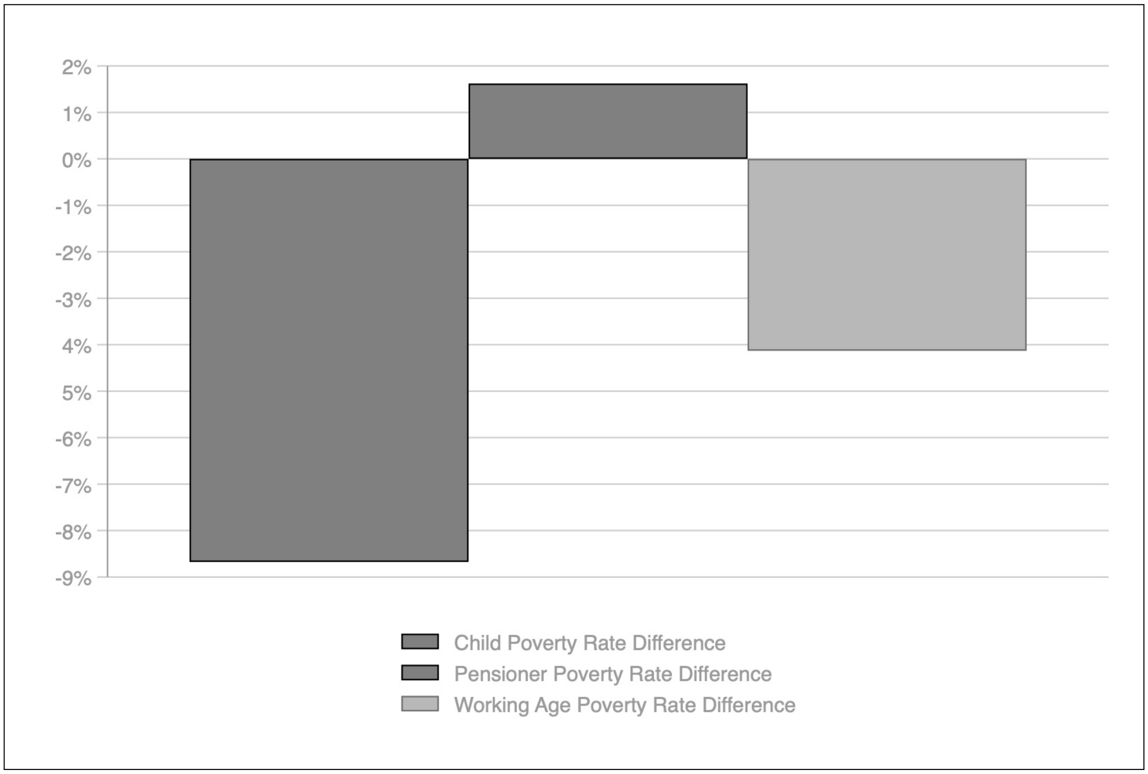
Poverty rates for children and working-age persons are significantly lower in the New Labour counterfactual, while pensioner poverty is slightly higher (Figure 2A.8). This provides further support for the account of multidimensional redistribution outlined in this chapter.




(a) Difference in Gini Coefficients (b) Difference in Poverty Rates

**Figure 2A.7: Differences in Inequality and Poverty Rates under New Labour and the Conservative-Led Government**

**Figure 2A.8: Difference in Subgroup Poverty Rates under New Labour and the Conservative-Led Government in 2019**



# XXV APPENDIX G: ROBUSTNESS CHECKS - FIVE INCOME GROUPS, TEN INCOME GROUPS, AND 2005 ELECTORAL IMPORTANCE

## XXV.1 Five Income Group Construction

**Table 2A.9: Standard DiD - 5 Income Group Robustness Check, Impact of Change in Relative Electoral Importance (2010) on Relative Redistribution (2005-2019)**

| | Uni/Multidimensional Group Type | | | |
|---|---|---|---|---|
| | Income Groups | Income x Age | Income x Child | Income x Age x Child |
| | (1) | (2) | (3) | (4) |
| $\rho$(Post-2010 Election) | 42.28 | 28.60 | 35.62 | 28.41 |
| | (22.64) | (21.85) | (20.95) | (17.30) |
| $\delta$ (Change in Relative Electoral Importance | 4.205*** | 1.611* | 2.798** | 1.507** |
| 2010 Election x Post-2010 Election) | (0.857) | (0.826) | (1.106) | (0.644) |
| Constant | 452.9*** | 448.8*** | 451.8*** | 449.0*** |
| | (30.99) | (23.69) | (25.41) | (22.15) |
| Group Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Individual Earnings-Specific Trends | Yes | Yes | Yes | Yes |
| No. of Groups | 5 | 15 | 10 | 30 |
| No. of Individuals | 41826 | 41826 | 41826 | 41826 |
| No. of Observations | 627390 | 627390 | 627390 | 627390 |
| Overall $R^2$ | .90 | .91 | .90 | .91 |

Robust standard errors, clustered by Groups, calculated. Standard Errors in parentheses
Empty cells in calculation of REI for income-age-child groups leads to 111 groups
& fewer observations.
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 2A.10: Linear First-Difference Regression: 5 Income Group Robustness Check, Impact of Differences in Uni/Multidimensional REI in 2010 on Uni/Multidimensional Relative Redistribution Difference (2011-2019)**

| | Multidimensional Group Difference | | |
|---|---|---|---|
| | Income x Age | Income x Child | Income x Age x Child |
| | (1) | (2) | (3) |
| $\delta$ (Uni/Multidimensional REI Difference) | 1.640** | 4.129*** | 1.704*** |
| | (0.557) | (0.570) | (0.515) |
| $\rho$(Earnings Growth(2011-2019)) | -0.379*** | -0.376*** | -0.383*** |
| | (0.0399) | (0.0485) | (0.0505) |
| Constant | -4.480 | -3.458 | -4.239 |
| | (5.439) | (3.553) | (6.113) |
| No. of Groups | 15 | 10 | 30 |
| No. of Individuals | 41826 | 41826 | 41826 |
| No. of Observations | 41826 | 41826 | 41826 |
| Overall $R^2$ | .36 | .39 | .36 |

Robust standard errors, clustered by Groups, calculated. Standard Errors in parentheses & fewer observations.

$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## XXV.2 Ten Income Group Construction

**Table 2A.11: Standard DiD - 10 Income Group Robustness Check, Impact of Change in Relative Electoral Importance (2010) on Relative Redistribution (2005-2019)**

| | Uni/Multidimensional Group Type | | | |
|---|---|---|---|---|
| | Income Groups | Income x Age | Income x Child | Income x Age x Child |
| | (1) | (2) | (3) | (4) |
| $\rho$(Post-2010 Election) | 42.25** | 28.51 | 35.55* | 28.02* |
| | (18.07) | (17.98) | (17.22) | (15.31) |
| $\delta$ (Change in Relative Electoral Importance | 3.898*** | 1.502** | 2.587*** | 1.327*** |
| 2010 Election x Post-2010 Election) | (0.731) | (0.617) | (0.782) | (0.464) |
| Constant | 452.0*** | 448.7*** | 451.4*** | 449.3*** |
| | (33.96) | (29.13) | (26.15) | (23.66) |
| Group Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Individual Earnings-Specific Trends | Yes | Yes | Yes | Yes |
| No. of Groups | 10 | 30 | 20 | 57 |
| No. of Individuals | 41826 | 41826 | 41826 | 41803 |
| No. of Observations | 627390 | 627390 | 627390 | 627045 |
| Overall $R^2$ | .90 | .91 | .91 | .91 |

Robust standard errors, clustered by Groups, calculated. Standard Errors in parentheses
Empty cells in calculation of REI for income-age-child groups leads to 57 groups
& fewer observations.
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 2A.12: Linear First-Difference Regression: 10 Income Group Robustness Check, Impact of Differences in Uni/Multidimensional REI in 2010 on Uni/Multidimensional Relative Redistribution Difference (2011-2019)**

| | Multidimensional Group Difference | | |
|---|---|---|---|
| | Income x Age | Income x Child | Income x Age x Child |
| | (1) | (2) | (3) |
| $\delta$ (Uni/Multidimensional REI Difference) | 1.483*** | 3.678*** | 1.440*** |
| | (0.373) | (0.311) | (0.333) |
| $\rho$(Earnings Growth(2011-2019)) | -0.381*** | -0.381*** | -0.383*** |
| | (0.0423) | (0.0448) | (0.0484) |
| Constant | -4.602 | -3.717 | -4.385 |
| | (3.869) | (3.353) | (3.842) |
| No. of Groups | 30 | 20 | 57 |
| No. of Individuals | 41826 | 41826 | 41803 |
| No. of Observations | 41826 | 41826 | 41803 |
| Overall $R^2$ | .36 | .38 | .36 |

Robust standard errors, clustered by Groups, calculated. Standard Errors in parentheses
Empty cells in calculation of REI for income-age-child groups leads to 111 groups
& fewer observations.
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## XXV.3 2005 REI Construction

**Table 2A.13: Standard DiD - 2005 REI Robustness Check, Impact of Change in Relative Electoral Importance (2010) on Relative Redistribution (2005-2019)**

| | Uni/Multidimensional Group Type | | | |
|---|---|---|---|---|
| | Income Groups | Income x Age | Income x Child | Income x Age x Child |
| | (1) | (2) | (3) | (4) |
| $\rho$(Post-2010 Election) | 32.66* | 25.89 | 25.34* | 27.58* |
| | (17.04) | (17.04) | (14.58) | (14.72) |
| $\delta$ (Change in Relative Electoral Importance | 2.829*** | 1.382*** | 2.444*** | 1.217*** |
| 2010 Election x Post-2010 Election) | (0.727) | (0.504) | (0.545) | (0.369) |
| Constant | 454.4*** | 450.5*** | 453.4*** | 450.7*** |
| | (33.18) | (29.79) | (24.95) | (23.46) |
| Group Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Individual Earnings-Specific Trends | Yes | Yes | Yes | Yes |
| No. of Groups | 20 | 60 | 40 | 107 |
| No. of Individuals | 41826 | 41826 | 41826 | 41767 |
| No. of Observations | 627390 | 627390 | 627390 | 626505 |
| Overall $R^2$ | .90 | .91 | .91 | .91 |

Robust standard errors, clustered by Groups, calculated. Standard Errors in parentheses
Empty cells in calculation of REI for income-age-child groups leads to 111 groups
& fewer observations.
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 2A.14: Linear First-Difference Regression: 2005 REI Robustness Check, Impact of Differences in Uni/Multidimensional REI in 2010 on Uni/Multidimensional Relative Redistribution Difference (2011-2019)**

| | Multidimensional Group Difference | | |
|---|---|---|---|
| | Income x Age | Income x Child | Income x Age x Child |
| | (1) | (2) | (3) |
| $\delta$ (Uni/Multidimensional REI Difference) | 0.767** | 2.006** | 0.682** |
| | (0.373) | (0.988) | (0.296) |
| $\rho$(Earnings Growth(2011-2019)) | -0.395*** | -0.401*** | -0.396*** |
| | (0.0405) | (0.0434) | (0.0452) |
| Constant | -4.290 | -4.181 | -4.298 |
| | (4.293) | (4.456) | (4.344) |
| No. of Groups | 60 | 40 | 107 |
| No. of Individuals | 41826 | 41826 | 41767 |
| No. of Observations | 41826 | 41826 | 41767 |
| Overall $R^2$ | .33 | .33 | .33 |

Robust standard errors, clustered by Groups, calculated. Standard Errors in parentheses
Empty cells in calculation of REI for income-age-child groups leads to 107 groups
& fewer observations.
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

# Chapter 3

# No Country for Non-Graduate Men: The Childish Roots of Adult Job Tasks & Employment

**Abstract**

Male employment has declined across advanced economies as non-graduate men found it increasingly difficult to gain jobs in the wake of technological change and globalisation. This has led to rising earnings and, subsequently, income inequality. Female employment, by contrast, has risen in this period. Previous work has shown changing job task demands explain this pattern - with declining manual tasks penalising men and rising non-routine tasks benefiting women. In this chapter, I test whether gendered differences in childhood & adolescent cognitive, social, perseverance, and emotional-health skills can help explain why men are less adept at non-routine tasks using long-term longitudinal data from the United Kingdom. I find that childhood & adolescent skills have a significant effect on adult job tasks and employment outcomes. Greater cognitive and childhood emotional-health skills lead to people performing more high-pay analytical and interactive job tasks as adults. Greater cognitive and non-cognitive skills are also associated with higher adult employment levels. Indicative calculations show that gendered differences in these childhood and adolescent skills explain an economically significant decline in the analytical and interactive job tasks performed by non-graduate men as well as their employment rates.

# I INTRODUCTION

Deindustrialisation has led to a dramatic fall in male non-graduate employment across the developed world that has, in turn, led to falling life expectancy, falling marriage rates, and rising populism (Autor et al. 2019; Case and Deaton 2020; Baccini and Weymouth 2021). The transition to the service economy led to falling demand for routine manual tasks that non-graduate men traditionally performed in the manufacturing sector and a rise in non-routine tasks that they have been relatively less adept at performing (Black and Spitz-Oener 2010; Olivetti and Petrongolo 2016; Cortes et al. 2018). The current literature does not, however, consider how (gendered) differences in childhood/adolescent skills can predict the full range of job tasks people perform as adults (Borghans et al. 2014; Deming 2017). Gregory (2011) notes that, *"Task based interpretations of technological change and its gender implications are highly suggesting but establishing a robust evidence base remains for future research"*.

The major contribution of this chapter is to fill this gap by analysing whether gendered differences in childhood/adolescent skills can provide an explanation for gendered differences in employment probabilities and the job tasks people perform as adults. I find that childhood and adolescent skills have economically significant effects on adult job tasks and employment status. These results also hold when restricting the sample to non-graduates who were employed at age 23, indicating that they are not driven by early employment experiences. Indicative calculations show that gendered differences in these childhood and adolescent skills may explain why non-graduate men are less adept at performing analytical and interactive job tasks as well as their falling employment rates in the postindustrial economy.

Technological change and globalisation have led to deindustrialisation. This changed the type of tasks, and so the types of skills, that are now demanded in the post-industrial labour market. In the Fordist mass-production economy, non-graduate men required physical skills to undertake repetitive manual tasks in mid-pay manufacturing jobs (Frey 2019; Iversen and Soskice 2019). These mid-pay manufacturing jobs were destroyed and there was a shift in employment toward high- and low-pay service sector jobs (Autor 2015). Low-wage service sector jobs that non-graduates tend to perform are now more person-facing roles that non-graduate men have proved less adept at performing (Nixon 2006; Black and Spitz-Oener 2010).

Early childhood experiences help determine the level of cognitive (abstract reasoning) and non-cognitive (socio-emotional) skills people possess, which in turn also determine the types of job tasks they can perform as adults (Heckman et al. 2006; Putnam 2015; Kautz et al. 2014; Bolt et al. 2021). The literature has tended to focus on how overall levels of cognitive and non-cognitive skills determine labour market outcomes (such as employment and wages), rather than the specific job tasks they help an individual perform (Lindqvist and Vestman 2011). In addition, this literature often groups together all non-cognitive skills into one non-cognitive factor (e.g. Heckman et al. (2006)). This perspective misses out important differences between non-cognitive skills - non-cognitive skills are weakly, or even negatively, related to one another (Humphries and Kosse 2017).

A growing strand of the literature that does estimate the effect of different non-cognitive skills on labour market outcomes follows the psychological literature, which diagnoses behavioural problems and accordingly splits them into two factors - internalising (behaviours directed inwards) and externalising (behaviours directed outwards) (Papageorge et al. 2019; Attanasio et al. 2020a,b; Plenty et al. 2021). However, this internalising/externalising split combines both social and perseverance skills into one externalising factor. This combination can miss important effects - perseverance is a different skill than sociability and both have been shown to have strong, and separate, impact on employment outcomes (Eisenberg et al. 2014; Kautz et al. 2014; Deming 2017). In this chapter, I separate out non-cognitive skills into perseverance, social, and emotional-health components (Duncan et al. 2011).

Skills also undergo rapid development between between childhood and adolescence and so skills at each age could have differing effects on future job outcomes (Almlund et al. 2011; Korhonen et al. 2018; Gutman and McMaster 2020). In addition, there are interdependencies between childhood and adolescent skills - higher levels of emotional-health skills in childhood leads to greater cognitive skills in adolescence, for example (Attanasio et al. 2020b; Donati et al. 2021). The differing effects of childhood and adolescent skills on adult outcomes is often overlooked in the literature that only measures skills at a single point in time (Heckman et al. 2006; Lindqvist and Vestman 2011; Attanasio et al. 2020a).

There are important gendered differences in the non-cognitive skills that children and adolescents possess. Girls possess greater social and perseverance skills as children and these differences persist into adolescence (Jacob 2002; Duncan et al. 2011; Bertrand and Pan 2013; Attanasio et al. 2020a). The current literature finds that lower levels of social and perseverance skills lead to lower employment levels as adults (Borghans et al. 2014; Kautz et al. 2014). However, while there is little difference in the emotional-health skills boys and girls possess as children, by the time they reach adolescence, teenage girls have lower emotional-health skills (Bask 2015; Gutman and McMaster 2020). The evidence on whether emotional-health skills matter for later employment outcomes is mixed (Goodman et al. 2015; Papageorge et al. 2019; Attanasio et al. 2020a; Plenty et al. 2021). As is shown below, the least-skilled boys have lower levels of cognitive and socio-emotional skills than the least-skilled girls. The gendered differences in skills is, then, a plausible explanation for falling employment rates for non-graduate men.

I test how gendered differences in skills effect job tasks and (relative) employment probabilities using data from the National Child Development Study that follows children born in 1958. I do so by measuring the association between childhood and adolescent measures of cognitive and non-cognitive skills and later job tasks as well as employment outcomes.

The variables used to measure cognitive, emotional-health, social, and perseverance skills do differ between childhood and adolescence. These questions still, however, correspond to our notions of what, for example, constitutes an indicator of perseverance and there is no standardised list of questions that define skills between studies (Almlund et al. 2011; Zhou 2017). In addition, within the NCDS, teacher ratings are used to measure non-cognitive skills in childhood while parent/self ratings of non-cognitive skills are used in adolescence. As teacher ratings of skills are more accurate, it is likely that the childhood measures of non-cognitive skills are somewhat more robust here than adolescent measures (Feng et al. 2022). Some caution should, therefore, be applied when interpreting these results but not to the point of not seeing them as measuring the same skill at different points in time. The same issue arises when comparing results across studies that mix teacher and parent/self ratings of skills as well as that uses different questions (Almlund et al. 2011; Kautz et al. 2014).

These estimates are also not causal - they show an association, and the specification could suffer from omitted variable bias. I progressively add childhood and adult-level controls that could also impact later employment probabilities, although these will attenuate the impact of skills. Childhood/adolescent skill levels will, for example, affect whether an individual obtains a degree, which will have a further impact on adult employment probabilities as well as job tasks.

I follow Autor et al. (2003) and split job tasks into non-routine analytical (NRA), non-routine interactive (NRI), non-routine manual (NRM), routine cognitive (RC), and routine manual (RM). Routine tasks are easily performed by programmable machines and non-routine tasks are not. This categorisation of tasks is widely used in the job task literature (e.g. Goos et al. (2014))

I find that cognitive skills are, as expected, positively related to non-routine analytical and interactive tasks and negatively related to manual tasks. Emotional-health skills in childhood (but not adolescence) are positively related to non-routine analytical and interactive job tasks. This may be because childhood emotional-health is important for later cognitive and non-cognitive skill development (Attanasio et al. 2020b; Donati et al. 2021). Happy kids learn more, and children who learn more, earn more. Perseverance in adolescence but not childhood is positively related to NRA and NRI tasks, which may be due to the fact that this skills continues to develop through adolescence and into early adulthood (Eisenberg et al.

2014; Kautz et al. 2014). These results hold even after controlling for adult-level conditions such as education, indicating that early conditions continue to have an enduring impact on job tasks throughout a person's life.

Surprisingly, social skills in childhood/adolescence are rarely related to any job tasks, including non-routine interactive tasks. This is in contrast to the growing literature that points to the increasing importance of social skills for adult labour market outcomes (Borghans et al. 2014; Weinberger 2014; Deming 2017; Deming and Kahn 2018). I find that this is due to the inclusion of perseverance and emotional-health skills in this specification. When I drop measures of perseverance and emotional-health, I find social skills become significantly related to NRA and NRI tasks. This may suggest that this literature that suffers from an omitted variable bias by not robustly accounting for perseverance or emotional-health skills.

There is little difference in the effect of skills on job task outcomes between genders. Where gender norms, discrimination, and childcare policies impact occupational outcomes, they do not appear to do so through gendered differences in the impact of skills on job tasks (Cobb-Clark and Tan 2011; Gregory 2011).

Holding everything else constant, indicative back-of-the-envelope calculations show that the least-skilled men would perform more NRA and NRI tasks as women if they had the same non-cognitive skill levels as girls as children and adolescents. Jobs with NRA and NRI tasks are more highly paid whereas those with more manual tasks have lower pay levels (Autor and Handel 2013; Autor 2015). It is therefore plausible that gendered differences in skills have made the least-skilled men less adapt at performing job tasks that are more highly demanded/have higher pay in the post-industrial economy.

I then test how cognitive and non-cognitive skills impact employment outcomes. All cognitive and non-cognitive skills are positively, and mostly significantly, related to employment outcomes in adulthood. Unsurprisingly, cognitive skills have the strongest effect on later employment outcomes (Goodman et al. 2015). Emotional-health skills have the next strongest effect impact followed by social and perseverance skills. There is little evidence that the impact of skills differs between genders, with weak and inconsistent results.

Using these results, back-of-the-envelope calculations show that the employment rate of the least skilled men would be about 2 to 3 percentage points higher if they had the same level of childhood/adolescent skills as the least skilled girls.

The rest of the chapter proceeds as follows. The literature review sections describes the gap I fill with this chapter - namely how non-graduate men may be less adept at performing the job tasks demanded in a post-industrial economy due to gendered differences in childhood/adolescent skills. I then outline the hypotheses to be tested in this chapter, followed by the data, empirical results and discussion.

## II EMPLOYMENT RATES AND OCCUPATIONS

Male employment and participation rates have fallen dramatically across the developed world while female employment and participation rates have risen. The decline in male employment rates have been driven by large falls in employment for non-graduate men (Górka et al. 2017; Binder and Bound 2019; Sandher 2021). Rising female employment and falling male employment is due to a combination of labour demand and labour supply forces. On the labour supply side, the availability of contraceptives, technological advances in home production, and the increased availability of childcare help explain why female employment rates have risen (Olivetti and Petrongolo 2016). Labour supply issues do not, however, explain why male employment rates have fallen so rapidly. Instead, technological change and globalisation have changed patterns of labour demand leading to a decline in the manufacturing sector (where men were previously employed) and a rise in service employment (Binder and Bound 2019; Abraham and Kearney 2020; Wolcott 2021).

Technological change and trade have led to a change in job tasks that have been demanded in the modern economy, and less-skilled men have been less adept at performing the tasks that have seen increasing demand in the post-industrial era. The routine manual tasks that were previously undertaken by semi-skilled men in the manufacturing sector are now performed by machines that are more adept at performing repeatable processes leading to large falls in employment for non-graduate men (Cortes et al. 2017; Yamaguchi 2018; Frey 2019). There has been a subsequent rise in the demand for non-routine job tasks that machines cannot undertake - interactive tasks that require social interaction with other human beings, analytical tasks that require creative and abstract thinking, and non-routine manual tasks that require flexible and adaptable movements to changing physical surroundings (Autor et al. 2003; Autor 2015).

The changing demand pattern in job tasks has led to a bifurcation in the labour market between high- and low-pay jobs. High-pay jobs generally require greater levels of non-routine interactive and analytical tasks while low-pay jobs tend to require more routine cognitive and (routine/non-routine) manual tasks (Goos and Manning 2007; Acemoglu and Autor 2011). These job tasks have an effect on wages separate from occupation - performing non-routine analytical and interactive tasks are associated with higher wages whereas routine and manual tasks are associated with lower wages (Autor and Handel 2013).

Non-routine manual tasks include low-pay service tasks like serving food and non-routine interactive tasks are also disproportionately present in person-facing occupations such as caring (Mihaylov and Tijdens 2019). Non-graduate men, when compared to non-graduate women, have proven less adept at performing these non-routine tasks that are more highly demanded in post-industrial economy (Nixon 2006; Black and Spitz-Oener 2010).

The changing labour demand for different tasks trends has led to a large fall in non-graduate male employment in the United Kingdom as shown in Figure 3.1 below. Both graduate and non-graduate women saw rising employment rates over this period.

This came with a changing set of job tasks and employment types. Manufacturing jobs made up 21.8% of jobs in 1981. This fell to 15.7 % of jobs in 1991 to 11.7% in 2002. It has since declined to 7.6% (Rhodes 2020). There has been a large, concomitant fall in routine manual tasks while non-routine analytic and interactive job tasks rose dramatically (Autor

**Figure 3.1: Male and Female Graduate/Non-Graduate Employment Rates**


Source: UK Labour Force Survey - Selected years 1979, 1984, 1990, 1995, 2005, 2007, 2010, 2015, 2019

et al. 2003; Górka et al. 2017)

Men have a comparative disadvantage in performing job tasks that are more demanded in the postindustrial labour market, which led to falls in their employment levels. I now turn to why skills gained in childhood & adolescence could explain why men are relatively less adept at the job tasks that are more highly demanded in the post-industrial labour market.

# III EMPLOYABLE SKILLS

Post-industrial jobs require more "brain" and less "brawn" - non-routine tasks require cognitive (abstract reasoning) and non-cognitive (socio-emotional) skills while the demand for the physical strength required to undertake routine manual tasks in the mass production industrial economy has declined (Nedelkoska and Quintini 2018). There is no single accepted breakdown of non-cognitive skills (Humphries and Kosse 2017). The literature has often grouped together all non-cognitive skills into a single factor (Heckman et al. 2006; Duncan et al. 2011; Kautz et al. 2014; Humphries and Kosse 2017; Attanasio et al. 2020a). For example, Lindqvist and Vestman (2011) show that non-cognitive skills are more important than cognitive ones for less-skilled men trying to gain employment but do not differentiate between emotional health, social, and perseverance socio-emotional skills.

Humphries and Kosse (2017) shows that the different components of non-cognitive skills are not strongly related to one another and, in some cases, are actually *negatively* related to one another. To combine all non-cognitive skills into one factor misses important differences between them. One growing strand of the literature that does differentiate between non-cognitive skills when examining labour market outcomes splits them into two components - internalising and externalising behaviour - as is common in the psychological literature (Zilanawala et al. 2019; Donati et al. 2021). They do so by combining measures of perseverance with social skills into a measure of externalising behaviour, which groups all behaviours directed away from the self, and internalising components, behaviours directed inwards. The results of these analyses are mixed (finding that none, one, or both of internalising and externalising skills predict employment outcomes) (Papageorge et al. 2019; Attanasio et al. 2020a; Plenty et al. 2021).

While splitting non-cognitive skills into two components represents an accepted categorisation of diagnosing mental health problems in children/adolescents, this grouping overlooks the separate impacts that perseverance and social skills are likely to have on employment outcomes and job tasks. Perseverance has consistently been shown to be a strong, positive predictor of school and labour market outcomes [1] (Duncan et al. 2011; Eisenberg et al. 2014; Kautz et al. 2014; Goodman et al. 2015). Other work has shown that higher levels of social skills predict higher employment rates (Heckman et al. 2013; Borghans et al. 2014; Goodman et al. 2015; Deming 2017).

There has been a rise in the demand for interpersonal (or non-routine interactive) job tasks that require social skills in the past two decades (Weinberger 2014; Deming 2017; Deming and Kahn 2018). Women, who have higher levels of social skills as teenagers, are more likely to have jobs that require interpersonal skills as adults, and this has contributed to their relative rise in employment rates as the demand for non-routine interactive job tasks has increased (Bertrand and Pan 2013; Borghans et al. 2014). There has been a similar rise in the demand for cognitive skills required for non-routine analytical tasks (Deming 2017; Górka et al. 2017).

The current literature does not test how cognitive and non-cognitive skills play in allowing people to perform the whole range of job tasks. The literature does, however, indicate that higher levels of these skills are positively related to non-routine interactive and analytical tasks that are increasingly present in high-pay jobs. Cognitive skills have consistently been found to be positively related to higher wages (Heckman et al. 2006; Lindqvist and Vestman 2011; Goodman et al. 2015; Deming 2017; Deming and Kahn 2018) as well as non-routine analytical and interactive job tasks (Górka et al. 2017). Weinberger (2014) with a combined measure of perseverance and emotional-health skills finds that they are positively related to non-routine analytical and interactive tasks. Similarly, Goodman et al. (2015) finds that perseverance is associated with being in managerial and professional roles while Deming (2017) & Deming and Kahn (2018) finds that both social and cognitive skills are positively related to wages. Both managerial and professional roles contain a higher degree of non-

[1] it is the constituent part of Conscientiousness, one of the Big Five personality traits, that is most strongly related to later labour market outcomes. Conscientiousness itself is the Big Five Personality trait most closely linked to be have a strong impact on employment probability, wages and job performance (Almlund et al. 2011; Eisenberg et al. 2014)

routine analytical and interactive job tasks.

The evidence on the relationship between emotional-health and labour market outcomes is mixed. Some work finds that they are positively related to wages, while others find little impact (Goodman et al. 2015; Attanasio et al. 2020a). Emotional-health in childhood may, however, have an indirect impact on later labour market outcomes. Emotional-health is important for later cognitive and social development. Children with greater levels of emotional health and social skills as children also have greater cognitive skills as adolescents (Attanasio et al. 2020b; Donati et al. 2021). Happy kids learn more, and kids who learn more, earn more. Lower emotional-health in childhood and adolescence also persists into adulthood. Low levels of emotional-health in childhood, therefore, make it harder to interact successfully with others as an adult through, for example, greater levels of depression and less social personality traits (Korhonen et al. 2018). High-pay jobs now require wider and deeper intra-firm working relationships and greater co-operative capabilities to constantly innovate production processes, and this may require a minimum level of emotional-health to interact productively with colleagues (Haskel 2018; Iversen and Soskice 2019; Unger 2019). This in turn, could mean that childhood emotional-health skills will predict their ability to undertake non-routine analytical and non-routine interactive tasks in later life.

Cognitive, emotional-health, social, and perseverance skills appear to have an impact on labour market outcomes nor their relative importance for performing different job tasks as adults. I now turn to how these skills develop in childhood and adolescence as well as the differences between genders.

# IV THE CHILDISH ROOTS OF ADULT SKILLS FOR BOYS AND GIRLS

Parental investments, neighbourhood and school quality have a strong influence on the cognitive and non-cognitive skills of children, which in turn have a strong impact on education and labour market outcomes (Heckman et al. 2006; Putnam 2015; Bolt et al. 2021). Skills are not immutable traits that are distributed at birth - parental and early education investments build skills in children, and a greater level of cognitive and non-cognitive skills in children makes later investments more productive (Cunha et al. 2006; Kautz et al. 2014; Cooper 2017). Children with greater cognitive and non-cognitive skills at early ages are able to learn more effectively at later ages.

The effect of early conditions on a child's cognitive and socio-emotional skill development begin *before* birth. Low-income mothers are more likely to give birth to low-weight and pre-term children, which can effect their subsequent brain development (Kramer et al. 2000; Larson 2007; Olsen et al. 2018). We can literally see the effects of these conditions in the brains of children as young as 9 months. By the age of 14 months, low-income children are already gesturing less than their richer counterparts and are less likely to be able to communicate, move and read to an adequate standard by the time they start school (Blair and Raver 2016; Social Mobility and Child Poverty Commission 2019). Early experiences help determine the cognitive and socio-emotional skills people will possess as adults, and a poor early environment cannot be fully remedied with later investments (Cunha et al. 2006). Cognitive and socio-emotional skills in early childhood help determine adult levels of these skills and are likely, therefore, to have an impact on the types of job tasks people are able to perform in adulthood.

While childhood levels of cognitive and non-cognitive skills are predictive of skill levels in later ages, they do not perfectly determine the level of skills an individual will possess as adolescents or adults - parental investments, teaching quality, and peers all impact the acquisition of skills into early adulthood (Duncan et al. 2011; Eisenberg et al. 2014; Kim and Kochanska 2019). Non-cognitive skills, in particular, are more malleable in late adolescence and early adulthood than cognitive skills (Almlund et al. 2011; Kautz et al. 2014).

A rich literature has analysed how cognitive and non-cognitive skills affect overall labour market outcomes (i.e. employment and wages) (Heckman et al. 2006; Lindqvist and Vestman 2011; Goodman et al. 2015; Deming and Kahn 2018; Heckman et al. 2018). However, this growing literature does not always consider the role of perseverance skills, does not always measure these skills in early childhood, nor does it relate the importance of these skills to the full range of job tasks (e.g. non-routine manual tasks) (Borghans et al. 2014; Deming 2017).

Individuals may require higher levels of perseverance skills to adapt to a changing labour market where demand shifts have rendered their previous job tasks obsolete. Non-graduates who lose their jobs find it harder to regain employment, and this has been linked to their lower levels of overall non-cognitive skills (Lindqvist and Vestman 2011; Quintini and Venn 2013). For low-skilled men in particular, non-cognitive skills have a strong impact on their ability to gain employment as adults (Heckman et al. 2006; Lindqvist and Vestman 2011).

Early childhood skills are important for determining adult skill levels, and so adult labour market outcomes, but the literature often measures skill levels in late childhood or adolescence (Heckman et al. 2006; Goodman et al. 2015; Papageorge et al. 2019). This perspective misses the impact that the earliest childhood experiences may have on adult labour market outcomes. Studies that do estimate the impact of childhood skills on adult outcomes confirm their importance for labour market outcomes (Heckman et al. 2013; Attanasio et al. 2020a).

Skills also undergo rapid development between childhood and adolescence. In particular, non-cognitive skills undergo later development than do cognitive skills (Almlund et al. 2011; Kautz et al. 2014). Measuring skills only in childhood or adolescence, as is common in the literature, misses out how skill levels at different ages could have differing effects on adult outcomes (Heckman et al. 2006; Attanasio et al. 2020a).

There are important gendered differences between the level of emotional-health, perseverance, and social skills that may have an impact on later employment outcomes. As children, boys have lower levels of social and perseverance skills than girls, and these differences persist into adolescence (Duncan et al. 2011; Bertrand and Pan 2013; Attanasio et al. 2020a). This has an impact on later outcomes including college attendance and their ability to gain employment as adults (Jacob 2002).

As children, there is little difference in the emotional-health skills between genders. However, by the time they reach adolescence, girls have lower levels of emotional-health skills than boys (Bask 2015; Gutman and McMaster 2020). Emotional-health skills have mixed impacts in the literature on employment outcomes (Goodman et al. 2015; Attanasio et al. 2020a; Plenty et al. 2021).

While there are clear gendered differences in the levels of cognitive, emotional-health, perseverance, and social skills, it is unclear whether the impacts of these skills differ by gender. The literature has mixed findings on whether boys and girls with the same level of cognitive, perseverance, emotional-health and social skills have different labour market outcomes (Goodman et al. 2015; Papageorge et al. 2019; Plenty et al. 2021).

However, while (gendered differences in) skill levels may be important determinants of both the probability of employment and the types of jobs adults do, it is clear that they are not the only the determinant. Men and women with the same levels of non-cognitive skills, education, and experience levels enter the same occupations at different rates with women having generally lower occupational attainment than would be expected on the basis of their skill levels alone (Cobb-Clark and Tan 2011). Gender norms, discrimination, childcare availability, as well as preferences all determine the employment and occupational choices of women (Gregory 2011).

This chapter fills a gap in the literature by testing how the level of emotional-health, social, perseverance, and cognitive skills in both childhood and adolescence effect the job tasks people perform as adults as well as their probability of employment. By doing so, I analyse whether gendered differences in childhood and adolescent skills can help explain falling employment rates for non-graduate men.

# V HYPOTHESES

I test the following hypotheses in this chapter:

**Hypothesis 1**: Cognitive, emotional-health and perseverance skills will be positively related to Non-Routine Analytical and Interactive Job Tasks while being negatively related to manual tasks. Social skills will be positively related to Non-Routine Interactive tasks.

Non-routine analytical tasks require abstract reasoning, creative thinking, and problem solving so I expect that higher levels of cognitive and perseverance skills to be associated with them. Emotional-health skills are important for later cognitive development and social interaction, and so I expect these to also be positively associated with non-routine analytical and interactive tasks. Social skills are expected to be positively related to interaction. Manual tasks require fewer abstract thinking and problem solving skills and so will require fewer cognitive, emotional-health, and social skills.

**Hypothesis 2**: Childhood and adolescent measures of cognitive, social, perseverance, and emotional skills will be positively related to adult employment probabilities

In line with the previous literature, I expect that higher levels of cognitive and non-cognitive skills in childhood/adolescence will lead to higher adult employment rates

# VI DATA

I use the National Child Development Study (NCDS) that tracked the lives of 17,415 people born in the same week in 1958. I use this data because of the rich information it has on both childhood experiences and adult outcomes.

## VI.1 Measuring Skills

There is no perfect way to measure personality traits. I here use measures of perseverance, emotional-health, and social skills as in Duncan et al. (2011). Unlike the commonly used Big 5 measures, the categories of skills used here are mutually exclusive, although not exhaustive, measures of personality (Almlund et al. 2011).

As is standard in the literature, I measure non-cognitive skills by using questions regarding child/adolescent behaviour and then using a data reduction technique to construct on a single factor. Similarly, cognitive skills are calculated by extracting a single factor from a set of standardised tests (Heckman et al. 2006; Almlund et al. 2011; Cobb-Clark and Tan 2011; Lindqvist and Vestman 2011; Bertrand and Pan 2013; Borghans et al. 2014; Kautz et al. 2014; Goodman et al. 2015; Humphries and Kosse 2017; Heckman et al. 2018; Papageorge et al. 2019; Attanasio et al. 2020a,b; Donati et al. 2021). This literature uses questions on skills answered by external experts such as teachers (Lindqvist and Vestman 2011; Bertrand and Pan 2013; Heckman et al. 2013; Kautz et al. 2014), parents (Attanasio et al. 2020a), and/or subject participants themselves (Cobb-Clark and Tan 2011; Borghans et al. 2014; Humphries and Kosse 2017).

In this chapter, cognitive skills are measured using teacher administered tests. Non-cognitive skills are measured using teacher evaluations in childhood and parent/self-evaluations in adolescence due to data availability. Other work has similarly mixed teacher, parent, and child ratings to construct measures of non-cognitive skills (Kautz et al. 2014). Teacher ratings have been shown to be the most internally consistent and predictive of later outcomes &

behaviours. The childhood measures of skills used here are, therefore, likely to be somewhat more accurate than adolescent ratings used in this chapter (Feng et al. 2022). This does not mean, however, that the parent/self-evaluations used to construct adolescent skill measures lack accuracy or predictive power. It only means that these adolescent skill measures are likely to be somewhat less accurate than the childhood ones.

These skill measures are, of course, based upon subjective measurements and therefore may be biased. As the focus of this study is how lower skill levels of non-graduate men may influence their occupational attainment as adults, a key concern is that these subjective assessments may be systematically biased in a way that is correlated with another characteristic, in particular social class. It is, however, unclear clear in which direction these biases will go in - there is evidence for the skills of low-income children being both systematically under- *and* over-stated in the literature (Ready and Wright 2011; Lundberg et al. 2017).

Low-income children may find their skill levels systematically *underrated* as their skills are measured using behaviours that are context dependent and/or they are rated as less proficient than they actually are due to stereotype biases (Ready and Wright 2011; Campbell 2015; Lundberg et al. 2017). Teachers, parents, and children themselves may believe they have lower skill levels due to their socioeconomic background. By contrast, reference biases may lead to *overestimates* of the skill levels of low-income children. That is because teachers, parents and the children themselves rate subject skills in relation to peers in their own classrooms and surrounding environment rather than the whole country (Almlund et al. 2011; Elder and Zhou 2021). As is shown below, within this sample, there appears to be little overt evidence of over- or under-estimation of skill levels by social class.

For cognitive, social, emotional, and perseverance measures of skills, I use exploratory factor analysis to extract one factor from a set of questions that measure each skill as is common in the literature (e.g. Attanasio et al. (2020a)). The questions used to construct each factor are shown in table 3.1 below (Shepherd 2013; Betthäuser et al. 2016). The relative loadings for each factor are shown in Appendix A.

These questions used to construct factors for the same skills differ between childhood and adolescence. These factors may, therefore, be measuring slightly different concepts at different ages. Slightly different concepts are not, however, the same as significantly different ones. While the questions used to construct each skill do differ between childhood and adolescence, they do still correspond to our notions of what, for example, emotional-health is. For example, emotional-health skills in childhood are measured by questions on *"Depression"*, *"Withdrawal"*, and *"Unforthcomingness"*. In adolescence, emotional-health is measured using questions on *"Solitary"*, *"Miserable"*, *"Fearful"* and others. The questions are not precisely the same between age periods but still correspond to our notions of the underlying concept of emotional-health skills. Being *"Depressed*, *"Withdrawn*, and *"Unforthcoming* are signs of low emotional-health skills as are being *"Solitary"*, *"Miserable"*, and *"Fearful"*.

Further, the same issue arises when comparing skill effects between datasets, countries, and time periods as there is no standardised set of questions used to construct these skills (Almlund et al. 2011; Zhou 2017). The questions used here, as in every study, are imperfect indicators of an underlying skill. As is discussed above, it is important to measure these different skills in childhood and adolescence due to both the development of skills between these time periods as well as the interdependencies between different skills at different ages (Almlund et al. 2011; Donati et al. 2021). Given the questions are different between time periods, some caution should be used when interpreting the results, but not to the point where it is felt no conclusion can be drawn on the different effects a given skill may have when measured in childhood and adolescence.

Tables 3.2 and 3.3 below shows the average skill level for girls and boys as children and adolescents in the NCDS data. T-tests indicate that the differences in means are all significant with a p-value of less than or equal to 0.0001. As children, girls have higher levels of perseverance, social, and emotional-health skills. As adolescents, however, girls have, on average, lower emotional-health skills but still possess higher social and perseverance skills.

**Table 3.1: Questions Used to Construct Skill Measures in NCDS**

| | NCDS - Age 7 | NCDS - Age 16 |
|---|---|---|
| Cognitive Skills | Southgate Group Reading Test Score<br>Problem Arithmetic Test Score<br>Copying Designs Test<br>Human Figure Drawing Test | Reading Comprehension Test<br>Mathematics Test |
| Emotional Skills | Depression<br>Withdrawal<br>Unforthcomingness | Worried<br>Fearful<br>Solitary<br>Miserable<br>Twitches<br>Sucks Thumb<br>Bites Nails<br>Fussy<br>Irritable |
| Social Skills | Hostility Towards Children<br>Hostility Towards Adults<br>Anxiety for Acceptance by Children<br>Anxiety | Bullies Others<br>Disobedient<br>Destroys Objects<br>Fights<br>Lies<br>Disliked |
| Perserverance Skills | Restlessness<br>Difficulty Concentrating<br>Squirmy, Fidgety<br>Writing off Adults and Standards<br>Inconsequential Behaviour | Lazy/Hardworking<br>Gets on with Classwork<br>Takes Work Seriously<br>Difficult to Keep Mind on Work<br>Fidgety<br>Restless |

Consistent with other findings in the literature, differences tend to be larger for non-cognitive skills than cognitive skills (Jacob 2002). However, one large and noticeable difference is that within this sample, boys have a much higher level of cognitive skills than girls in adolescence.

This is a surprising reversal from the differences in childhood, where girls had a slightly higher cognitive score. Analysing this further, I find that this is due to boys seeing both a general increase in cognitive skills as well as a greater increase at the top of the distribution (the median cognitive score increases by .12 points compared to .22 points for the mean). For emotional-health skills, girls experienced a large general fall in skills between childhood and adolescence while the top of the distribution remains relatively unchanged (a median fall of 0.4 compared to a fall in the mean of .22).

**Table 3.2: Average Skill Level for Boys and Girls Age 7**

| | Cognitive | Emotional-Health | Social | Perseverance |
|---|---|---|---|---|
| Female | -.042 | .159 | .154 | .167 |
| Male | -.110 | -.008 | .003 | -.151 |
| Difference (Female - Male) | .068 | .167 | .151 | .318 |

**Table 3.3: Average Skill Level for Boys and Girls Age 16**

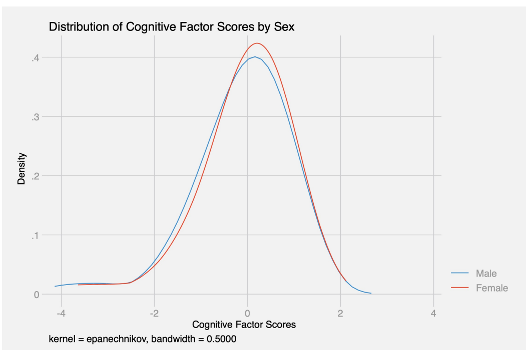
| | Cognitive | Emotional-Health | Social | Perseverance |
|---|---|---|---|---|
| Female | .010 | -.074 | .066 | .131 |
| Male | .119 | .112 | .027 | -.065 |
| Difference (Female - Male) | -.109 | -.186 | .039 | .195 |

The distributions of these scores are shown in Figures 3.1 and 3.2 below (as well as tables 3.6 and 3.7 in Section 9 of this chapter). They show that gendered differences in child/adolescent skills are largely driven by boys at the bottom of the skill distribution falling far behind girls at the bottom of the skill distribution. Crucially, boys in adolescence have a wider distribution of cognitive skills than girls with a higher average *and* a lower minimum level than their female counterparts. In the middle and at the top of the skill distribution, by contrast, there is less difference been boys and girls in terms of skill levels.

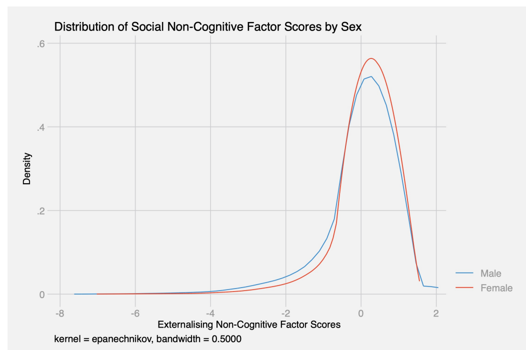
Below I also examine whether these skill measures are systematically biased - either due

**Figure 3.2: Cognitive, Emotional-Health, Social, and Perseverance Skills at Age 7 in the NCDS by Sex**

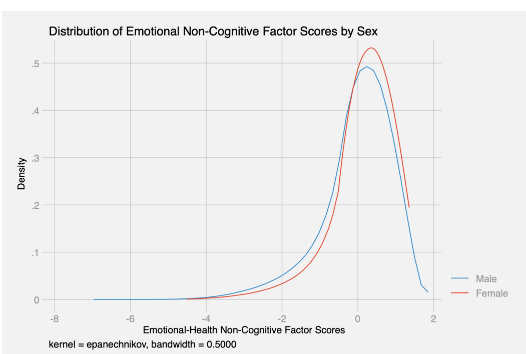
(a) Cognitive Skills




(b) Social Skills




(c) Emotional Health Skills




(d) Perseverance Skills

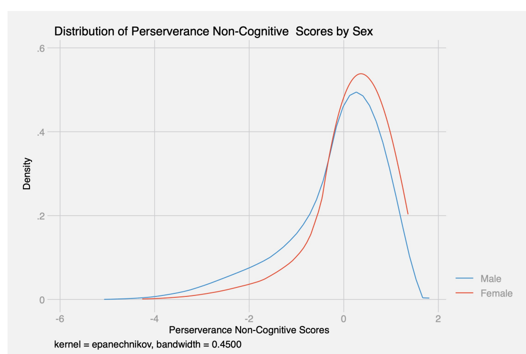
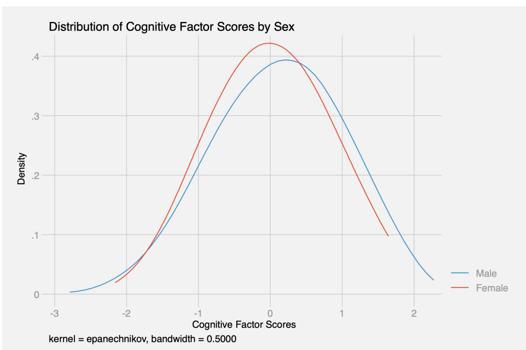
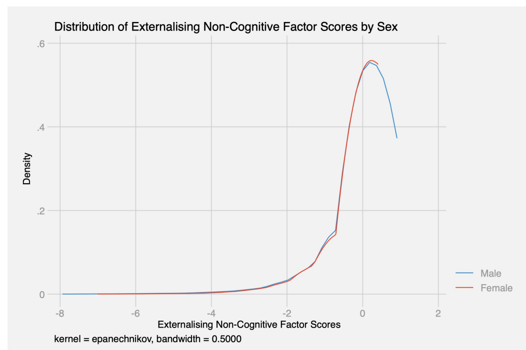


**Figure 3.3: Cognitive, Emotional-Health, Social, and Perseverance Skills at Age 16 in the NCDS by Sex**

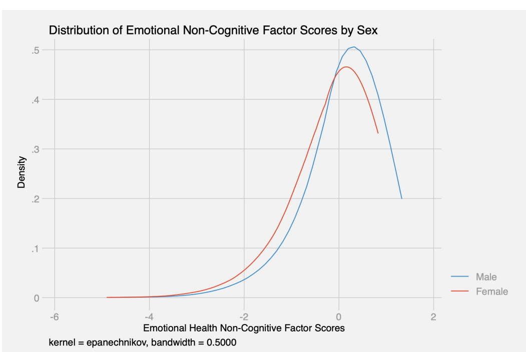
(a) Cognitive Skills




(b) Social Skills




(c) Emotional Health Skills




(d) Perseverance Skills

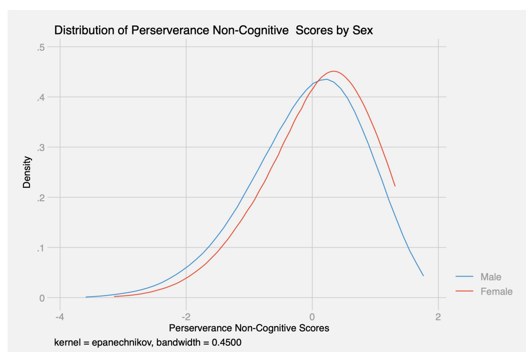


**Table 3.4: Correlation between Childhood Skills and Social Class**

| Childhood Skill | Correlation Coefficient |
|---|---|
| Cognitive | -.16 |
| Perseverance | -.10 |
| Emotional-Health | -.05 |
| Social | -.10 |

**Table 3.5: Correlation between Adolescent Skills and Social Class**

| Adolescent Skill | Correlation Coefficient |
|---|---|
| Cognitive | -.30 |
| Perseverance | -.02 |
| Emotional-Health | -.10 |
| Social | -.12 |

to reference or stereotype bias that would under/over-estimate skill levels related to a child's background. Tables 3.4 & 3.5 show the correlations between father's social class and the various skill measures in childhood and adolescence - lower values indicate a higher socio-economic class. There is no strong relationship between skill measures and social background for subjective skill measures. The strongest relationship between class and skill levels are cognitive skills, which are based upon more objective tests. While I still cannot rule out bias, it does not appear that they are systematically biased due to social class.

## VI.2 Measuring Tasks

I measure tasks using the classification from Mihaylov and Tijdens (2019), which breaks down job tasks within ISCO-08 occupation codes into the schema used in Autor et al. (2003): routine manual, routine cognitive, non-routine interactive, non-routine analytical, and non-routine manual. Each score gives the proportion of job tasks that falls within that category. For example, a score of 0.3 on the non-routine analytical measure, indicates that 30% of the job tasks are non-routine analytical tasks. I translate the ISCO-08 codes to SOC2000 codes and match this to the NCDS data using the classification developed by Morris (2012).

In common with other classifications (e.g. Acemoglu and Autor (2011)), non-routine interactive and analytical tasks are most common in high-pay jobs whereas low-pay jobs have a greater number of routine and non-routine manual tasks. This is also shown in Figure 3.4 below for the NCDS data, where I summarize occupational task intensities by one-digit SOC2000 codes.

Non-routine analytical and non-routine interactive indicate complex tasks that require complex cognitive abilities (Autor et al. 2003). Examples of non-routine analytical tasks include researching, analysing, and forecasting. Non-routine interactive tasks include advising, teaching, and negotiating.

By contrast, routine cognitive and manual tasks require fewer cognitive abilities. Routine cognitive tasks include inputting data and filing; routine manual operating machinery and making standardised products; while non-routine manual include cleaning, barwork, and caring (Mihaylov and Tijdens 2019).

High-pay jobs have a higher proportion of Non-Routine Interactive job tasks than low-pay service jobs, which tend to have a higher proportion of Non-Routine Manual job tasks. This usually holds even when these low-pay service jobs are customer facing. For example, waiters have an Non-Routine Interactive Job Task score of 0.14 and Non-Routine Manual score of 0.71. This is in contrast to Accountants that have an Non-Routine Interactive score

**Figure 3.4: Job Tasks by One-Digit SOC2000 Occupations**


of 0.27 with an Non-Routine Manual score of 0 (and Non-Routine Analytical score of 0.55).

Job tasks also tend to come in bundles - where analytical and interactive tasks are positively correlated with each other within occupations as shown in Table 3.4 below. This is as expected - high-wage occupations tend to require both analytical skills and the ability to work with others in flexible teams to solve complex problems (Weinberger 2014; Haskel 2018). By contrast, low-pay jobs tend to require specific commands and instructions to be followed rather than higher-level problem-solving or complex co-operation (Bloom et al. 2014; Garicano and Rossi-Hansberg 2015).

**Table 3.6: Cross-correlation table**

| Variables | NRAscore | NRIscore | RCscore | RMscore | NRMscore |
|---|---|---|---|---|---|
| NRAscore | 1.000 | | | | |
| NRIscore | 0.382 | 1.000 | | | |
| RCscore | -0.320 | -0.233 | 1.000 | | |
| RMscore | -0.317 | -0.389 | -0.124 | 1.000 | |
| NRMscore | -0.558 | -0.462 | -0.362 | -0.001 | 1.000 |

# VII HOW DO COGNITIVE AND NON-COGNITIVE SKILLS AFFECT ADULT JOB TASKS?

I estimate the below equation to analyse the association between childhood/adolescent skills and adult job tasks:

$$\begin{aligned}\text{Job-Task}_i = a_i + \text{Male Dummy}_i + \text{Cognitive Skills}_i + \text{Social Skills}_i + \\ \text{Emotional-Health Skills}_i + \text{Perserverance}_i + (\text{Childhood Controls}_i) + \\ (\text{Adult Controls}_i) + \epsilon_{i,t}\end{aligned} \tag{3.1}$$

Where separate models are estimated for each job task: Non-Routine Analytical, Non-Routine Interactive, Routine Cognitive, and Routine Manual, and Non-Routine Manual

For all specifications in this chapter, I progressively control for ethnicity, childhood conditions, and then adult conditions. I first estimate a parsimonious specification with only ethnicity controls. This specification would suffer from omitted variable bias - there will be other childhood factors that are likely to impact employment probabilities and job tasks. In the second specification, I control for childhood conditions that could also impact future employment probabilities and job tasks. This is the preferred specification. It is important to note that these variables are measured at birth. They will influence the acquisition of cognitive and other skills but will not be influenced by them in return. In the last specification, I include adult controls as well. This specification is likely to reduce the impact of cognitive and other skills as they are impacted by them. For example, greater perseverance skills in childhood/adolescence will lead to a greater probability of gaining a university degree (Jacob 2002; Heckman et al. 2006).

The childhood controls are: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother smoked in pregnancy, and birthweight), and region of childhood (Lindqvist and Vestman 2011; Attanasio et al. 2020a). The adult-level controls are: region of residence, marital status, a graduate dummy, and general health status.

I also estimate models with a restricted sample of non-graduates that are employed at age 23. This restricted sample robustness test allows me to analyse whether the childhood/adolescent skill measures used here are, in fact, simply serving as a proxy for skills or experience gained in early employment. It could be the case that higher childhood/adolescent skills help non-graduates gain early employment and/or that it is in this early employment where non-graduates are gaining the experience needed to perform certain job tasks later in their career within a post-industrial labour market. In this case, the coefficients on childhood/adolescent skills would actually be measuring the impact of these early employment experiences rather than experiences in early life. Further, by restricting the sample to non-graduates, I am able to test whether coefficients are biased by imposing the same relationship between childhood/adolescent skills for both graduates and non-graduates. It is plausible that, for example, perseverance skills lead to greater non-routine analytical tasks for graduates alone rather than also extending to non-graduate. This effect would be missed missed in the full sample regression.

This restricted sample robustness checks have substantively identical results as the full model sample. This indicates that the full sample models are not biased by suffering from omitted variable bias (in the form of early employment experiences) and/or by the inclusion of graduates within the analysis.

Results for the full sample are shown in Tables 3.7 to 3.12 below and results for the restricted sample of non-graduates employed at age 23 is shown in Appendix B. Figures 3.5 to 3.7 below show the coefficients for skills with childhood controls, including for the restricted sample.

There is mixed support for Hypothesis 1. Cognitive skills in childhood & adolescence are, as expected, strongly and positively related to NRA and NRI tasks while being negatively related to manual tasks at both age 33 and 42. A greater level of cognitive skills is necessary both to carry out more complex NRA and NRI tasks, which require creative thinking and complex communication skills (Autor et al. 2003; Acemoglu and Autor 2011; Weinberger 2014). For non-cognitive skills, perseverance and emotional-health skills have differing effects on NRA and NRI skills. These effects also differ between childhood and adolescence.

Emotional-health skills in childhood, but not adolescence, are positively related to NRA and NRI tasks at ages 33 and 42. Lower levels of emotional-health in childhood leads children down a negative trajectory with severe adult repercussions - these children have higher levels of depression, lower adult sociability, and lower cognitive skills making them less suited to NRA and NRI tasks that require sustained application, creative thinking, and interaction with others (Korhonen et al. 2018; Attanasio et al. 2020b; Donati et al. 2021). That these effects do not persist into adolescence may indicate that the effect of emotional-health skills in childhood on adult job tasks operates through their impact on the acquisition of cognitive and other socio-emotional skills. For example, lower emotional-health skills in childhood reduces the level of cognitive and other non-cognitive skills in adolescence (Attanasio et al. 2020b; Donati et al. 2021). Therefore, the impact of emotional-health skills in adolescence may be operating through other skills.

Perseverance in adolescence, but not childhood, is positively related to NRA skills and negatively related to manual skills at ages 33 and 42. Perseverance continues to develop into adolescence and young adulthood and so later skill levels may more closely resemble adulthood levels of perseverance (Eisenberg et al. 2014; Kautz et al. 2014). The fact that it is still significant even after controlling for cognition and later education status suggests that it continues to have an independent effect on NRA job tasks despite it contributing to educational attainment.

Surprisingly, social skills are not significantly related to NRI or NRA tasks. This is surprising because, firstly, NRA and NRI tasks are associated with higher wages and current findings indicate that indicate that higher social skills lead to higher wages (Autor and

Handel 2013; Deming 2017; Deming and Kahn 2018). In addition, other findings in the literature do find a strong impact of social skills on interpersonal interaction tasks as adults (Borghans et al. 2014; Weinberger 2014). This may be because Borghans et al. (2014) does not include measures of perseverance and emotional health in their specification, leading to an omitted variable bias in their specification. Similarly, it is unclear *prima facie* whether the Weinberger (2014) social skill measure, namely the participation in sports or extra-curricular activities, does actually measure sociability as opposed to perseverance. One does not have to be sociable to play sports or be on the chess team. One may, however, need a certain amount of perseverance to pursue extra-curricular activities. Noticeably, when I drop measures of perseverance and emotional-health skills, I do find a positive impact of social skills on NRA and NRI tasks (Appendix D). The current literature may, therefore, suffer from an omitted variable bias.

Childhood/adolescent skills make workers more adept at performing a bundle of job tasks. Workers cannot, of course, simply perform a set of job tasks at random. Instead, these job tasks are embedded in occupations, and occupations with higher NRA and NRI tasks tend to have lower levels of manual tasks (Autor and Handel 2013). Generally, these results show that skills that have a positive impact on NRA tasks also have a positive impact on NRI tasks and a negative impact on manual tasks.

Finally, childhood/adolescent skills that are significant with childhood controls are usually also significantly related to job tasks even after controlling for adult conditions including graduate status, marital status, and region, although with somewhat weaker effects. This is similar to other findings in the literature (Borghans et al. 2014). This indicates that childhood/adolescent skills have an enduring impact on adult job tasks even after controlling for a rich set of covariates such as childhood background and adult education levels. In short, early experiences matter above and beyond the adult conditions they help foster such as a degree and marriage.

**Figure 3.5: Effect of Child Skills on Job Tasks with childhood controls**

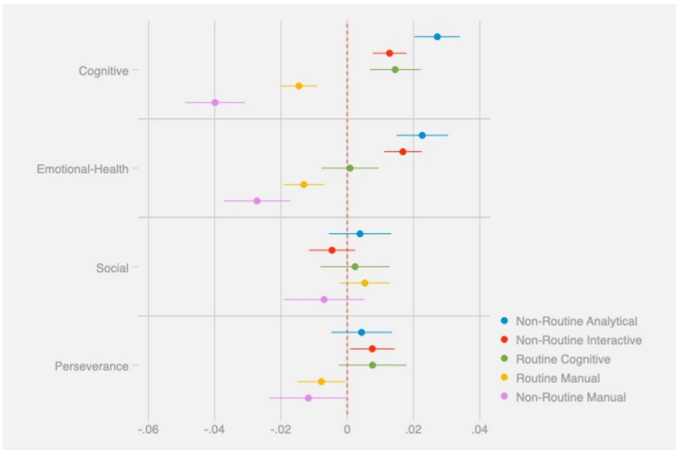
(a) Tasks at age 33 (b) Tasks at age 42


**Figure 3.6: Effect of Adolescent Skills on Job Tasks with childhood controls**

(a) Tasks at age 33 (b) Tasks at age 42

**Figure 3.7: Effect of Child Skills on Job Tasks with childhood controls for Non-Graduates Employed at Age 23**

(a) Tasks at age 33




(b) Tasks at age 42

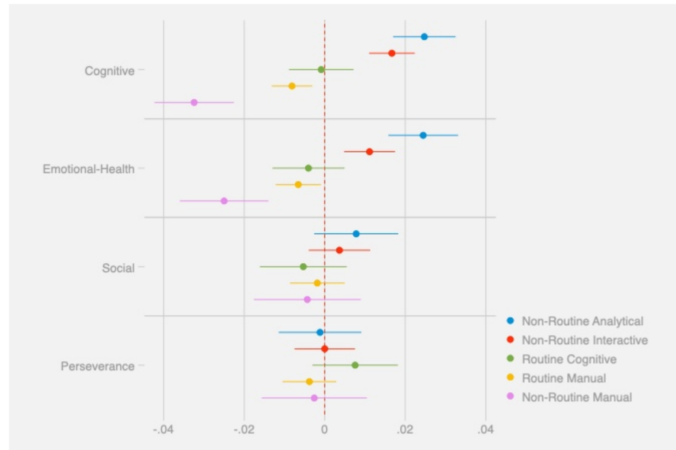
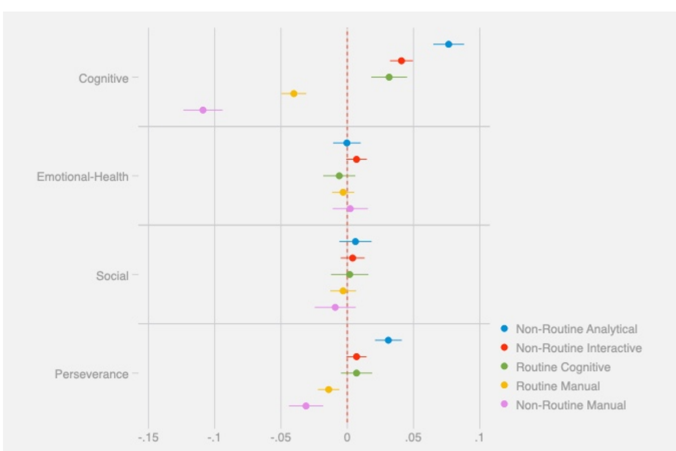



**Figure 3.8: Effect of Adolescent Skills on Job Tasks with childhood controls for Non-Graduates Employed at Age 23**

(a) Tasks at age 33




(b) Tasks at age 42

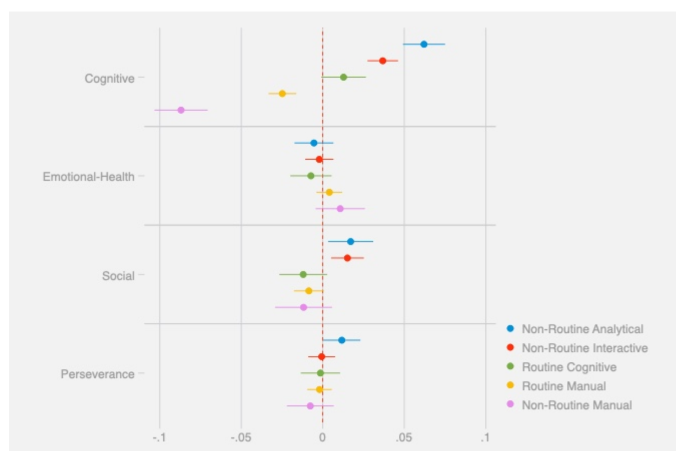


**Table 3.7: Impact of Skills Measured at Ages 7/16 on Job Tasks at Age 33**

| | (1) NRA Age 7 | (2) NRA Age 7 | (3) NRA Age 7 | (4) NRA Age 16 | (5) NRA Age 16 | (6) NRA Age 16 | (7) NRI Age 7 | (8) NRI Age 7 | (9) NRI Age 7 | (10) NRI Age 16 | (11) NRI Age 16 | (12) NRI Age 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Male Dummy | 0.078*** | 0.080*** | 0.071*** | 0.063*** | 0.070*** | 0.067*** | -0.027*** | -0.029*** | -0.033*** | -0.044*** | -0.041*** | -0.043*** |
| | (0.004) | (0.005) | (0.004) | (0.005) | (0.006) | (0.006) | (0.003) | (0.004) | (0.003) | (0.004) | (0.005) | (0.004) |
| Cognitive | 0.044*** | 0.036*** | 0.019*** | 0.106*** | 0.092*** | 0.055*** | 0.022*** | 0.015*** | 0.006*** | 0.059*** | 0.050*** | 0.026*** |
| | (0.002) | (0.003) | (0.003) | (0.004) | (0.005) | (0.005) | (0.002) | (0.002) | (0.002) | (0.003) | (0.004) | (0.004) |
| Emotional | 0.026*** | 0.022*** | 0.014*** | 0.000 | 0.000 | 0.000 | 0.019*** | 0.017*** | 0.013*** | 0.008*** | 0.008** | 0.009*** |
| | (0.003) | (0.003) | (0.003) | (0.004) | (0.004) | (0.004) | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) |
| Social | 0.013*** | 0.010*** | 0.003 | 0.002 | 0.005 | 0.004 | 0.002 | 0.000 | -0.004 | 0.000 | -0.001 | -0.002 |
| | (0.003) | (0.004) | (0.003) | (0.004) | (0.005) | (0.005) | (0.003) | (0.003) | (0.003) | (0.003) | (0.004) | (0.004) |
| Perseverance | 0.005 | 0.005 | 0.004 | 0.025*** | 0.029*** | 0.018*** | 0.009*** | 0.009*** | 0.009*** | 0.010*** | 0.012*** | 0.005 |
| | (0.003) | (0.004) | (0.003) | (0.004) | (0.004) | (0.004) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Constant | 0.191*** | 0.016 | 0.082 | 0.191*** | 0.181** | 0.189** | 0.237*** | 0.115** | 0.152*** | 0.242*** | 0.283*** | 0.292*** |
| | (0.003) | (0.062) | (0.058) | (0.004) | (0.077) | (0.075) | (0.002) | (0.047) | (0.046) | (0.003) | (0.061) | (0.060) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes | No | No | Yes | No | No | Yes |
| *N* | 9756 | 8345 | 8113 | 6074 | 4917 | 4799 | 9756 | 8345 | 8113 | 6074 | 4917 | 4799 |
| r2 | 0.081 | 0.136 | 0.278 | 0.197 | 0.218 | 0.302 | 0.050 | 0.078 | 0.159 | 0.107 | 0.117 | 0.180 |

Standard errors in parentheses

Ethnicity controls: ethnicity of child

Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother smoked in pregnancy, and birthweight), region of childhood

Adult Controls:region of residence, marital status, a graduate dummy, and general health status

$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 3.8: Impact of Skills Measured at Ages 7/16 on Job Tasks at Age 42**

| | (1) NRA Age 7 | (2) NRA Age 7 | (3) NRA Age 7 | (4) NRA Age 16 | (5) NRA Age 16 | (6) NRA Age 16 | (7) NRI Age 7 | (8) NRI Age 7 | (9) NRI Age 7 | (10) NRI Age 16 | (11) NRI Age 16 | (12) NRI Age 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Male Dummy | 0.044*** | 0.042*** | 0.037*** | 0.030*** | 0.032*** | 0.030*** | -0.033*** | -0.035*** | -0.039*** | -0.038*** | -0.041*** | -0.044*** |
| | (0.005) | (0.005) | (0.005) | (0.006) | (0.007) | (0.007) | (0.004) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) |
| Cognitive | 0.031*** | 0.027*** | 0.018*** | 0.076*** | 0.068*** | 0.044*** | 0.019*** | 0.016*** | 0.009*** | 0.043*** | 0.041*** | 0.025*** |
| | (0.003) | (0.003) | (0.003) | (0.004) | (0.005) | (0.006) | (0.002) | (0.003) | (0.002) | (0.003) | (0.004) | (0.004) |
| Emotional | 0.025*** | 0.024*** | 0.020*** | -0.004 | -0.004 | -0.002 | 0.015*** | 0.014*** | 0.010*** | -0.001 | 0.000 | 0.000 |
| | (0.003) | (0.003) | (0.004) | (0.004) | (0.005) | (0.005) | (0.002) | (0.003) | (0.003) | (0.003) | (0.004) | (0.004) |
| Social | 0.005 | 0.005 | 0.002 | 0.004 | 0.004 | 0.000 | 0.002 | 0.002 | 0.001 | 0.006 | 0.008* | 0.005 |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.006) | (0.003) | (0.003) | (0.003) | (0.004) | (0.004) | (0.005) |
| Perseverance | 0.006* | 0.004 | 0.00 | 0.014*** | 0.017*** | 0.009* | 0.004 | 0.002 | 0.002 | 0.002 | 0.000 | -0.005 |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.004) |
| Constant | 0.229*** | 0.101 | 0.209*** | 0.231*** | 0.0627 | 0.106 | 0.266*** | 0.191*** | 0.238*** | 0.265*** | 0.235*** | 0.249*** |
| | (0.003) | (0.070) | (0.073) | (0.004) | (0.088) | (0.094) | (0.003) | (0.052) | (0.056) | (0.003) | (0.067) | (0.071) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes | No | No | Yes | No | No | Yes |
| *N* | 8639 | 7396 | 6371 | 5425 | 4404 | 3881 | 8639 | 7396 | 6371 | 5425 | 4404 | 3881 |
| r2 | 0.040 | 0.061 | 0.121 | 0.089 | 0.099 | 0.134 | 0.037 | 0.047 | 0.082 | 0.057 | 0.063 | 0.087 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother smoked in pregnancy, and birthweight), region of childhood
Adult Controls:region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## Table 3.9: Impact of Skills Measured at age 7/16 on RC Tasks Aged 33

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | RC | RC | RC | RC | RC | (RC |
| | Age 7 | Age 7 | Age 7 | Age 16 | Age16 | Age16 |
| Male Dummy | -0.102*** | -0.103*** | -0.0984*** | -0.100*** | -0.104*** | -0.102*** |
| | (0.005) | (0.005) | (0.005) | (0.006) | (0.007) | (0.007) |
| Cognitive | 0.007** | 0.009*** | 0.018*** | 0.004 | 0.015*** | 0.048*** |
| | (0.003) | (0.003) | (0.003) | (0.004) | (0.005) | (0.005) |
| Emotional- Health | 0.000 | 0.002 | 0.006* | -0.006 | -0.004 | -0.007 |
| | (0.003) | (0.003) | (0.003) | (0.004) | (0.005) | (0.005) |
| Social | -0.001 | 0.000 | 0.004 | 0.005 | 0.003 | 0.005 |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.005) |
| Perseverance | 0.006* | 0.008** | 0.008** | 0.007 | 0.007 | 0.017*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) |
| Constant | 0.272*** | 0.294*** | 0.258*** | 0.274*** | 0.293*** | 0.270*** |
| | (0.003) | (0.067) | (0.067) | (0.004) | (0.089) | (0.088) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| $N$ | 9756 | 8345 | 8113 | 6074 | 4917 | 4799 |
| r2 | 0.055 | 0.070 | 0.113 | 0.052 | 0.067 | 0.132 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 3.10: Impact of Skills Measured at age 7/16 on RC Tasks Aged 42**

| | (1) RC Age 7 | (2) RC Age 7 | (3) RC Age 7 | (4) RC Age 16 | (5) RC Age16 | (6) (RC Age16 |
|---|---|---|---|---|---|---|
| Male Dummy | -0.049*** | -0.048*** | -0.045*** | -0.043*** | -0.043*** | -0.038*** |
| | (0.005) | (0.005) | (0.006) | (0.006) | (0.007) | (0.007) |
| Cognitive | -0.001 | 0.000 | 0.004 | -0.002 | 0.000 | 0.018*** |
| | (0.003) | (0.003) | (0.003) | (0.004) | (0.005) | (0.006) |
| Emotional- Health | -0.002 | -0.002 | -0.001 | -0.006 | -0.007 | -0.010* |
| | (0.003) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) |
| Social | -0.003 | -0.005 | -0.002 | 0.005 | 0.006 | 0.006 |
| | (0.004) | (0.004) | (0.005) | (0.005) | (0.006) | (0.006) |
| Perseverance | 0.005 | 0.006 | 0.009* | -0.003 | -0.003 | 0.005 |
| | (0.004) | (0.004) | (0.005) | (0.004) | (0.005) | (0.005) |
| Constant | 0.225*** | 0.294*** | 0.276*** | 0.225*** | 0.336*** | 0.316*** |
| | (0.003) | (0.070) | (0.076) | (0.0044) | (0.0930) | (0.099) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| $N$ | 8639 | 7396 | 6371 | 5425 | 4404 | 3881 |
| r2 | 0.015 | 0.021 | 0.038 | 0.013 | 0.021 | 0.045 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## Table 3.11: Impact of Skills Measured at Ages 7/16 on Job Tasks at Age 33

| | (1) RM Age 7 | (2) RM Age 7 | (3) RM Age 7 | (4) RM Age 16 | (5) RM Age 16 | (6) RM Age 16 | (7) RM Age 7 | (8) NRM Age 7 | (9) NRM Age 7 | (10) NRM Age 16 | (11) NRM Age 16 | (12) NRM Age 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Male Dummy | 0.006* | 0.007* | 0.009** | 0.017*** | 0.015*** | 0.014*** | 0.046*** | 0.044*** | 0.052*** | 0.065*** | 0.060*** | 0.063*** |
| | (0.003) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) |
| Cognitive | -0.018*** | -0.015*** | -0.010*** | -0.044*** | -0.039*** | -0.029*** | -0.054*** | -0.045*** | -0.033*** | -0.125*** | -0.117*** | -0.100*** |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.004) | (0.004) | (0.003) | (0.004) | (0.004) | (0.005) | (0.006) | (0.006) |
| Emotional-Health | -0.014*** | -0.012*** | -0.010*** | -0.001 | -0.002 | -0.002 | -0.032*** | -0.028*** | -0.023*** | 0.000 | 0.000 | -0.001 |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.005) |
| Social | 0.000 | 0.000 | 0.003 | -0.002 | -0.002 | -0.002 | -0.014*** | -0.012** | -0.007 | -0.005 | -0.005 | -0.005 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.005) | (0.006) | (0.006) |
| Perseverance | -0.004* | -0.005* | -0.006** | -0.012*** | -0.016*** | -0.014*** | -0.016*** | -0.017*** | -0.016*** | -0.029*** | -0.031*** | -0.026*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.004) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Constant | 0.063*** | 0.119** | 0.102** | 0.062*** | 0.010 | -0.007 | 0.238*** | 0.455*** | 0.406*** | 0.231*** | 0.234** | 0.255** |
| | (0.002) | (0.048) | (0.048) | (0.003) | (0.062) | (0.063) | (0.004) | (0.080) | (0.080) | (0.005) | (0.099) | (0.100) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes | No | No | Yes | No | No | Yes |
| $N$ | 9756 | 8345 | 8113 | 6074 | 4917 | 4799 | 9756 | 8345 | 8113 | 6074 | 4917 | 4799 |
| r2 | 0.022 | 0.042 | 0.066 | 0.061 | 0.074 | 0.087 | 0.074 | 0.109 | 0.157 | 0.163 | 0.180 | 0.196 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother smoked in pregnancy, and birthweight), region of childhood
Adult Controls:region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 3.12: Impact of Skills Measured at Ages 7/16 on Job Tasks at Age 42**

| | (1) RM Age 7 | (2) RM Age 7 | (3) RM Age 7 | (4) RM Age 16 | (5) RM Age 16 | (6) RM Age 16 | (7) RM Age 7 | (8) NRM Age 7 | (9) NRM Age 7 | (10) NRM Age 16 | (11) NRM Age 16 | (12) NRM Age 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Male Dummy | 0.008*** | 0.009*** | 0.012*** | 0.009** | 0.010** | 0.012*** | 0.031*** | 0.032*** | 0.035*** | 0.042*** | 0.041*** | 0.040*** |
| | (0.003) | (0.003) | (0.004) | (0.004) | (0.004) | (0.005) | (0.006) | (0.006) | (0.007) | (0.007) | (0.008) | (0.008) |
| Cognitive | -0.007*** | -0.007*** | -0.004** | -0.024*** | -0.021*** | -0.016*** | -0.041*** | -0.035*** | -0.027*** | -0.093*** | -0.088*** | -0.071*** |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.004) | (0.003) | (0.004) | (0.004) | (0.005) | (0.006) | (0.007) |
| Emotional-Health | -0.006*** | -0.006*** | -0.005** | 0.004 | 0.004 | 0.003 | -0.032*** | -0.030*** | -0.023*** | 0.007 | 0.008 | 0.007 |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) | (0.004) | (0.004) | (0.005) | (0.005) | (0.006) | (0.006) |
| Social | -0.001 | -0.001 | 0.001 | -0.002 | -0.004 | -0.002 | -0.004 | -0.001 | -0.002 | -0.013** | -0.014** | -0.008 |
| | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) | (0.004) | (0.005) | (0.005) | (0.005) | (0.006) | (0.006) | (0.007) |
| Perseverance | -0.004* | -0.003 | -0.003 | -0.003 | -0.002 | -0.001 | -0.012** | -0.010* | -0.009 | -0.010* | -0.013** | -0.008 |
| | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.006) |
| Constant | 0.0459*** | 0.0948** | 0.0444 | 0.0476*** | 0.0300 | 0.00548 | 0.234*** | 0.319*** | 0.233** | 0.231*** | 0.336*** | 0.323*** |
| | (0.002) | (0.043) | (0.047) | (0.003) | (0.066) | (0.061) | (0.004) | (0.086) | (0.091) | (0.005) | (0.110) | (0.115) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes | No | No | Yes | No | No | Yes |
| *N* | 8639 | 7396 | 6371 | 5425 | 4404 | 3881 | 8639 | 7396 | 6371 | 5425 | 4404 | 3881 |
| r2 | 0.010 | 0.019 | 0.030 | 0.023 | 0.028 | 0.035 | 0.045 | 0.059 | 0.090 | 0.083 | 0.093 | 0.098 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother smoked in pregnancy, and birthweight), region of childhood
Adult Controls:region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## VIII ARE THERE GENDERED DIFFERENCES IN THE EFFECT OF COGNITIVE AND NON-COGNITIVE SKILLS ON ADULT JOB TASKS?

I estimate the below regression to measure whether there are gender-specific differences in the effect of childhood/adolescent skills on adult job tasks. Specifically, I interact a male dummy with each skill to analyse whether there is a gendered impact in the effect of skills on job tasks. A positive coefficient on the interaction terms would indicate that men gain an extra benefit for a given level of skills while a negative one indicates that women gain an extra effect.

The interaction coefficients for the specification with childhood controls are shown in Figures 3.7 and 3.8 below. The full regression tables are in section 2A.3.

$$\begin{aligned}\text{Job-Task}_i = a_i &+ \text{Male Dummy}_i + \text{Cognitive Skills}_i + \text{Social Skills}_i + \\ &\text{Emotional-Health Skills}_i + \text{Perseverance}_i + \\ &\text{Cognitive Skills}_i \times \text{Male Dummy}_i + \\ &\text{Emotional-Health Skills}_i \times \text{Male Dummy}_i + \\ &\text{Social Skills}_i \times \text{Male Dummy}_i + \\ &\text{Perseverance}_i \times \text{Male Dummy}_i + \\ &(\text{Childhood Controls}_i) + (\text{Adult Controls}_i) + \epsilon_{i,t}\end{aligned} \tag{3.2}$$

The results show there is little in the way of gender specific differences in the effect of childhood and adolescent skills to adult job tasks. Neither men nor women tend to gain an extra benefit for a given level of skills in childhood or adolescence.

The only consistent effect is that, for a given level of cognitive skills in adolescence, men are more likely to undertake more highly paid NRA and NRI tasks while being less likely to undertake lower paid NRM tasks. This could indicate discrimination, childcare policies and/or gender norms lead to men with the same level of cognitive skills as women being more likely to enter occupations with greater levels of these tasks (Gregory 2011).

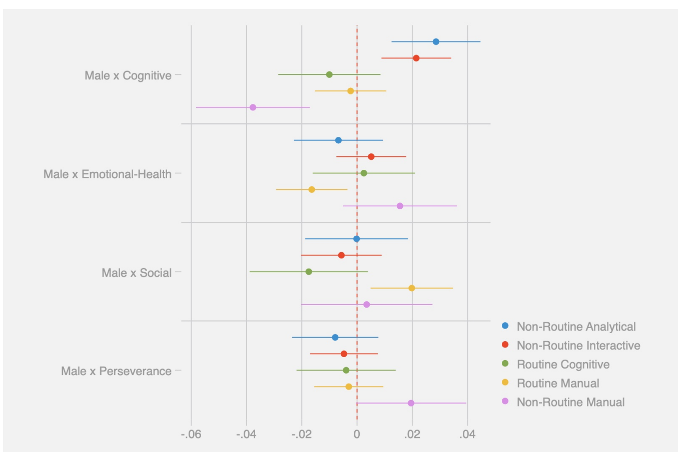
There is little evidence of any other gendered specific skill effects on job tasks. Cobb-Clark and Tan (2011) finds that men and women with the same level of cognitive and non-cognitive skills enter occupations at different rates. The findings here indicate that this is not due to cognitive and non-cognitive skills being more or less valued in men/women. Instead, it indicates that differential skill levels, occupational choices and/or discrimination is what leads to occupational segregation. In addition, it could indicate that men and women with similar skills choose different occupations with similar task profiles. Examining these issues in further detail is beyond the scope of this chapter.

**Figure 3.9: Gender Specific Effects of Child Skills on Job Tasks with Childhood controls**

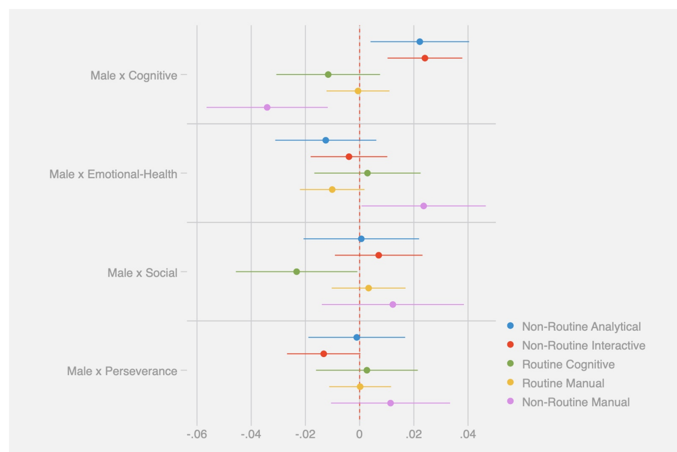
(a) Tasks at age 33 (b) Tasks at age 42

**Figure 3.10: Gender Specific Effects of Adolescent Skills on Job Tasks with childhood controls**

(a) Tasks at age 33




(b) Tasks at age 42



# IX HOW DO GENDERED DIFFERENCES IN CHILDHOOD AND ADOLESCENT SKILLS AFFECT JOB TASKS COMPLETED AS ADULTS?

I conduct an indicative, back-of-the envelope exercise to estimate how job tasks of men would differ if they had the same level of cognitive and non-cognitive skills as women while holding everything else constant. This is a static, partial-equilibrium calculation that does not consider, for example, whether the demand for occupations with the constituent job tasks is high enough to accommodate a higher supply of men who have the same skill profile as women. The calculation here gives an approximate estimate of how men's job tasks could change if they had the same skills as women.

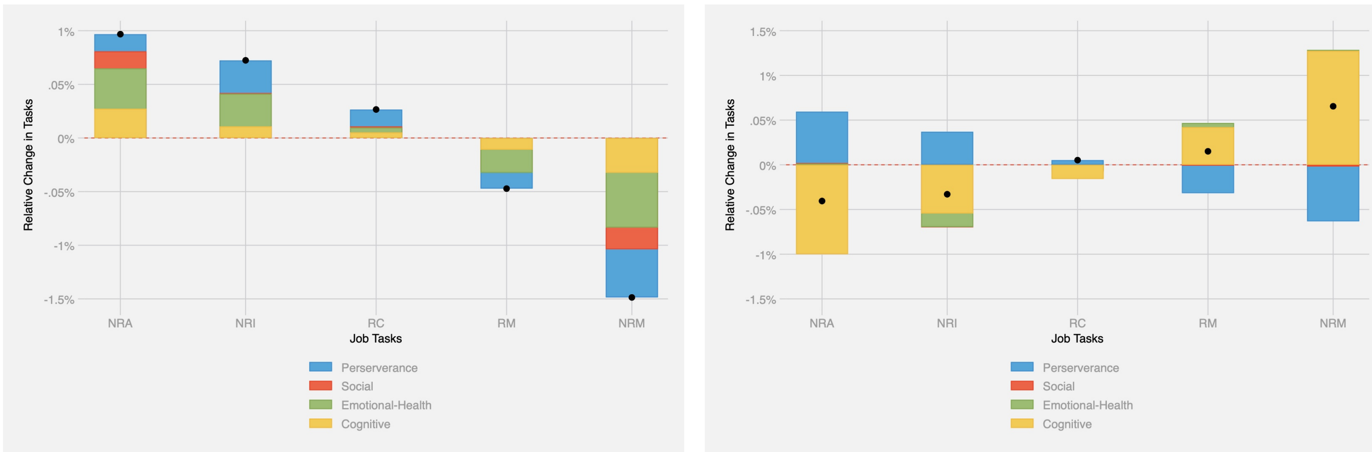
I estimate the difference in job tasks by multiplying the difference in average cognitive and non-cognitive skills between girls and boys in childhood/adolescence from Tables 3.2 and 3.3 with the coefficients from equations 1 and 2 with childhood controls. To make this concrete, I use an example of how NRA tasks for men would differ if they had the same level of emotional-health skills as girls at age 7.

At age 7 the difference in emotional-health skills between boys and girls is 0.167. I then multiply this difference, 0.167, by the Emotional-health coefficient from table 3.5 with childhood controls in column 2 (0.022). This then gives a partial-equilibrium estimate of how NRA tasks for men would differ if they had the same amount of emotional-health skills as girls at age 7, 0.3%. I then repeat this for each cognitive and non-cognitive skills for every type of job task. The results are shown in Figure 3.11 below.

I repeat this exercise using the gender-specific coefficients from equation 2. Here I add the coefficients from each cognitive/non-cognitive skill and the gender specific interaction. For example to estimate effect of emotional-health skills on NRA tasks at age 7 including gender-specific effects, I add together the Emotional-health (.017) and Emotional-Health x

**Figure 3.11: Gender Specific Effects of Child Skills on Job Tasks with Childhood controls**

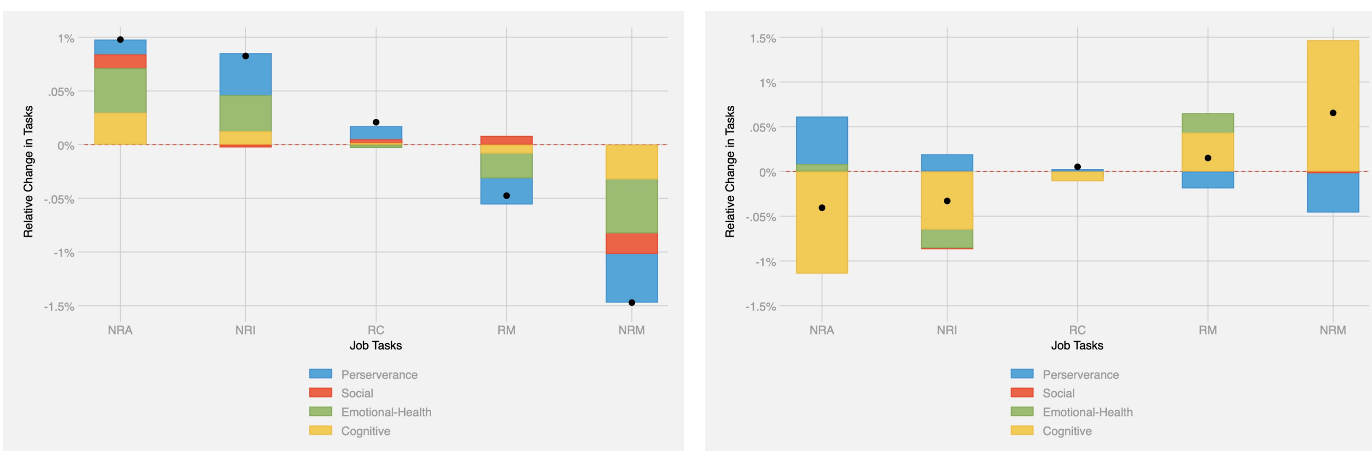
(a) Effect of Child Skill Differences (b) Effect of Adolescent Skill Differences




Male dummy (.008) coefficients from column 2 of Table 3A.9. I then multiply this by the average difference in emotional-health skills at age 7 as before (0.167) giving an increase in NRA tasks of 0.4 % in childhood. The results are shown in Figure 3.12 below.

**Figure 3.12: Relative Change in Male Job Tasks From Gendered Differences in Childhood/Adolescent Skills with Gender-Specific Impacts)**

(a) Effect of Child Skill Differences (b) Effect of Adolescent Skill Differences



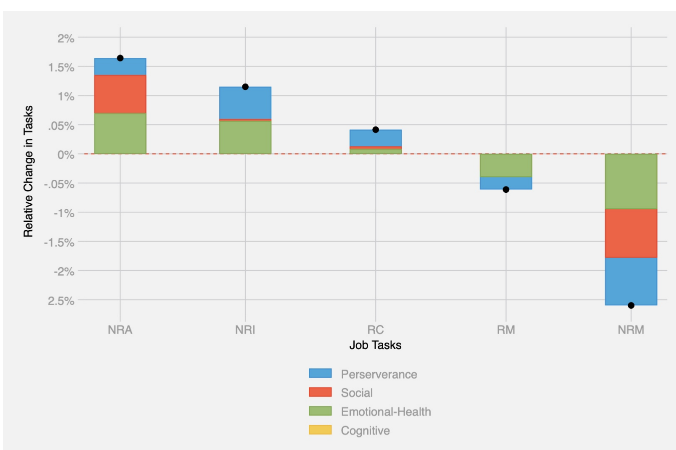

As can be seen from Figures 3.11 and 3.12 above, this indicative calculation suggests that if boys had the same average cognitive and non-cognitive skill levels as girls at aged 7 then they would undertake more NRA and NRI tasks while undertaking fewer manual tasks when working as adults.

By contrast, in adolescence, boys would be *less* likely to undertake NRA and NRI tasks and more likely to undertake low-paid manual tasks. This result is being driven almost entirely by differences in the cognitive score in adolescence. Boys have higher average cognitive skills in adolescence within this sample. Non-cognitive skill differences in adolescence still lead to men performing fewer NRA and NRI tasks than women. The overall effect of gendered differences in skill on task outcomes is, therefore, smaller in adolescence than in childhood as cognitive and non-cognitive skill differences have offsetting effects.

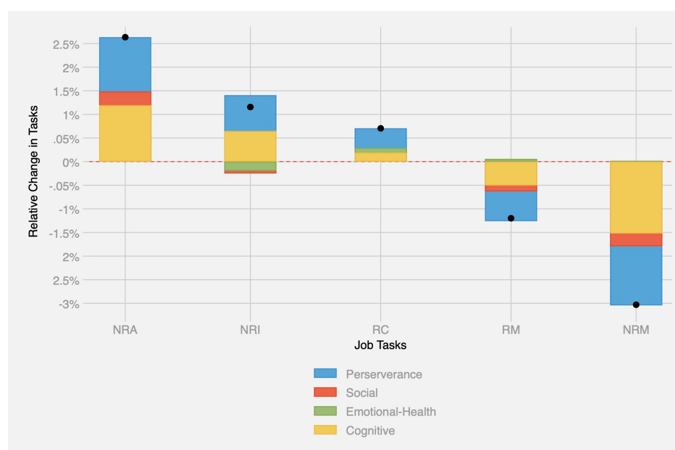
While boys have, on average, higher cognitive skills than girls is adolescence, these differences only open up in the middle and top of the skill distribution. At the bottom of the skill distribution, boys have lower cognitive skills than girls. Re-calculating the effect of skills for boys at the bottom of the skill distribution [2] shows that these boys would perform more NRA and NRI tasks if they had the same level of skills as girls in both childhood *and* adolescence (Figure 3.13).

**Figure 3.13: Relative Change in Male Job Tasks From Gendered Differences in Childhood/Adolescent Skills at the Bottom of the Skill Distribution**

(a) Effect of Child Skill Differences




(b) Effect of Adolescent Skill Differences




The evidence presented here shows that it is plausible that differences in non-cognitive

[2] Calculating the difference in skills between boys and girls at the 1st percentile in Table 3.13 & 3.14 and then multiplying it by the coefficients from Tables 3.5 to 3.10

skills have led to the men undertaking fewer NRA and NRI tasks that are more highly demanded in modern labour markets (Autor and Handel 2013). Gendered differences in cognitive skills that arise in adolescence do, however, appear to be ensuring that men who do enter the labour market are, on average, undertaking more highly paid NRA and NRI tasks than girls. For boys at the bottom of the skill distribution, however, these results unambiguously indicate they would be performing more highly paid NRA and NRI tasks if they had the same level of cognitive and non-cognitive skills as girls in childhood/adolescence.

There is a selection effect present in the analysis of job tasks thus far - only those men who are able to gain employment in the first place are able to undertake job tasks. Cognitive and non-cognitive skills do affect whether individuals are able to gain jobs in the first place. It is to this which I now turn.

# X DO CHILDHOOD AND ADOLESCENT COGNITIVE AND NON-COGNITIVE SKILLS AFFECT EMPLOYMENT PROBABILITY AS ADULTS?

I use a linear probability model to estimate how the cognitive and non-cognitive skills of children are related to adult probability of employment at age 33 and age 42. Linear probability models are common in the skill literature. This estimator is preferred as the parameters are easier to interpret and it is possible to estimate the impact where an entire group[3] is employed in the sample as is the case here (Caudill et al. 1988; Lindqvist and Vestman 2011; Attanasio et al. 2020a). Logit models are shown in Appendix F and give the same substantive results.

All models below exclude women whose youngest child is under 5, when mothers may be unable to work due to the lack of full-time public pre-school provision at the time (Stewart 2013). Employment rates for new mothers drops sharply in the first year after the birth of a child before steadily rising in each year after that (Stewart 2014; Roantree and Vira 2018). Specifications including mothers with children under 5 are shown in Appendix E. Their exclusion makes minor differences to the results, with the point estimates for some skills dropping to insignificance (although still remaining positive).

I estimate equation (3.3) below for the impact of childhood/adolescent skills on adult employment outcomes.

$$\begin{aligned}\text{Employment}_i = a_i + \text{Sex}_i + \text{Ethnicity}_i + \text{Cognitive Skills}_i + \text{Social Skills}_j + \\ \text{Emotional-Health Skills}_i + \text{Perseverance}_i + (\text{Childhood Controls}_i) + \\ (\text{Adult Controls}_i) + \epsilon_i\end{aligned} \tag{3.3}$$

[3]Specifically, an entire ethnic group

Where Employment is a dummy that takes a value of 1 if the individual is employed. Models are measured with employment probabilities at age 33 (in 1991) and age 42 (in 2000). While the employment rates were relatively similar in each year, this masks a change in employment type over this time. Male non-graduate employment had fallen as shown in Figure 3.1, with a concomitant decline in manufacturing jobs and routine manual tasks (Autor et al. 2003; Goos and Manning 2007; Górka et al. 2017; Sandher 2021).

The results of equation (3.3) are shown in Tables 3.11 & 3.12 and Figures 3.14 to 3.15 below. There is support for Hypothesis 2 from this specification. In the preferred specification with childhood controls, all cognitive and emotional-health skills in both childhood and adolescence are positively, and mostly significantly, related to employment outcomes at age 33 and 42. These effects are reduced when controlling for adult level conditions that will subsume some of the effects as cognitive and non-cognitive skills that help further educational attainment. These results are consistent with the literature (Heckman et al. 2006; Goodman et al. 2015).

The strongest relationship is between cognitive skills and employment outcomes. This is unsurprising given the strong relationship in the literature between cognitive skills and employment (Almlund et al. 2011; Goodman et al. 2015; Attanasio et al. 2020a). In the literature, non-cognitive skills have an effect on employment outcomes that are as strong as cognitive skills, but this is when they are combined into one non-cognitive factor and not separated out as we do here (Heckman et al. 2006; Lindqvist and Vestman 2011). While it is beyond the scope of this chapter, it is probable that separating out the measure of cognitive skills in to its constituent parts would reveal a similar weaker relationship.

After cognitive skills, emotional-health skills have the next strongest relationship with employment outcomes and these effects are somewhat stronger at age 7 than age 16. Emotional-health problems at early ages both damage later cognitive development *and* lead to later emotional-health problems, making it more difficult to gain employment (Donati et al. 2021). These effects remain in adolescence although are somewhat weaker. The results here do differ from other findings that use British Cohort Data (of children born in 1970 and outcomes measured in 2012), which find little impact of emotional-health skills on employment outcomes (Goodman et al. 2015; Attanasio et al. 2020a). It is possible that wider changes in unemployment explain the differences between British cohorts. The 1980s were a time of economic upheaval with a large decline of the manufacturing sector and unemployment remaining elevated for an extended period of time - it was above 10% between 1981 and 1986 (Vaitilingam 2009). Many workers who could not find a job simply left the labour market altogether (McVicar 2008; Beatty and Fothergill 2017). A certain level of emotional resilience could have been required to get through this period as well as to be able to look for a job once it had ended.

Perseverance has a relatively weaker (although still strong), relationship with employment. In contrast to job tasks, effects here on employment are somewhat weaker in adolescence than in childhood. This is consistent with the literature that tends to find positive impacts of perseverance on employment outcomes (Eisenberg et al. 2014; Goodman et al. 2015).

In contrast to findings on job tasks, social skills have a relatively strong impact on later employment probability. The effects of social skills are somewhat stronger at age 42, and this may reflect growing service sector employment at this time requiring more person-facing interaction and/or the (re-)entry of mothers who were not working at age 33 due to childbirth (Olivetti and Petrongolo 2016; Deming 2017). Finally, the impact of non-cognitive skills does fall significantly when controlling for adult level conditions but often remain significant. Non-cognitive skills have been shown to have a strong impact on education status, and so their impact is attenuated when including educational status (Jacob 2002). Their continued significance, however, indicates a child/adolescent with greater non-cognitive skills will, generally, be more likely to be employed than an otherwise similar child with the same level of education.

As before, I also restrict the sample to non-graduates who were also employed at age

23 (Figure 3.16 - 3.17 and Appendix G). The effects here are in the same direction as the full sample specifications although generally weaker. This is to be expected. Many non-graduates from this cohort who gained manufacturing jobs when they left school would have lost them by the time they turned 23 in 1981 as the manufacturing sector had already begun to decline. Between 1978 and 1981, unemployment had risen dramatically (from 5.6% to 9.6%) and manufacturing employment had fallen by 15% (from 6.7 million to 5.8 million). In particular, it would have been young non-graduates with the lowest level of skills that are the most likely to have lost their jobs in this period (Vaitilingam 2009). The restricted sample, therefore, is likely to include those with relatively higher skills who had survived the initial wave of de-industrialisation. Point estimates for this restricted sample tend to increase between ages 33 and 42, when the manufacturing industry continues to decline and more non-graduates employed in 1981 continue to lose their jobs i.e. it captures more of those who lost their jobs due to technological change & trade. This robustness test indicates that the full sample result is not biased. Non-graduates with greater childhood and adolescent skills were more likely to be employed after deindustrialisation took hold

**Figure 3.14: Effect of Childhood Skills on Adult Employment**

(a) Effect of Skills on Employment Age 33 (b) Effect of Skills on Employment Age 42

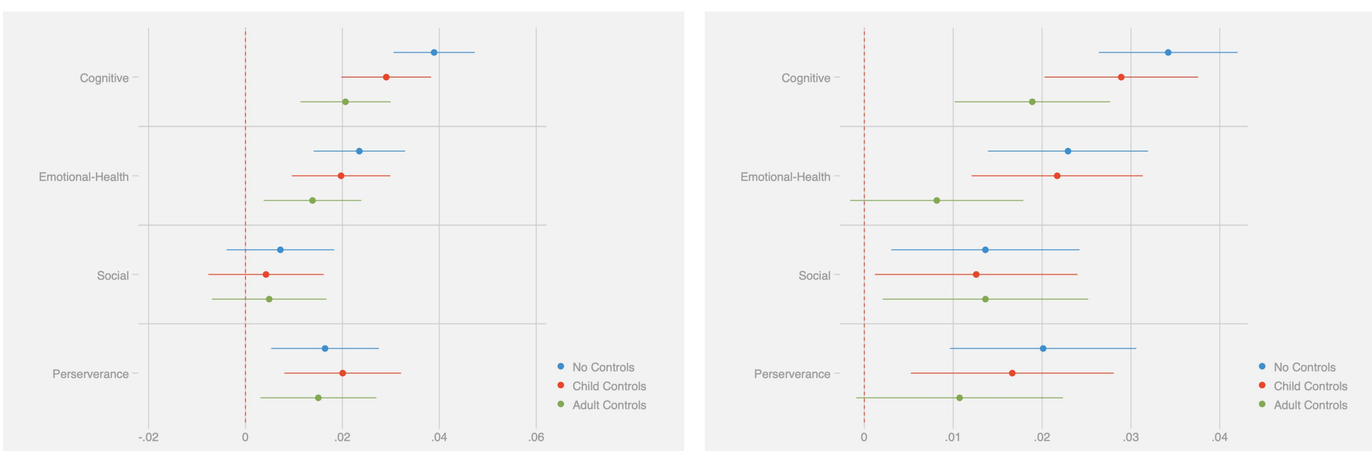


**Table 3.13: Impact of Skills Measured at age 7/16 on Employment aged 33**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Age 7 | Age 7 | Age 7 | Age 16 | Age16 | Age16 |
| Male Dummy | 0.127*** | 0.124*** | 0.118*** | 0.111*** | 0.106*** | 0.111*** |
| | (0.008) | (0.008) | (0.008) | (0.010) | (0.011) | (0.011) |
| Cognitive | 0.039*** | 0.029*** | 0.018*** | 0.052*** | 0.051*** | 0.034*** |
| | (0.004) | (0.005) | (0.005) | (0.007) | (0.008) | (0.008) |
| Emotional-Health | 0.024*** | 0.020*** | 0.014*** | 0.012* | 0.014* | 0.014* |
| | (0.005) | (0.005) | (0.005) | (0.007) | (0.007) | (0.007) |
| Social | 0.007 | 0.004 | 0.003 | 0.029*** | 0.035*** | 0.018** |
| | (0.006) | (0.006) | (0.006) | (0.007) | (0.008) | (0.008) |
| Perserverance | 0.016*** | 0.020*** | 0.014** | 0.019*** | 0.017** | 0.008 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) |
| Constant | 0.785*** | 0.569*** | 0.507*** | 0.799*** | 0.750*** | 0.693*** |
| | (0.006) | (0.109) | (0.109) | (0.007) | (0.138) | (0.139) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| $N$ | 8242 | 7055 | 6764 | 5078 | 4105 | 3957 |
| r2 | 0.052 | 0.062 | 0.112 | 0.065 | 0.074 | 0.109 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

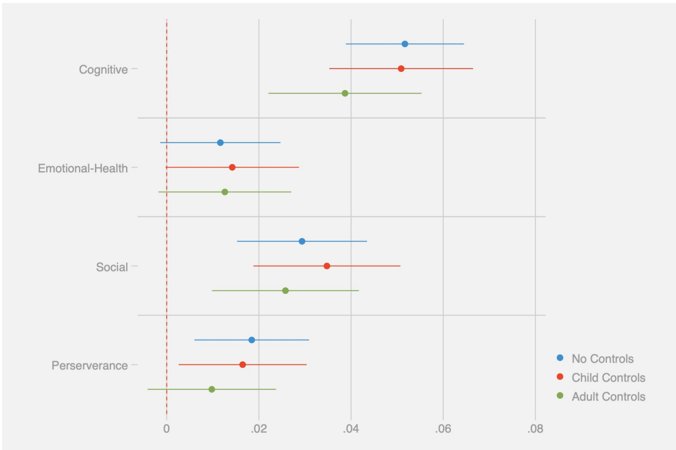
**Table 3.14: Impact of Skills Measured at age 7/16 on Employment aged 42**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Age 7 | Age 7 | Age 7 | Age 16 | Age16 | Age16 |
| Male Dummy | 0.104*** | 0.101*** | 0.095*** | 0.073*** | 0.076*** | 0.076*** |
| | (0.007) | (0.008) | (0.008) | (0.008) | (0.010) | (0.010) |
| Cognitive | 0.034*** | 0.029*** | 0.019*** | 0.044*** | 0.042*** | 0.042*** |
| | (0.004) | (0.004) | (0.004) | (0.006) | (0.007) | (0.007) |
| Emotional- Health | 0.023*** | 0.022*** | 0.008 | 0.018*** | 0.017** | 0.017** |
| | (0.005) | (0.005) | (0.005) | (0.006) | (0.007) | (0.007) |
| Social | 0.014** | 0.013** | 0.014** | 0.019*** | 0.018** | 0.018** |
| | (0.005) | (0.006) | (0.006) | (0.007) | (0.008) | (0.008) |
| Perserverance | 0.020*** | 0.017*** | 0.011* | 0.012** | 0.009 | 0.009 |
| | (0.005) | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) |
| Constant | 0.806*** | 0.648*** | 0.748*** | 0.834*** | 0.940*** | 0.926*** |
| | (0.005) | (0.101) | (0.101) | (0.006) | (0.128) | (0.128) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| $N$ | 9549 | 8129 | 6892 | 5893 | 4762 | 4762 |
| r2 | 0.044 | 0.052 | 0.161 | 0.041 | 0.054 | 0.057 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Figure 3.15: Effect of Adolescent Skills on Adult Employment**

(a) Effect of Skills on Employment Age 33




(b) Effect of Skills on Employment Age 42

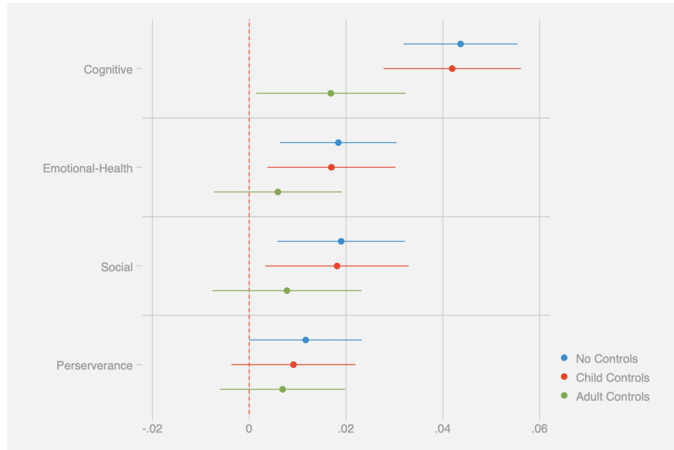
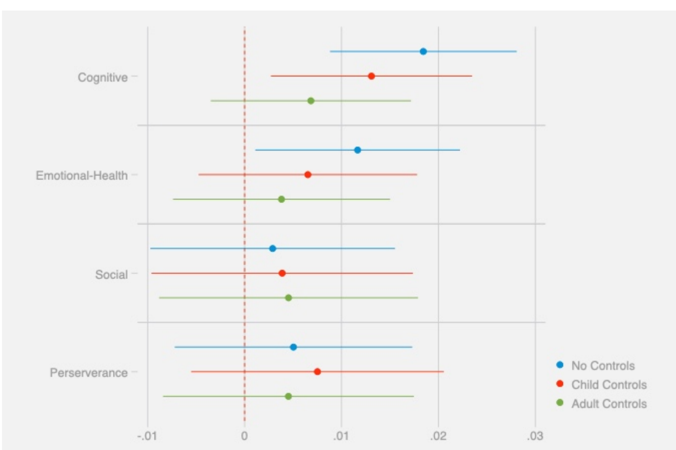



**Figure 3.16: Effect of Childhood Skills on Adult Employment for Non-Graduates Employed at Age 23**

(a) Effect of Skills on Employment Age 33




(b) Effect of Skills on Employment Age 42

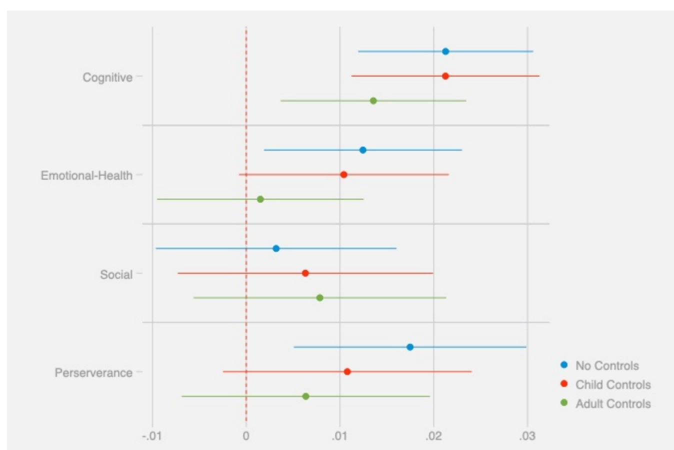
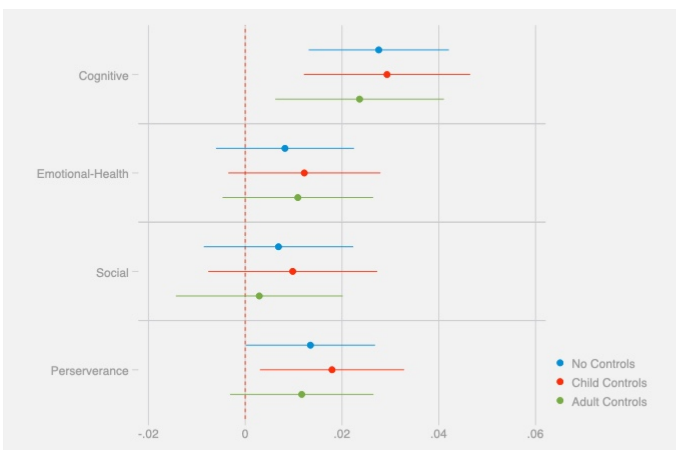
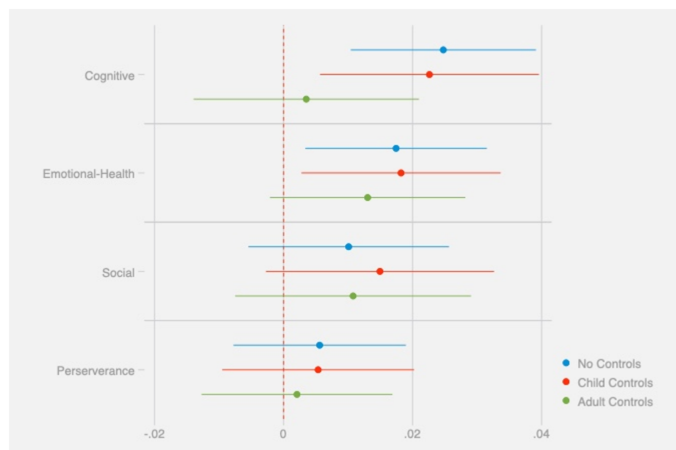


**Figure 3.17: Effect of Adolescent Skills on Adult Employment for Non-Graduates Employed at Age 23**

(a) Effect of Skills on Employment Age 33




(b) Effect of Skills on Employment Age 42



# XI DO COGNITIVE AND NON-COGNITIVE SKILLS HAVE DIFFERENT EFFECTS ON EMPLOYMENT FOR MEN AND WOMEN?

I estimate equation 3.4 below to analyse whether the effects of cognitive and non-cognitive skills differ for men and women in the labour market. The key coefficients are on whether the interactions of these skills with the Male Dummy has an impact on employment probabilities as adults. Positive interactions indicate that men are more likely to be employed for a given level of skills, while a negative coefficient indicates that women gain a greater employment bonus from a given level of skills. The key coefficients are shown in Figures 3.18 and 3.19 below. Full regression tables are shown in Appendix H.

$$\begin{aligned} \text{Employment}_i = a_i &+ \text{Male Dummy}_i + \text{Cognitive Skills}_i \times \text{Male Dummy}_i + \\ &\text{Social Skills}_i \times \text{Male Dummy}_i + \text{Emotional-Health Skills}_i \times \text{Male Dummy}_i + \\ &\text{Perseverance}_i \times \text{Male Dummy}_i (+\text{Childhood Controls}_i) \\ &(+\text{Adult Controls}_i) + \epsilon_i \end{aligned} \tag{3.4}$$

As with job tasks, I find almost no evidence, again, that the effect of cognitive and non-cognitive skills differs between genders. There is very little difference in the impact of cognitive, emotional-health, perseverance and social skills. The effects that are found are generally weak and inconsistent. For example, boys appear to gain from social skills at age 33 in childhood but then girls get an extra bonus as adolescents. These effects are somewhat consistent with the literature. The literature finds little difference in the impact of emotional-health skills on employment outcomes between genders, with mixed findings on the whether the effect of cognitive skills and externalising skills differs between genders

(Papageorge et al. 2019; Attanasio et al. 2020a). The results here are broadly in line with findings that differences in education levels (that are correlated with employment outcomes) are due to differences in cognitive and non-cognitive skill levels rather than differences in their effects (Jacob 2002).

The results here indicate that the differential employment outcomes between men and women is not due to their skills being differentially rewarded between genders. Instead, differences in their employment probabilities may reflect their overall skill levels as well as differences in gender norms, discrimination, and childcare policies (Gregory 2011).

**Figure 3.18: Gender-Specific Effect of Childhood Skills on Adult Employment**

(a) Effect of Skills on Employment Age 33 (b) Effect of Skills on Employment Age 42

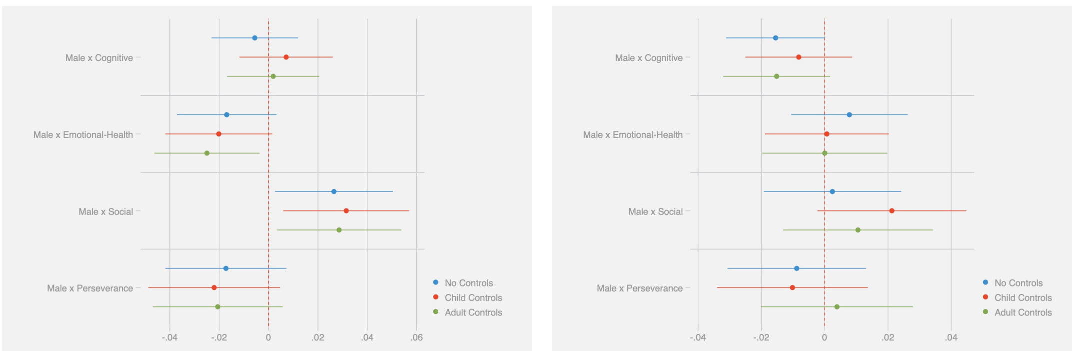
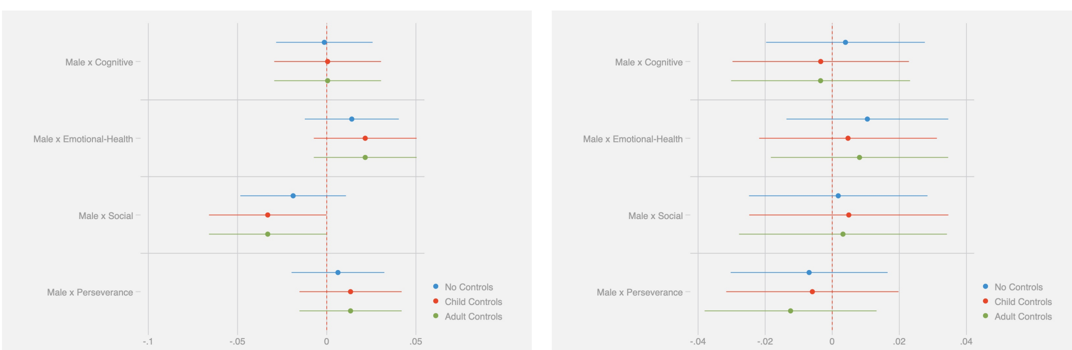



**Figure 3.19: Gender-Specific Effect of Adolescent Skills on Adult Employment**

(a) Effect of Skills on Employment Age 33 (b) Effect of Skills on Employment Age 42



# XII HOW DID COGNITIVE AND NON-COGNITIVE SKILLS DIFFERENCES BETWEEN BOYS AND GIRLS AFFECT EMPLOYMENT RATES?

Here I provide an illustrative calculation of how gendered differences in childhood/adolescent skills could affect adult employment. I do this by estimating how the employment rates for men would change if they had the same level of skills as girls in childhood and adolescence using the results from equations 3.3 and 3.4 while holding everything else constant. This is a static, back-of-the-envelope calculation that does not consider dynamic responses to changes in skill levels. I use the results at age 33 with childhood controls and show differences across the skill distribution. Non-graduates have far lower skill levels than graduates. Across skill categories, an average of 85% of those in the bottom quartile are non-graduates (ranging from 75 to 95% across skill categories).

I calculate the illustrative skill-based difference in employment rates by first measuring the difference in cognitive, internalising, perseverance, and social skills between boys and girls at the 1st, 25th, 50th, 75th, and 99th percentiles as shown in Tables 3.15 and 3.16 below. I then multiply these differences by the coefficients from columns 2 and 4 in Table 3.13 (that include childhood controls).

**Table 3.15: Differences in Skill levels for Girls and Boys at age 7 at Skill Percentiles**

| Girl - Boy Difference | p1 | p25 | p50 | p75 | p99 |
|---|---|---|---|---|---|
| Cognitive | 0.000 | 0.130 | 0.075 | 0.027 | -0.024 |
| Emotional-health | 0.309 | 0.258 | 0.220 | 0.000 | 0.000 |
| Social | 0.616 | 0.211 | 0.000 | 0.000 | 0.000 |
| Perseverance | 0.580 | 0.582 | 0.177 | 0.085 | 0.000 |

For example, at age 7 boys in the 1st percentile of the skill distribution have perseverance skills of -3.22 compared to -2.64 for girls at the same age leading to a difference in 0.58 (Table

**Table 3.16: Differences in Skill levels for Girls and Boys at age 16**

| Girl - Boy Difference | p1 | p25 | p50 | p75 | p99 |
|---|---|---|---|---|---|
| Cognitive | 0.130 | -0.066 | -0.189 | -0.193 | -0.128 |
| Emotional-health | -0.240 | -0.295 | -0.277 | -0.110 | 0.000 |
| Social | 0.537 | 0.000 | 0.000 | 0.000 | 0.000 |
| Perseverance | 0.399 | 0.229 | 0.191 | 0.183 | 0.000 |

3.13). I then multiply this difference, 0.58, by the perseverance coefficient from table 3.11, column 2 (0.020) to measure how much employment probabilities would change if boys had the amount of Perseverance skills at this percentile (1.16%).

In childhood, girls have higher cognitive and non-cognitive skill levels than boys in every skill across almost the entire distribution (with the sole exception of cognitive skills at the 99th percentile). In adolescence, girls have generally lower cognitive (except at the 1st percentile) and emotional-health skills across the skill distribution. They still have higher social and perseverance skill levels across the distribution.

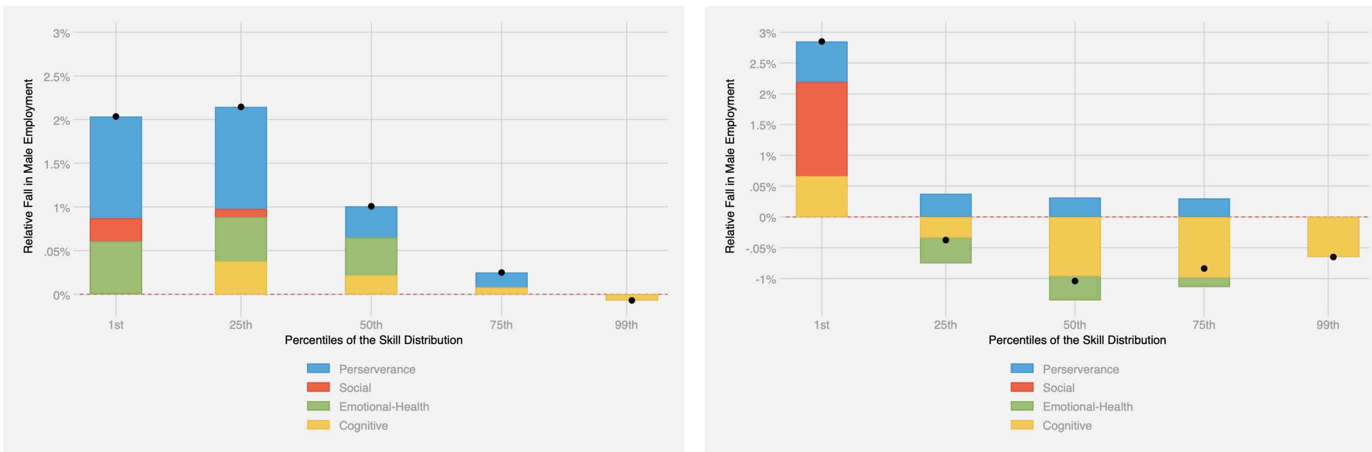
The results of this illustrative, static employment calculation are shown in Figures 3.20a and 3.20b below. Noticeably, the impact of childhood/adolescent has a significant impact at the bottom of the skill distribution reducing relative employment for men by around 2 points in childhood and 3 percentage points in adolescence. Similar to findings in Heckman et al. (2006) and Lindqvist and Vestman (2011), I find that non-cognitive skills make a much larger impact at the bottom than at the top of the distribution.

In the middle and top of the skill distribution, gendered differences in childhood skills have less of an impact on employment outcomes. In adolescence, however, differences in skills would drive down employment rates for men relative to women by around 0.5 %. This is not only driven by differences in cognitive skills. Emotional-health skill differences have a positive and strong impact on employment outcomes for men.

It is worth comparing these results with the job task results in section There we found that differences in adolescent skills led to an *average* increase in NRA job and NRI job tasks for men. At the bottom of the skill distribution, we saw that opposite is true. Similarly here, I find that it is boys at the bottom of the skill distribution that gain the most if they had the same skill levels as girls in childhood and adolescence.

**Figure 3.20: Relative Fall in Male Employment Rates due to Skill Differences (with no Gender Specific Impacts)**

(a) Impact of Child Skill Differences (b) Impact of Adolescent Skill Differences

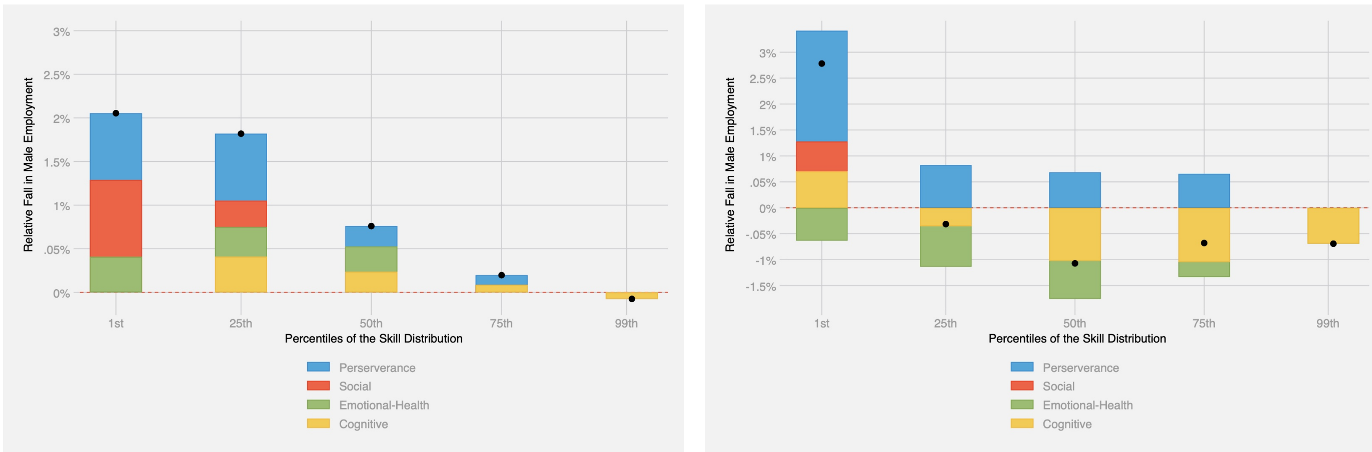



I conduct the same calculations using the gender-specific results. Here I sum together the results for both cognitive and male dummy interaction measures to get the total impact for men. So, for example, from Appendix H, I use the coefficients from "Emotional-Health" and "Male Dummy x Emotional", add these together, and multiply this by the difference between Boy and Girl Emotional-Health Skills at age 7 and 16. As can be seen in Figures 3.21 below, the effect is still largest at the bottom of the skill distribution, and again reduces employment for the least skilled men by around 2 to 3 percentage points.

In summation, these results indicate that cognitive, social, emotional-health and perseverance skills in childhood/adolescence are important predictors of adult employment outcomes. In childhood, these differences unambiguously reduce employment for men across the skill distribution. In adolescence, it is the least-skilled men who lose out due to gender differences in skills. As the least-skilled boys possess lower levels of skills than the least-skilled girls, the gendered differences in cognitive and non-cognitive skills could provide an important ex-

**Figure 3.21: Relative Fall in Male Employment Rates due to Skill Differences with Gender Specific Effects**

(a) Effect of Child Skill Differences (b) Effect of Adolescent Skill Differences




planation of the falling employment rates non-graduate men have seen in the postindustrial economy. It is likely that the least-skilled boys have lost out on employment opportunities in the post-industrial economy due to their lower skill levels relative to girls.

# XIII DISCUSSION AND CONCLUSION

In this chapter, I provided evidence that gendered differences in childhood and adolescent skills are an important explanation for why less-skilled men are less likely to undertake highly paid non-routine analytical and interactive tasks that are more highly demanded in the post-industrial economy. The least-skilled men, in particular, would benefit from having the same cognitive and non-cognitive skills as girls in children and adolescence. Indicative calculations indicate that these least skilled men would perform more highly paid analytical (NRA) and interactive (NRI) tasks as well as be see their employment rates rise by 2 to 3 percentage points.

The most important contribution to the literature that this chapter makes is to test the effect of a wide range of cognitive and non-cognitive skills on the full range of job tasks. When combined with the evidence that boys have generally lower cognitive and non-cognitive skills then girls, this gives an explanation of why non-graduate men have been less adept at performing the tasks demanded in the post-industrial economy. I believe this is the first piece of work to show this.

Using regressions that iteratively controlled for childhood and then adult level conditions, I found that these cognitive and non-cognitive skills had existing effects even after controlling for education status. These results also held when restricting the sample to non-graduates who were employed at age 23. Early childhood and adolescent experiences matter for labour market outcomes over and above their impact on educational attainment and employment experiences.

When it came to analysing job tasks, cognitive tasks had the strongest effect on job tasks with a positive effect on analytical and interactive tasks and negative effect on manual tasks. Emotional-health in childhood was also strongly related to NRA and NRI tasks, which may be due to its importance for later cognitive development (Donati et al. 2021). Perseverance skills in adolescence, but not childhood, were positively related to later NRA tasks, which may be due to the later development of these skills in adolescence.

This chapter also makes an important contribution by showing that previous findings of the importance of social skills for person tasks may suffer from an omitted variable bias. Surprisingly, and in contrast to the rest of the literature, social skills had little effect on NRI tasks as expected - and the results here indicate that this could be due to me including measures of emotional-health and perseverance that are often missing from other work in this area (Borghans et al. 2014; Weinberger 2014). There was little effect of gender-specific effects of skills.

Illustrative back-of-the-envelope calculations indicate that the least-skilled men would have undertaken more NRA and NRI job tasks as well as fewer manual tasks if they had the same level of cognitive and non-cognitive skills as girls in childhood/adolescence. Men in general would have performed more NRA and NRI tasks as adults if, as children, they had the same skill levels as women. As adolescents, however, boys have greater cognitive skills than girls in the middle and top of the skill distribution. Equalising their skill levels to girls would have then led to an overall decrease in the NRA and NRI tasks they perform.

The results for the effect of childhood/adolescent skills on employment outcomes were subtly different than that of job tasks. Cognitive skills were, again, the most important for predicting employment outcomes. Social skills had a strong effect on employment outcomes, and this was stronger at age 42 than 33, which may indicate the changing job tasks demand at this time and/or the re-entry of mothers into the labour market. Emotional-health and perseverance skills were also positively related to employment outcomes.

The clear policy implication from this chapter is that measures to improve early childhood and adolescent experiences are crucial for later labour market outcomes. While the previous literature has convincingly pointed to the importance of childhood cognitive skills and general non-cognitive skills for labour market outcomes, this chapter also provides clear evidence of the importance of emotional-health skills for both employment outcomes and high-skill tasks. A warm, nurturing environment for children is as important as stimulating activities (Putnam 2015). As the non-cognitive skills of boys are more sensitive to home environments than girls, more nurturing environments are likely to lead to a relative rise in male employment rates (Bertrand and Pan 2013).

Improving these skills in childhood and adolescence is, therefore, crucial for improving labour market outcomes in general and for boys in particular. As Cooper and Stewart (2021) show, a lack of money itself damages cognitive and non-cognitive skills in children. The effects of parental income on childhood cognitive and socio-emotional development begin before children are born (Blair and Raver 2016). Parents with more money have more material *and* psychological resources to invest in their children and this, in turn, leads to greater cognitive, emotional-health, perseverance, and social skills (Mullainathan 2013; Cooper 2017; Reeves et al. 2021). Measures that increase incomes for the most deprived will, by providing parents with greater resources to invest in their children, lead to these children growing up to undertake jobs with higher-paying tasks and better employment programs

(Almlund et al. 2011; Autor and Handel 2013).

As well as more money, pre-school programs that aim to improve the early experiences for children can also improve cognitive and non-cognitive skills. Only programs that start before the age of 3 have, however, consistently improved IQ outcomes (Kautz et al. 2014). Other pre-school programs that improve parenting practices, such as Sure Start in the UK, and other early education programs can improve non-cognitive skills in young children and so improve both the quality of their jobs as well as the likelihood of them having a job when they become adults (Heckman et al. 2013; Stewart 2013; Kautz et al. 2014).

There are a number of limitations in this chapter that could be addressed with future work. Firstly, these estimates cannot be considered "causal" and instead measure associations between skills in childhood/adolescence and later labour market outcomes. It is possible that other childhood experiences account for employment and skill outcomes that are not covered here. However, the wide range of covariates, including adult-level controls that would attenuate the impacts of childhood skills (such as graduate education), do make these estimates more robust. Many of the effects remain even when controlling for adult-level conditions, indicating they have an important and enduring effect on outcomes, separate from childhood conditions and educational attainment.

Secondly, the measures of emotional-health, social, and perseverance skills used here tend to measure the presence or absence of problems rather than a child excelling in a particular area. When it comes to social skills, for example, the factor includes measures such as hostility toward others and fighting rather than whether they are liked by other children. While this adequately captures differences at the bottom of the skill distribution, this work may be less suited to analysing differences between boys and girls in the middle and top of the distribution.

Thirdly, there is no perfect measure of non-cognitive skills and this chapter's skill measurements could be improved in future work (Almlund et al. 2011). In particular, different skill taxonomies and/or data sources could be used as is discussed above. Here I use a single taxonomy where I split non-cognitive skills into emotional-health, perseverance, and social skills (Duncan et al. 2011). There are other taxonomies such as the Big Five and I look forward to future work that uses these measures instead to analyse whether they are consistent with the findings here (Kautz et al. 2014). Further, as is stated above, both the questions used and the questioners differ for assessing childhood and adolescent skills. While this has also been present in previous work, it could lead to biases that were not initially apparent here (Ready and Wright 2011; Kautz et al. 2014; Lundberg et al. 2017; Elder and Zhou 2021). In addition, the childhood measures of non-cognitive skills used teacher assessments that are somewhat more accurate than the self/teacher evaluations of adolescent skills (Feng et al. 2022). Future work could consider data sources where questions and questioners are consistent across childhood & adolescence to further probe the robustness of these results.

Fourthly, tasks vary within jobs as well and these measures here cannot account for such intra-occupation variation (Autor and Handel 2013). Tasks within jobs can also change over time, whereas the measure used here effectively fixes the task content of occupations when they are measured. Methods that could account for these intra-occupation task differences could give more precise estimates.

Finally, the work completed here shows impacts from one particular country, the United Kingdom, and one cohort of people born in 1958 and measuring their outcomes in 1991 and 2000. The labour market has changed in the past 20 years, with a continuing rise in job tasks requiring analytical and interactive tasks demanded (Deming 2017; Górka et al. 2017). Future work could consider whether the impact of skills has changed for younger generations as well as in other countries.

# XIV APPENDIX A: CONSTRUCTION OF COGNITIVE, EMOTIONAL-HEALTH, SOCIAL AND PERSEVERANCE SKILLS

## XIV.1 Childhood Skills

**Table 3A.1: Loadings for Cognitive Skills**

| Item | Title | Factor Loading |
|---|---|---|
| 1 | Reading Test Score | 0.655 |
| 2 | Problem Arithmetic Score | 0.637 |
| 3 | Drawing-a-Man Test | 0.533 |
| 4 | Copying Designs Test | 0.505 |

**Table 3A.2: Loadings for Emotional-Health Skills**

| Item | Title | Factor Loading |
|---|---|---|
| 1 | Depression | 0.652 |
| 2 | Withdrawal | 0.648 |
| 3 | Unforthcomingness | 0.624 |

**Table 3A.3: Loadings for Social Skills**

| Item | Title | Factor Loading |
|---|---|---|
| 1 | Hostility Toward Other Children | 0.694 |
| 2 | Hostility Toward Adults | 0.637 |
| 3 | Anxiety for Acceptance by Children | 0.628 |
| 4 | Anxiety | 0.388 |

**Table 3A.4: Loadings for Perseverance Skills**

| Item | Title | Factor Loading |
|---|---|---|
| 1 | Inconsequential Behaviour | 0.820 |
| 2 | Restlessness | 0.666 |
| 3 | Squirmy, Fidgety | 0.665 |
| 4 | Writing off Adults and Standards | 0.500 |
| 5 | Difficulty Concentrating | 0.207 |

## XIV.2 Adolescent Skills

**Table 3A.5: Loadings for Cognitive Skills**

| Item | Title | Factor Loading |
|---|---|---|
| 1 | Reading Test | 0.727 |
| 2 | Mathematics Test | 0.727 |

**Table 3A.6: Loadings for Emotional-Health Skills**

| Item | Title | Factor Loading |
|---|---|---|
| 1 | Worried | 0.541 |
| 2 | Miserable | 0.518 |
| 3 | Fearful | 0.443 |
| 4 | Irritable | 0.436 |
| 5 | Solitary | 0.313 |
| 6 | Fussy | 0.305 |
| 7 | Twitches | 0.187 |
| 8 | Bites Nails | 0.171 |
| 9 | Sucks Thumb | 0.131 |

**Table 3A.7: Loadings for Social Skills**

| Item | Title | Factor Loading |
|---|---|---|
| 1 | Disobedient | 0.576 |
| 2 | Lies | 0.563 |
| 3 | Fights | 0.562 |
| 4 | Bullies | 0.524 |
| 5 | Destroys Objects | 0.438 |
| 6 | Disliked | 0.300 |

**Table 3A.8: Loadings for Perseverance Skills**

| Item | Title | Factor Loading |
|---|---|---|
| 1 | Takes Work Seriously | 0.554 |
| 2 | Difficult to Keep Mind on Work | 0.535 |
| 3 | Lazy/Hardworking | 0.505 |
| 4 | Gets on with Classwork | 0.466 |
| 5 | Restless | 0.426 |
| 6 | Fidgety | 0.384 |

# XV APPENDIX B: IMPACT OF SKILLS ON TASKS FOR NON-GRADUATES EMPLOYED AT AGE 23

**Table 3A.9: Impact of Skills Measured at Ages 7/16 on Job Tasks at Age 33**

| | (1) NRA Age 7 | (2) NRA Age 7 | (3) NRI Age 7 | (4) NRI Age 16 | (5) RC Age 16 | (6) RC Age 16 | (7) RM Age 7 | (8) RM Age 7 | (9) NRM Age 7 | (10) NRM Age 16 |
|---|---|---|---|---|---|---|---|---|---|---|
| Male Dummy | 0.0653*** | 0.0686*** | -0.0309*** | -0.0425*** | -0.139*** | -0.139*** | 0.0173*** | 0.0275*** | 0.0870*** | 0.0854*** |
| | (0.00603) | (0.00743) | (0.00446) | (0.00553) | (0.00671) | (0.00864) | (0.00479) | (0.00597) | (0.00782) | (0.00948) |
| Cognitive | 0.0272*** | 0.0765*** | 0.0128*** | 0.0409*** | 0.0145*** | 0.0316*** | -0.0146*** | -0.0403*** | -0.0399*** | -0.109*** |
| | (0.00351) | (0.00593) | (0.00260) | (0.00441) | (0.00391) | (0.00689) | (0.00279) | (0.00476) | (0.00456) | (0.00756) |
| Emotional | 0.0226*** | -0.000250 | 0.0168*** | 0.00702* | 0.000851 | -0.00599 | -0.0131*** | -0.00307 | -0.0272*** | 0.00229 |
| | (0.00396) | (0.00531) | (0.00292) | (0.00395) | (0.00440) | (0.00617) | (0.00314) | (0.00427) | (0.00513) | (0.00678) |
| Social | 0.00386 | 0.00621 | -0.00460 | 0.00409 | 0.00238 | 0.00185 | 0.00533 | -0.00308 | -0.00697 | -0.00907 |
| | (0.00480) | (0.00619) | (0.00355) | (0.00461) | (0.00533) | (0.00720) | (0.00381) | (0.00498) | (0.00622) | (0.00790) |
| Perseverance | 0.00434 | 0.0310*** | 0.00757** | 0.00703* | 0.00763 | 0.00702 | -0.00781** | 0.00702 | -0.0117* | -0.0311*** |
| | (0.00466) | (0.00516) | (0.00345) | (0.00384) | (0.00519) | (0.00600) | (0.00370) | (0.00415) | (0.00605) | (0.00659) |
| Constant | 0.0258 | 0.162 | 0.0999* | 0.242*** | 0.400*** | 0.396*** | 0.0811 | -0.0141 | 0.394*** | 0.214* |
| | (0.0805) | (0.0998) | (0.0595) | (0.0743) | (0.0896) | (0.116) | (0.0639) | (0.0802) | (0.104) | (0.127) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 5011 | 3080 | 5011 | 3080 | 5011 | 3080 | 5011 | 3080 | 5011 | 3080 |
| r2 | 0.0759 | 0.140 | 0.0570 | 0.0837 | 0.111 | 0.109 | 0.0419 | 0.0777 | 0.0975 | 0.154 |

Standard errors in parentheses

Ethnicity controls: ethnicity of child

Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother smoked in pregnancy, and birthweight), region of childhood

Adult Controls:region of residence, marital status, a graduate dummy, and general health status

$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## Table 3A.10: Impact of Skills Measured at Ages 7/16 on Job Tasks at Age 42

| | (1) NRA Age 7 | (2) NRA Age 7 | (3) NRI Age 7 | (4) NRI Age 16 | (5) RC Age 16 | (6) RC Age 16 | (7) RM Age 7 | (8) RM Age 7 | (9) NRM Age 7 | (10) NRM Age 16 |
|---|---|---|---|---|---|---|---|---|---|---|
| Male Dummy | 0.0323*** | 0.0271*** | -0.0384*** | -0.0404*** | -0.0597*** | -0.0533*** | 0.0148*** | 0.0169*** | 0.0510*** | 0.0460*** |
| | (0.00671) | (0.00836) | (0.00491) | (0.00607) | (0.00693) | (0.00783) | (0.00435) | (0.00551) | (0.00853) | (0.0106) |
| Cognitive | 0.0247*** | 0.0621*** | 0.0167*** | 0.0368*** | -0.000868 | 0.00966* | -0.00813*** | -0.0248*** | -0.0324*** | -0.0869*** |
| | (0.00396) | (0.00659) | (0.00290) | (0.00479) | (0.00409) | (0.00580) | (0.00257) | (0.00435) | (0.00503) | (0.00833) |
| Emotional | 0.0245*** | -0.00540 | 0.0111*** | -0.00212 | -0.00404 | -0.00960* | -0.00657** | 0.00405 | -0.0250*** | 0.0107 |
| | (0.00442) | (0.00609) | (0.00323) | (0.00442) | (0.00456) | (0.00574) | (0.00287) | (0.00402) | (0.00561) | (0.00770) |
| Social | 0.00782 | 0.0171** | 0.00366 | 0.0151*** | -0.00532 | -0.00613 | -0.00184 | -0.00851* | -0.00433 | -0.0118 |
| | (0.00533) | (0.00706) | (0.00390) | (0.00513) | (0.00551) | (0.00647) | (0.00346) | (0.00465) | (0.00677) | (0.00892) |
| Perseverance | -0.00117 | 0.0117** | 0.00000801 | -0.000658 | 0.00756 | 0.000947 | -0.00380 | -0.00197 | -0.00259 | -0.00764 |
| | (0.00524) | (0.00580) | (0.00383) | (0.00421) | (0.00541) | (0.00542) | (0.00340) | (0.00382) | (0.00666) | (0.00733) |
| Constant | 0.0972 | 0.0126 | 0.225*** | 0.241*** | 0.364*** | 0.240*** | 0.128** | 0.0945 | 0.186 | 0.272* |
| | (0.0889) | (0.112) | (0.0650) | (0.0815) | (0.0919) | (0.00590) | (0.0577) | (0.0740) | (0.113) | (0.142) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 4473 | 2744 | 4473 | 2744 | 4473 | 3362 | 4473 | 2744 | 4473 | 2744 |
| r2 | 0.0483 | 0.0763 | 0.0449 | 0.0598 | 0.0275 | 0.0200 | 0.0243 | 0.0353 | 0.0479 | 0.0742 |

Standard errors in parentheses

Ethnicity controls: ethnicity of child

Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother smoked in pregnancy, and birthweight), region of childhood

$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

# XVI APPENDIX C: GENDER SPECIFIC SKILL IMPACTS ON TASKS

## Table 3A.11: Impact of Skills Measured at Ages 7/16 on Job Tasks at Age 33

| | (1) NRA Age 7 | (2) NRA Age 7 | (3) NRA Age 7 | (4) NRA Age 16 | (5) NRA Age 16 | (6) NRA Age 16 | (7) NRI Age 7 | (8) NRI Age 7 | (9) NRI Age 7 | (10) NRI Age 16 | (11) NRI Age 16 | (12) NRI Age 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Male Dummy | 0.079*** | 0.080*** | 0.072*** | 0.062*** | 0.067*** | 0.064*** | -0.027*** | -0.030*** | -0.034*** | -0.046*** | -0.044*** | -0.045*** |
| | (0.004) | (0.005) | (0.004) | (0.005) | (0.006) | (0.006) | (0.003) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) |
| Cognitive | 0.038*** | 0.028*** | 0.012*** | 0.096*** | 0.076*** | 0.042*** | 0.022*** | 0.013*** | 0.004 | 0.049*** | 0.038*** | 0.016*** |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.006) | (0.006) | (0.003) | (0.003) | (0.003) | (0.004) | (0.005) | (0.005) |
| Cognitive x Male | 0.011** | 0.014*** | 0.013*** | 0.020*** | 0.029*** | 0.024*** | 0.0000 | 0.005 | 0.003 | 0.018*** | 0.021*** | 0.019*** |
| | (0.005) | (0.005) | (0.005) | (0.007) | (0.008) | (0.008) | (0.004) | (0.004) | (0.004) | (0.006) | (0.006) | (0.006) |
| Emotional-Health | 0.024*** | 0.017*** | 0.011** | 0.004 | 0.002 | 0.002 | 0.015*** | 0.013*** | 0.010*** | 0.007* | 0.006 | 0.005 |
| | (0.005) | (0.005) | (0.004) | (0.005) | (0.005) | (0.005) | (0.003) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Emotional-Health x Male | 0.003 | 0.008 | 0.005 | -0.009 | -0.007 | -0.003 | 0.006 | 0.007 | 0.006 | 0.001 | 0.005 | 0.008 |
| | (0.006) | (0.006) | (0.006) | (0.007) | (0.008) | (0.008) | (0.004) | (0.005) | (0.005) | (0.006) | (0.006) | (0.006) |
| Social | 0.018*** | 0.013** | 0.008 | 0.004 | 0.005 | 0.004 | 0.008** | 0.004 | 0.002 | 0.000 | 0.002 | 0.002 |
| | (0.005) | (0.006) | (0.005) | (0.006) | (0.007) | (0.007) | (0.004) | (0.004) | (0.004) | (0.005) | (0.006) | (0.005) |
| Social x Male | -0.008 | -0.005 | -0.008 | -0.003 | 0.000 | 0.000 | -0.011** | -0.007 | -0.010* | -0.003 | -0.006 | -0.007 |
| | (0.006) | (0.007) | (0.007) | (0.008) | (0.010) | (0.009) | (0.005) | (0.006) | (0.005) | (0.007) | (0.007) | (0.007) |
| Perseverance | 0.003 | 0.005 | 0.005 | 0.029*** | 0.033*** | 0.023*** | 0.030 | 0.004 | 0.003 | 0.012*** | 0.015*** | 0.008* |
| | (0.005) | (0.006) | (0.005) | (0.005) | (0.006) | (0.006) | (0.004) | (0.005) | (0.004) | (0.004) | (0.005) | (0.005) |
| Perseverance x Male | 0.003 | 0.000 | -0.002 | -0.007 | -0.008 | -0.008 | 0.010* | 0.009 | 0.009 | -0.003 | -0.005 | -0.006 |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.008) | (0.008) | (0.005) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| Constant | 0.191*** | 0.0158 | 0.0809 | 0.191*** | 0.179** | 0.188** | 0.238*** | 0.116** | 0.153*** | 0.242*** | 0.280*** | 0.290*** |
| | (0.003) | (0.062) | (0.058) | (0.004) | (0.077) | (0.075) | (0.002) | (0.047) | (0.046) | (0.003) | (0.061) | (0.060) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes | No | No | Yes | No | No | Yes |
| *N* | 9756 | 8345 | 8113 | 6074 | 4917 | 4799 | 9756 | 8345 | 8113 | 6074 | 4917 | 4799 |
| r2 | 0.081 | 0.14 | 0.280 | 0.198 | 0.220 | 0.304 | 0.051 | 0.079 | 0.160 | 0.109 | 0.119 | 0.182 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## Table 3A.12: Impact of Skills Measured at Ages 7/16 on Job Tasks at Age 42

| | (1)<br>NRA<br>Age 7 | (2)<br>NRA<br>Age 7 | (3)<br>NRA<br>Age 7 | (4)<br>NRA<br>Age 16 | (5)<br>NRA<br>Age 16 | (6)<br>NRA<br>Age 16 | (7)<br>NRI<br>Age 7 | (8)<br>NRI<br>Age 7 | (9)<br>NRI<br>Age 7 | (10)<br>NRI<br>Age 16 | (11)<br>NRI<br>Age 16 | (12)<br>NRI<br>Age 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Male Dummy | 0.044*** | 0.043*** | 0.039*** | 0.028*** | 0.029*** | 0.029*** | -0.034*** | -0.036*** | -0.040*** | -0.040*** | -0.044*** | -0.048*** |
| | (0.005) | (0.005) | (0.006) | (0.006) | (0.007) | (0.007) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.005) |
| Cognitive | 0.034*** | 0.028*** | 0.019*** | 0.066*** | 0.056*** | 0.037*** | 0.021*** | 0.015*** | 0.010*** | 0.033*** | 0.027*** | 0.014** |
| | (0.004) | (0.004) | (0.005) | (0.006) | (0.007) | (0.008) | (0.003) | (0.003) | (0.004) | (0.005) | (0.005) | (0.006) |
| Cognitive x Male | -0.006 | -0.002 | -0.002 | 0.018** | 0.022** | 0.015 | -0.004 | 0.002 | -0.002 | 0.018*** | 0.024*** | 0.019** |
| | (0.006) | (0.006) | (0.006) | (0.008) | (0.009) | (0.01) | (0.004) | (0.004) | (0.005) | (0.006) | (0.007) | (0.008) |
| Emotional-Health | 0.025*** | 0.020*** | 0.017*** | 0.00390 | 0.002 | 0.005 | 0.014*** | 0.015*** | 0.010** | 0.003 | 0.002 | 0.004 |
| | (0.005) | (0.005) | (0.006) | (0.006) | (0.006) | (0.007) | (0.004) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) |
| Emotional-Health x Male | 0.000 | 0.005 | 0.004 | -0.017** | -0.013 | -0.015 | 0.000 | -0.002 | 0.000 | -0.008 | -0.004 | -0.005 |
| | (0.007) | (0.007) | (0.007) | (0.009) | (0.010) | (0.010) | (0.005) | (0.005) | (0.006) | (0.006) | (0.007) | (0.008) |
| Social | 0.014** | 0.013** | 0.009 | 0.001 | 0.004 | 0.001 | 0.006 | 0.005 | 0.005 | 0.002 | 0.004 | -0.003 |
| | (0.006) | (0.006) | (0.007) | (0.007) | (0.008) | (0.009) | (0.004) | (0.005) | (0.005) | (0.005) | (0.006) | (0.007) |
| Social x Male | -0.016** | -0.013 | -0.012 | 0.005 | 0.001 | -0.002 | -0.006 | -0.005 | -0.007 | 0.006 | 0.007 | 0.015 |
| | (0.008) | (0.008) | (0.009) | (0.010) | (0.011) | (0.012) | (0.006) | (0.006) | (0.007) | (0.007) | (0.008) | (0.009) |
| Perseverance | 0.000 | 0.001 | 0.003 | 0.005 | 0.001 | -0.002 | -0.002 | -0.006 | -0.005 | 0.006 | 0.007 | 0.015 |
| | (0.006) | (0.007) | (0.007) | (0.010) | (0.011) | (0.012) | (0.005) | (0.005) | (0.005) | (0.007) | (0.008) | (0.009) |
| Perseverance x Male | 0.012 | 0.006 | -0.002 | -0.002 | -0.001 | 0.006 | 0.099* | 0.012* | 0.011 | -0.008 | -0.013* | -0.014* |
| | (0.008) | (0.009) | (0.009) | (0.008) | (0.009) | (0.010) | (0.006) | (0.006) | (0.007) | (0.006) | (0.007) | (0.007) |
| Constant | 0.228*** | 0.102 | 0.207*** | 0.233*** | 0.0606 | 0.104 | 0.267*** | 0.192*** | 0.238*** | 0.266*** | 0.233*** | 0.246*** |
| | (0.004) | (0.070) | (0.073) | (0.004) | (0.088) | (0.094) | (0.003) | (0.052) | (0.056) | (0.003) | (0.067) | (0.071) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes | No | No | Yes | No | No | Yes |
| *N* | 8639 | 7396 | 6371 | 5425 | 4404 | 3881 | 8639 | 7396 | 6371 | 5425 | 4404 | 3881 |
| r2 | 0.041 | 0.061 | 0.121 | 0.091 | 0.101 | 0.135 | 0.037 | 0.048 | 0.082 | 0.058 | 0.066 | 0.089 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation,
maternal background (height at pregnancy, age, and marital status),
pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## Table 3A.13: Impact of Skills Measured at age 7/16 on RC Tasks Aged 33

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | RC | RC | RC | RC | RC | (RC |
| | Age 7 | Age 7 | Age 7 | Age 16 | Age16 | Age16 |
| Male Dummy | -0.102*** | -0.102*** | -0.0978*** | -0.0978*** | -0.101*** | -0.0990*** |
| | (0.00467) | (0.00508) | (0.00507) | (0.00608) | (0.00677) | (0.00667) |
| Cognitive | 0.0127*** | 0.0162*** | 0.0255*** | 0.00730 | 0.0200*** | 0.0516*** |
| | (0.00380) | (0.00419) | (0.00418) | (0.00627) | (0.00727) | (0.00735) |
| Cognitive x Male Dummy | -0.0121** | -0.0143** | -0.0141** | -0.00634 | -0.0100 | -0.00667 |
| | (0.00524) | (0.00567) | (0.00565) | (0.00848) | (0.00944) | (0.00931) |
| Emotional- Health | 0.00204 | 0.00596 | 0.0101** | -0.0103* | -0.00583 | -0.00667 |
| | (0.00478) | (0.00511) | (0.00507) | (0.00572) | (0.00619) | (0.00608) |
| Emotional- Health x Male Dummy | -0.00270 | -0.00691 | -0.00647 | 0.00916 | 0.00246 | -0.000890 |
| | (0.00621) | (0.00665) | (0.00660) | (0.00862) | (0.00945) | (0.00930) |
| Social | -0.00545 | -0.00198 | 0.000785 | 0.0143** | 0.0130 | 0.0144* |
| | (0.00552) | (0.00599) | (0.00599) | (0.00726) | (0.00809) | (0.00793) |
| Social x Male Dummy | 0.00654 | 0.00441 | 0.00519 | -0.0168* | -0.0175 | -0.0164 |
| | (0.00726) | (0.00785) | (0.00784) | (0.00975) | (0.0109) | (0.0107) |
| Perseverance | 0.0135** | 0.0140** | 0.0134** | 0.0107* | 0.00856 | 0.0179*** |
| | (0.00575) | (0.00636) | (0.00629) | (0.00617) | (0.00670) | (0.00663) |
| Perseverance x Male Dummy | -0.0109 | -0.00872 | -0.00766 | -0.00772 | -0.00394 | -0.00120 |
| | (0.00734) | (0.00804) | (0.00799) | (0.00835) | (0.00916) | (0.00903) |
| Constant | 0.271*** | 0.294*** | 0.258*** | 0.271*** | 0.296*** | 0.273*** |
| | (0.00338) | (0.0666) | (0.0668) | (0.00426) | (0.0889) | (0.0882) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| $N$ | 9756 | 8345 | 8113 | 6074 | 4917 | 4799 |
| r2 | 0.0567 | 0.0710 | 0.115 | 0.0526 | 0.0680 | 0.133 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 3A.14: Impact of Skills Measured at age 7/16 on RC Tasks Aged 42**

| | (1)<br>RC<br>Age 7 | (2)<br>RC<br>Age 7 | (3)<br>RC<br>Age 7 | (4)<br>RC<br>Age 16 | (5)<br>RC<br>Age16 | (6)<br>(RC<br>Age16 |
|---|---|---|---|---|---|---|
| Male Dummy | -0.048*** | -0.048*** | -0.044*** | -0.041*** | -0.039*** | -0.034*** |
| | (0.005) | (0.005) | (0.006) | (0.006) | (0.007) | (0.008) |
| Cognitive | -0.002 | 0.001 | 0.005 | 0.000 | 0.007 | 0.020** |
| | (0.004) | (0.005) | (0.005) | (0.006) | (0.008) | (0.008) |
| Cognitive x Male Dummy | 0.001 | -0.003 | -0.002 | -0.002 | -0.012 | -0.003 |
| | (0.006) | (0.006) | (0.007) | (0.009) | (0.010) | (0.011) |
| Emotional-Health | -0.003 | -0.005 | -0.004 | -0.011* | -0.009 | -0.009 |
| | (0.005) | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) |
| Emotional- Health x Male Dummy | 0.002 | 0.004 | 0.004 | 0.009 | 0.003 | -0.003 |
| | (0.007) | (0.007) | (0.008) | (0.009) | (0.010) | (0.011) |
| Social | -0.004 | -0.007 | 0.000 | 0.019** | 0.019** | 0.022** |
| | (0.006) | (0.006) | (0.007) | (0.008) | (0.009) | (0.010) |
| Social x Male Dummy | 0.003 | 0.004 | -0.003 | -0.026*** | -0.023** | -0.028** |
| | (0.007) | (0.008) | (0.009) | (0.010) | (0.011) | (0.013) |
| Perseverance | 0.011* | 0.013* | 0.012 | -0.005 | -0.004 | 0.004 |
| | (0.006) | (0.007) | (0.008) | (0.006) | (0.007) | (0.008) |
| Perseverance x Male Dummy | -0.009 | -0.010 | -0.005 | 0.003 | 0.003 | 0.002 |
| | (0.008) | (0.009) | (0.009) | (0.009) | (0.010) | (0.010) |
| Constant | 0.225*** | 0.293*** | 0.275*** | 0.223*** | 0.338*** | 0.320*** |
| | (0.004) | (0.070) | (0.076) | (0.004) | (0.093) | (0.100) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| $N$ | 8639 | 7396 | 6371 | 5425 | 4404 | 3881 |
| r2 | 0.016 | 0.021 | 0.039 | 0.014 | 0.022 | 0.046 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## Table 3A.15: Impact of Skills Measured at Ages 7/16 on Job Tasks at Age 33

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | RM | RM | RM | RM | RM | RM | NRM | NRM | NRM | NRM | NRM | NRM |
| | Age 7 | Age 7 | Age 7 | Age 16 | Age 16 | Age 16 | Age 7 | Age 7 | Age 7 | Age 16 | Age 16 | Age 16 |
| Male Dummy | 0.006* | 0.007* | 0.008** | 0.016*** | 0.014*** | 0.013*** | 0.045*** | 0.044*** | 0.051*** | 0.066*** | 0.063*** | 0.066*** |
| | (0.003) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.006) | (0.006) | (0.006) | (0.007) | (0.008) | (0.008) |
| Cognitive | -0.019*** | -0.014*** | -0.010*** | -0.045*** | -0.037*** | -0.028*** | -0.054*** | -0.043*** | -0.032*** | -0.106*** | -0.097*** | -0.081*** |
| | (0.003) | (0.003) | (0.003) | (0.004) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.007) | (0.008) | (0.008) |
| Cognitive x Male | 0.001 | -0.002 | 0.000 | 0.002 | -0.002 | -0.001 | 0.000 | -0.003 | -0.002 | -0.034*** | -0.038*** | -0.035*** |
| | (0.004) | (0.004) | (0.004) | (0.006) | (0.007) | (0.007) | (0.006) | (0.007) | (0.007) | (0.009) | (0.011) | (0.011) |
| Emotional-Health | -0.011*** | -0.010*** | -0.008** | 0.005 | 0.005 | 0.006 | -0.031*** | -0.026*** | -0.022*** | -0.005 | -0.007 | -0.007 |
| | (0.003) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) |
| Emotional-Health x Male | -0.004 | -0.004 | -0.003 | -0.013** | -0.016** | -0.017*** | -0.002 | -0.005 | -0.002 | 0.012 | 0.016 | 0.013 |
| | (0.004) | (0.005) | (0.005) | (0.006) | (0.007) | (0.007) | (0.008) | (0.008) | (0.008) | (0.010) | (0.011) | (0.011) |
| Social | -0.006 | -0.005 | -0.004 | -0.010** | -0.013** | -0.013** | -0.015** | -0.011 | -0.007 | -0.009 | -0.008 | -0.007 |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) | (0.008) | (0.009) | (0.009) |
| Social x Male | 0.009* | 0.009* | 0.012** | 0.015** | 0.020*** | 0.021*** | 0.0031 | -0.002 | 0.000 | 0.008 | 0.003 | 0.002 |
| | (0.005) | (0.006) | (0.006) | (0.007) | (0.008) | (0.008) | (0.008) | (0.009) | (0.009) | (0.011) | (0.012) | (0.012) |
| Perseverance | -0.001 | -0.002 | -0.002 | -0.010** | -0.014*** | -0.012** | -0.019*** | -0.021*** | -0.020*** | -0.041*** | -0.042*** | -0.037*** |
| | (0.004) | (0.005) | (0.005) | (0.004) | (0.005) | (0.005) | (0.007) | (0.008) | (0.008) | (0.007) | (0.007) | (0.008) |
| Perseverance x Male | -0.006 | -0.006 | -0.007 | -0.004 | -0.003 | -0.004 | 0.004 | 0.007 | 0.007 | 0.022** | 0.020* | 0.019* |
| | (0.0053) | (0.0058) | (0.0058) | (0.0058) | (0.006) | (0.006) | (0.009) | (0.010) | (0.010) | (0.009) | (0.010) | (0.010) |
| | 0.063*** | 0.118** | 0.102** | 0.063*** | 0.013 | -0.005 | 0.238*** | 0.456*** | 0.406*** | 0.232*** | 0.232** | 0.254** |
| | (0.002) | (0.048) | (0.048) | (0.003) | (0.062) | (0.063) | (0.004) | (0.080) | (0.080) | (0.005) | (0.099) | (0.100) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes | No | No | Yes | No | No | Yes |
| *N* | 9756 | 8345 | 8113 | 6074 | 4917 | 4799 | 9756 | 8345 | 8113 | 6074 | 4917 | 4799 |
| r2 | 0.023 | 0.043 | 0.067 | 0.062 | 0.076 | 0.089 | 0.074 | 0.110 | 0.157 | 0.165 | 0.183 | 0.198 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation,
maternal background (height at pregnancy, age, and marital status),
pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## Table 3A.16: Impact of Skills Measured at Ages 7/16 on Job Tasks at Age 42

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | RM | RM | RM | RM | RM | RM | NRM | NRM | NRM | NRM | NRM | NRM |
| | Age 7 | Age 7 | Age 7 | Age 16 | Age 16 | Age 16 | Age 7 | Age 7 | Age 7 | Age 16 | Age 16 | Age 16 |
| Male Dummy | 0.008*** | 0.010*** | 0.012*** | 0.010*** | 0.010** | 0.013*** | 0.030*** | 0.031*** | 0.033*** | 0.043*** | 0.043*** | 0.041*** |
| | (0.003) | (0.003) | (0.004) | (0.004) | (0.004) | (0.005) | (0.006) | (0.007) | (0.007) | (0.007) | (0.008) | (0.009) |
| Cognitive | -0.007*** | -0.006** | -0.004 | -0.021*** | -0.021*** | -0.016*** | -0.047*** | -0.038*** | -0.030*** | -0.077*** | -0.070*** | -0.055*** |
| | (0.0025) | (0.003) | (0.003) | (0.004) | (0.005) | (0.005) | (0.005) | (0.006) | (0.006) | (0.008) | (0.009) | (0.010) |
| Cognitive x Male | -0.001 | -0.001 | 0.000 | -0.005 | -0.001 | 0.000 | 0.010 | 0.004 | 0.006 | -0.028*** | -0.034*** | -0.030** |
| | (0.003) | (0.004) | (0.004) | (0.005) | (0.006) | (0.007) | (0.007) | (0.007) | (0.008) | (0.010) | (0.011) | (0.012) |
| Emotional-Health | -0.002 | 0.000 | 0.001 | 0.009** | 0.009** | 0.007 | -0.035*** | -0.030*** | -0.024*** | -0.005 | -0.003 | -0.006 |
| | (0.003) | (0.003) | (0.004) | (0.004) | (0.004) | (0.004) | (0.006) | (0.007) | (0.007) | (0.007) | (0.008) | (0.008) |
| Emotional-Health x Male | -0.007* | -0.009** | -0.010** | -0.010* | -0.010* | -0.008 | 0.005 | 0.001 | 0.002 | 0.027** | 0.024** | 0.031** |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.006) | (0.007) | (0.008) | (0.009) | (0.009) | (0.011) | (0.012) | (0.012) |
| Social | -0.005 | -0.003 | -0.003 | -0.003 | -0.005 | -0.003 | -0.011 | -0.008 | -0.011 | -0.019** | -0.021** | -0.016 |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) | (0.006) | (0.007) | (0.008) | (0.008) | (0.009) | (0.010) | (0.011) |
| Social x Male | 0.006 | 0.002 | 0.006 | 0.003 | 0.003 | 0.002 | 0.013 | 0.011 | 0.017 | 0.012 | 0.012 | 0.013 |
| | (0.005) | (0.005) | (0.006) | (0.006) | (0.007) | (0.008) | (0.010) | (0.010) | (0.011) | (0.012) | (0.013) | (0.015) |
| Perseverance | -0.004 | -0.003 | -0.003 | -0.003 | -0.002 | 0.000 | -0.005 | -0.005 | -0.007 | -0.013* | -0.019** | -0.013 |
| | (0.004) | (0.004) | (0.005) | (0.004) | (0.004) | (0.005) | (0.008) | (0.009) | (0.009) | (0.008) | (0.008) | (0.009) |
| Perseverance x Male | 0.000 | 0.001 | 0.001 | 0.000 | 0.000 | -0.003 | -0.012 | -0.009 | -0.004 | 0.006 | 0.011 | 0.009 |
| | (0.005) | (0.005) | (0.006) | (0.005) | (0.006) | (0.006) | (0.010) | (0.011) | (0.011) | (0.010) | (0.011) | (0.012) |
| Constant _cons | 0.046*** | 0.094** | 0.044 | 0.048*** | 0.031 | 0.007 | 0.235*** | 0.319*** | 0.236*** | 0.231*** | 0.338*** | 0.323*** |
| | (0.002) | (0.043) | (0.047) | (0.003) | (0.056) | (0.061) | (0.004) | (0.086) | (0.091) | (0.005) | (0.109) | (0.115) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes | No | No | Yes | No | No | Yes |
| *N* | 8639 | 7396 | 6371 | 5425 | 4404 | 3881 | 8639 | 7396 | 6371 | 5425 | 4404 | 3881 |
| r2 | 0.011 | 0.019 | 0.030 | 0.024 | 0.029 | 0.036 | 0.046 | 0.059 | 0.090 | 0.085 | 0.096 | 0.102 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation,
maternal background (height at pregnancy, age, and marital status),
pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

# XVII APPENDIX D: IMPACT OF NRA AND NRI TASKS INCLUDING ONLY COGNITIVE AND SOCIAL SKILLS

## XVII.1 NRA Tasks

**Table 3A.17: Impact of Skills Measured at age 7/16 on NRA Tasks Aged 33**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | NRA | NRA | NRA | NRA | NRA | NRA |
| | Age 7 | Age 7 | Age 7 | Age 16 | Age16 | Age16 |
| Male Dummy | 0.073*** | 0.076*** | 0.068*** | 0.057*** | 0.063*** | 0.062*** |
| | (0.004) | (0.005) | (0.004) | (0.005) | (0.005) | (0.005) |
| Cognitive | 0.048*** | 0.040*** | 0.022*** | 0.114*** | 0.102*** | 0.059*** |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.004) | (0.004) |
| Social | 0.023*** | 0.018*** | 0.009*** | 0.007* | 0.011** | 0.007 |
| | (0.003) | (0.003) | (0.003) | 0.007* | 0.011** | 0.007 |
| Constant | 0.195*** | 0.0291 | 0.091 | 0.194*** | 0.190** | 0.198*** |
| | (0.003) | (0.062) | (0.059) | (0.003) | (0.075) | (0.072) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| *N* | 9757 | 8346 | 8114 | 6549 | 5296 | 5166 |
| r2 | 0.0725 | 0.130 | 0.276 | 0.189 | 0.207 | 0.300 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 3A.18: Impact of Skills Measured at age 7/16 on NRA Tasks Aged 42**

| | (1) NRA Age 7 | (2) NRA Age 7 | (3) NRA Age 7 | (4) NRA Age 16 | (5) NRA Age16 | (6) NRA Age16 |
|---|---|---|---|---|---|---|
| Male Dummy | 0.039*** | 0.039*** | 0.034*** | 0.027*** | 0.029*** | 0.028*** |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.006) | (0.006) |
| Cognitive | 0.036*** | 0.030*** | 0.020*** | 0.080*** | 0.073*** | 0.047*** |
| | (0.002) | (0.003) | (0.003) | (0.004) | (0.005) | (0.005) |
| Social | 0.036*** | 0.030*** | 0.020*** | 0.008* | 0.009* | 0.003 |
| | (0.002) | (0.003) | (0.003) | (0.004) | (0.005) | (0.005) |
| Constant | 0.233*** | 0.110 | 0.220*** | 0.231*** | 0.104 | 0.141 |
| | (0.003) | (0.070) | (0.073) | (0.004) | (0.085) | (0.090) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| $N$ | 8639 | 7396 | 6371 | 5844 | 4743 | 4165 |
| r2 | 0.033 | 0.054 | 0.117 | 0.089 | 0.098 | 0.134 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## XVII.2 NRI Tasks

### Table 3A.19: Impact of Skills Measured at age 7/16 on NRI Tasks Aged 33

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | NRI | NRI | NRI | NRI | NRI | NRI |
| | Age 7 | Age 7 | Age 7 | Age 16 | Age16 | Age16 |
| Male Dummy | -0.032*** | -0.033*** | -0.037*** | -0.043*** | -0.042*** | -0.041*** |
| | (0.003) | (0.004) | (0.003) | (0.004) | (0.004) | (0.004) |
| Cognitive | 0.027*** | 0.020*** | 0.010*** | 0.062*** | 0.054*** | 0.027*** |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) |
| Social | 0.012*** | 0.009*** | 0.004** | 0.005 | 0.005 | 0.003 |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) |
| Constant | 0.240*** | 0.129*** | 0.164*** | 0.242*** | 0.255*** | 0.260*** |
| | (0.002) | (0.047) | (0.046) | (0.003) | (0.058) | (0.058) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| $N$ | 9757 | 8346 | 8114 | 6549 | 5296 | 5166 |
| r2 | 0.041 | 0.070 | 0.154 | 0.103 | 0.110 | 0.173 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

### Table 3A.20: Impact of Skills Measured at age 7/16 on NRI Tasks Aged 42

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | NRI | NRI | NRI | NRI | NRI | NRI |
| | Age 7 | Age 7 | Age 7 | Age 16 | Age16 | Age16 |
| Male Dummy | -0.036*** | -0.037*** | -0.041*** | -0.039*** | -0.040*** | -0.043*** |
| | (0.003) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) |
| Cognitive | 0.022*** | 0.018*** | 0.010*** | 0.045*** | 0.042*** | 0.023*** |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.004) |
| Social | 0.008*** | 0.007*** | 0.004* | 0.006* | 0.007** | 0.004 |
| | (0.002) | (0.002) | (0.003) | (0.003) | (0.004) | (0.004) |
| Constant | 0.268*** | 0.196*** | 0.245*** | 0.265*** | 0.228*** | 0.231*** |
| | (0.003) | (0.052) | (0.056) | (0.003) | (0.065) | (0.069) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| $N$ | 8639 | 7396 | 6371 | 5425 | 4404 | 3881 |
| r2 | 0.032 | 0.043 | 0.080 | 0.059 | 0.066 | 0.088 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

# XVIII APPENDIX E: INCLUDING MOTHER ROBUSTNESS CHECKS

**Table 3A.21: Impact of Skills Measured at age 7/16 on Employment aged 33**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Age 7 | Age 7 | Age 7 | Age 16 | Age16 | Age16 |
| Male Dummy | 0.126*** | 0.123*** | 0.112*** | 0.106*** | 0.106*** | 0.103*** |
| | (0.009) | (0.009) | (0.009) | (0.012) | (0.012) | (0.012) |
| Cognitive | 0.040*** | 0.031*** | 0.021*** | 0.056*** | 0.056*** | 0.038*** |
| | (0.004) | (0.005) | (0.005) | (0.008) | (0.008) | (0.009) |
| Emotional-Health | 0.040*** | 0.031*** | 0.021*** | 0.017** | 0.017** | 0.016** |
| | (0.004) | (0.005) | (0.005) | 0.017** | 0.017** | 0.016** |
| Social | 0.007 | 0.004 | 0.003 | 0.033*** | 0.033*** | 0.025*** |
| | (0.006) | (0.006) | (0.006) | (0.008) | (0.008) | (0.009) |
| Perseverance | 0.011** | 0.014** | 0.010 | 0.007 | 0.007 | 0.000 |
| | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) |
| Constant | 0.785*** | 0.655*** | 0.678*** | 0.764*** | 0.764*** | 0.765*** |
| | (0.007) | (0.109) | (0.110) | (0.141) | (0.141) | (0.142) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| $N$ | 10360 | 8849 | 8603 | 5189 | 5189 | 5064 |
| r2 | 0.150 | 0.158 | 0.186 | 0.162 | 0.162 | 0.184 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation,
maternal background (height at pregnancy, age, and marital status),
pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 3A.22: Impact of Skills Measured at age 7/16 on Employment aged 42**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Age 7 | Age 7 | Age 7 | Age 16 | Age16 | Age16 |
| Male Dummy | 0.104*** | 0.102*** | 0.095*** | 0.075*** | 0.079*** | 0.084*** |
| | (0.007) | (0.008) | (0.008) | (0.010) | (0.010) | (0.010) |
| Cognitive | 0.034*** | 0.029*** | 0.018*** | 0.044*** | 0.043*** | 0.019** |
| | (0.004) | (0.004) | (0.005) | (0.006) | (0.007) | (0.008) |
| Emotional-Health | 0.023*** | 0.022*** | 0.008 | 0.014** | 0.013** | 0.002 |
| | (0.005) | (0.005) | (0.005) | (0.006) | (0.007) | (0.007) |
| Social | 0.008 | 0.006 | 0.006 | 0.025*** | 0.026*** | 0.016** |
| | (0.005) | (0.006) | (0.006) | (0.007) | (0.008) | (0.008) |
| Perseverance | 0.021*** | 0.018*** | 0.013** | 0.016** | 0.013** | 0.011 |
| | (0.005) | (0.005) | (0.00608) | (0.006) | (0.007) | (0.007) |
| Constant | 0.807*** | 0.622*** | 0.720*** | 0.904*** | 0.904*** | 0.859*** |
| | (0.00539) | (0.102) | (0.103) | (0.128) | (0.128) | (0.130) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| $N$ | 10423 | 8882 | 7563 | 5194 | 5194 | 4557 |
| r2 | 0.0591 | 0.0693 | 0.160 | 0.0779 | 0.0779 | 0.170 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation,
maternal background (height at pregnancy, age, and marital status),
pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

# XIX APPENDIX F: LOGIT MODELS ROBUSTNESS CHECKS

**Table 3A.23: Impact of Skills Measured at age 7/16 on Employment aged 33**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Age 7 | Age 7 | Age 7 | Age 16 | Age16 | Age16 |
| Male Dummy | 1.073*** | 1.077*** | 1.055*** | 1.026*** | 1.006*** | 1.049*** |
| | (0.068) | (0.076) | (0.080) | (0.091) | (0.103) | (0.109) |
| Cognitive | 0.315*** | 0.249*** | 0.189*** | 0.525*** | 0.527*** | 0.410*** |
| | (0.035) | (0.041) | (0.044) | (0.065) | (0.080) | (0.087) |
| Emotional-Health | 0.185*** | 0.156*** | 0.117*** | 0.0908 | 0.122* | 0.106 |
| | (0.037) | (0.042) | (0.044) | (0.059) | (0.067) | (0.070) |
| Social | 0.063 | 0.041 | 0.050 | 0.200*** | 0.239*** | 0.177** |
| | (0.045) | (0.050) | (0.053) | (0.058) | (0.066) | (0.071) |
| Perseverance | 0.141*** | 0.170*** | 0.128** | 0.168*** | 0.150** | 0.0902 |
| | (0.046) | (0.052) | (0.054) | (0.059) | (0.066) | (0.070) |
| Constant | 1.332*** | -0.470 | -1.120 | 1.454*** | 1.123 | 0.438 |
| | (0.045) | (0.974) | (1.050) | (0.060) | (1.329) | (1.428) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| $N$ | 8224 | 7024 | 6733 | 5070 | 4088 | 3940 |
| r2 | 0.062 | 0.075 | 0.133 | 0.083 | 0.093 | 0.135 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 3A.24: Impact of Skills Measured at age 7/16 on Employment aged 42**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Age 7 | Age 7 | Age 7 | Age 16 | Age16 | Age16 |
| Male Dummy | 0.920*** | 0.928*** | 1.071*** | 0.728*** | 0.780*** | 0.990*** |
| | (0.064) | (0.072) | (0.089) | (0.086) | (0.099) | (0.119) |
| Cognitive | 0.277*** | 0.245*** | 0.190*** | 0.445*** | 0.435*** | 0.202** |
| | (0.033) | (0.038) | (0.047) | (0.060) | (0.073) | (0.092) |
| Emotional-Health | 0.180*** | 0.171*** | 0.083* | 0.154*** | 0.154** | 0.051 |
| | (0.035) | (0.039) | (0.050) | (0.055) | (0.063) | (0.075) |
| Social | 0.106** | 0.106** | 0.136** | 0.130** | 0.126* | 0.045 |
| | (0.042) | (0.047) | (0.058) | (0.056) | (0.0654) | (0.0849) |
| Perseverance | 0.166*** | 0.142*** | 0.105* | 0.110** | 0.087 | 0.071 |
| | (0.043) | (0.048) | (0.060) | (0.056) | (0.063) | (0.075) |
| Constant | 1.466*** | 0.332 | 1.068 | 1.674*** | 3.080** | 2.482* |
| | (0.040) | (0.902) | (1.090) | (0.054) | (1.247) | (1.470) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| $N$ | 9531 | 8112 | 6876 | 5885 | 4754 | 4151 |
| r2 | 0.053 | 0.064 | 0.170 | 0.053 | 0.072 | 0.179 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

# XX APPENDIX G: IMPACT OF SKILLS ON EMPLOYMENT FOR NON-GRADUATES EMPLOYED AT AGE 23

**Table 3A.25: Impact of Skills Measured at age 7/16 on Employment aged 33**

| | (1)<br>Age 7 | (2)<br>Age 7 | (3)<br>Age 7 | (4)<br>Age 16 | (5)<br>Age16 | (6)<br>Age16 |
|---|---|---|---|---|---|---|
| Male Dummy | 0.0723*** | 0.0697*** | 0.0642*** | 0.0636*** | 0.0575*** | 0.0546*** |
| | (0.00904) | (0.00961) | (0.00954) | (0.0108) | (0.0119) | (0.0117) |
| Cognitive | 0.0184*** | 0.0131** | 0.00684 | 0.0276*** | 0.0293*** | 0.0236*** |
| | (0.00491) | (0.00529) | (0.00527) | (0.00739) | (0.00876) | (0.00888) |
| Emotional-Health | 0.0184*** | 0.0131** | 0.00684 | 0.00822 | 0.0122 | 0.0109 |
| | (0.00491) | (0.00529) | (0.00527) | (0.00727) | (0.00802) | (0.00794) |
| Social | 0.0184*** | 0.0131** | 0.00684 | 0.00688 | 0.00982 | 0.00291 |
| | (0.00491) | (0.00529) | (0.00527) | (0.00787) | (0.00890) | (0.00879) |
| Perseverance | 0.0184*** | 0.0131** | 0.00684 | 0.0135** | 0.0179** | 0.0117 |
| | (0.00491) | (0.00529) | (0.00527) | (0.00681) | (0.00760) | (0.00756) |
| Constant | 0.863*** | 0.671*** | 0.665*** | 0.874*** | 0.872*** | 0.879*** |
| | (0.00749) | (0.120) | (0.119) | (0.00890) | (0.148) | (0.147) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| $N$ | 4753 | 4086 | 3978 | 3077 | 2491 | 2436 |
| r2 | 0.0205 | 0.0257 | 0.0669 | 0.0314 | 0.0383 | 0.0779 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 3A.26: Impact of Skills Measured at age 7/16 on Employment aged 42**

| | (1)<br>Age 7 | (2)<br>Age 7 | (3)<br>Age 7 | (4)<br>Age 16 | (5)<br>Age16 | (6)<br>Age16 |
|---|---|---|---|---|---|---|
| Male Dummy | 0.0716*** | 0.0687*** | 0.0661*** | 0.0509*** | 0.0533*** | 0.0575*** |
| | (0.00833) | (0.00889) | (0.00862) | (0.01000) | (0.0111) | (0.0109) |
| Cognitive | 0.0213*** | 0.0213*** | 0.0136*** | 0.0248*** | 0.0226*** | 0.00353 |
| | (0.00476) | (0.00512) | (0.00505) | (0.00732) | (0.00865) | (0.00890) |
| Emotional-Health | 0.0125** | 0.0104* | 0.00151 | 0.0175** | 0.0182** | 0.0130* |
| | (0.00538) | (0.00571) | (0.00562) | (0.00717) | (0.00787) | (0.00772) |
| Social | 0.00319 | 0.00631 | 0.00786 | 0.0101 | 0.0150* | 0.0108 |
| | (0.00655) | (0.00695) | (0.00688) | (0.00793) | (0.00902) | (0.00932) |
| Perseverance | 0.0175*** | 0.0108 | 0.00636 | 0.00561 | 0.00537 | 0.00209 |
| | (0.00633) | (0.00677) | (0.00675) | (0.00681) | (0.00758) | (0.00754) |
| Constant | 0.860*** | 0.766*** | 0.780*** | 0.876*** | 0.932*** | 0.906*** |
| | (0.00645) | (0.115) | (0.114) | (0.00764) | (0.147) | (0.146) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| *N* | 5504 | 4731 | 4150 | 3554 | 2879 | 2577 |
| r2 | 0.0225 | 0.0280 | 0.134 | 0.0188 | 0.0315 | 0.130 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation,
maternal background (height at pregnancy, age, and marital status),
pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

# XXI APPENDIX H: GENDER SPECIFIC EFFECTS ON EMPLOYMENT

**Table 3A.27: Impact of Skills Measured at age 7/16 on Employment aged 33**

| | (1) Age 7 | (2) Age 7 | (3) Age 7 | (4) Age 16 | (5) Age 16 | (6) Age 16 |
|---|---|---|---|---|---|---|
| Male Dummy | 0.127*** | 0.125*** | 0.119*** | 0.112*** | 0.107*** | 0.113*** |
| | (0.008) | (0.009) | (0.008) | (0.010) | (0.011) | (0.011) |
| Cognitive | 0.042*** | 0.024*** | 0.014* | 0.053*** | 0.044*** | 0.030** |
| | (0.007) | (0.008) | (0.008) | (0.011) | (0.013) | (0.013) |
| Emotional-Health | 0.035*** | 0.033*** | 0.027*** | 0.003 | -0.001 | 0.002 |
| | (0.008) | (0.009) | (0.008) | (0.010) | (0.011) | (0.011) |
| Male Dummy x Emotional-Health | -0.017* | -0.020* | -0.019* | 0.014 | 0.028* | 0.021 |
| | (0.010) | (0.011) | (0.011) | (0.013) | (0.015) | (0.015) |
| Social | -0.011 | -0.017 | -0.015 | 0.042*** | 0.054*** | 0.046*** |
| | (0.010) | (0.011) | (0.011) | (0.012) | (0.014) | (0.013) |
| Male Dummy x Social | 0.027** | 0.032** | 0.026** | -0.019 | -0.030* | -0.045*** |
| | (0.012) | (0.013) | (0.013) | (0.015) | (0.017) | (0.017) |
| Perseverance | 0.028*** | 0.035*** | 0.027** | 0.014 | 0.007 | -0.004 |
| | (0.011) | (0.012) | (0.011) | (0.011) | (0.012) | (0.012) |
| Male Dummy x Perseverance | -0.017 | -0.022 | -0.019 | 0.006 | 0.016 | 0.018 |
| | (0.013) | (0.014) | (0.013) | (0.013) | (0.015) | (0.015) |
| Constant | 0.785*** | 0.569*** | 0.508*** | 0.798*** | 0.744*** | 0.686*** |
| | (0.006) | (0.109) | (0.109) | (0.008) | (0.138) | (0.139) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| $N$ | 8242 | 7055 | 6764 | 5078 | 4105 | 3957 |
| r2 | 0.053 | 0.063 | 0.113 | 0.065 | 0.075 | 0.111 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation, maternal background (height at pregnancy, age, and marital status), pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 3A.28: Impact of Skills Measured at age 7/16 on Employment aged 42**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Age 7 | Age 7 | Age 7 | Age 16 | Age 16 | Age 16 |
| Male Dummy | 0.103*** | 0.099*** | 0.093*** | 0.072*** | 0.076*** | 0.082*** |
| | (0.007) | (0.007) | (0.008) | (0.009) | (0.010) | (0.010) |
| Cognitive | 0.042*** | 0.033*** | 0.027*** | 0.042*** | 0.044*** | 0.019* |
| | (0.006) | (0.007) | (0.006) | (0.009) | (0.011) | (0.011) |
| Male Dummy x Cognitive | -0.016* | -0.008 | -0.015* | 0.004 | -0.003 | -0.003 |
| | (0.008) | (0.008) | (0.009) | (0.012) | (0.013) | (0.014) |
| Emotional-Health | 0.018** | 0.022*** | 0.008 | 0.016* | 0.015 | 0.002 |
| | (0.007) | (0.008) | (0.008) | (0.008) | (0.009) | (0.009) |
| Male Dummy x Emotional-Health | 0.008 | 0.002 | 0.000 | 0.011 | 0.005 | 0.008 |
| | (0.010) | (0.010) | (0.010) | (0.012) | (0.014) | (0.014) |
| Social | 0.012 | -0.001 | 0.007 | 0.017* | 0.015 | 0.006 |
| | (0.009) | (0.009) | (0.009) | (0.010) | (0.011) | (0.012) |
| Male Dummy x Social | 0.002 | 0.021* | 0.011 | 0.002 | 0.005 | 0.003 |
| | (0.011) | (0.012) | (0.012) | (0.014) | (0.015) | (0.016) |
| Perserverance | 0.026*** | 0.023** | 0.008 | 0.016* | 0.0124 | 0.0135 |
| | (0.009) | (0.010) | (0.010) | (0.009) | (0.010) | (0.010) |
| Male Dummy x Perserverance | -0.009 | -0.011 | 0.004 | -0.007 | -0.006 | -0.012 |
| | (0.011) | (0.012) | (0.012) | (0.012) | (0.013) | (0.013) |
| Constant | 0.807*** | 0.648*** | 0.750*** | 0.833*** | 0.941*** | 0.901*** |
| | (0.005) | (0.101) | (0.101) | (0.006) | (0.128) | (0.128) |
| Ethnicity Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Childhood Controls | No | Yes | Yes | No | Yes | Yes |
| Adult Control | No | No | Yes | No | No | Yes |
| *N* | 9549 | 8129 | 6892 | 5898 | 4762 | 4160 |
| r2 | 0.045 | 0.053 | 0.162 | 0.040 | 0.0537 | 0.165 |

Standard errors in parentheses
Ethnicity controls: ethnicity of child
Childhood controls: maternal education, maternal employment, father's occupation,
maternal background (height at pregnancy, age, and marital status),
pregnancy characteristics (mother in pregnancy, and birthweight), region of childhood
Adult Controls: region of residence, marital status, a graduate dummy, and general health status
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

# Chapter 4

# Familiar Faces, Worn Out Places: The Effect of Personal and Place Prosperity On Well-Being

**Abstract**

Places have an effect on well-being outcomes such as health and safety. These effects, however, differ between spatial scales, which is largely overlooked in the current place-effects literature. In this chapter, I analyse the effect of place-based prosperity at the granular neighbourhood and larger labour market spatial scales on a wide range of well-being domains using fixed effects regressions and event studies. I find that place effects do differ between the labour market and neighbourhood level spatial scales. Local labour market prosperity gives its residents higher potential incomes and is associated with greater financial & physical security as well as more friends. Moving to a more prosperous labour market also indirectly improves other well-being by increasing potential incomes. Neighbourhood prosperity is associated with greater overall well-being, physical security, and a lower probability of death. These results suggest that policies aimed at improving labour markets and neighbourhoods are needed to create a *"good life"* for all citizens.

# 4.1 INTRODUCTION

Places affect well-being outcomes such as health (Hagedoorn and Helbich 2021), happiness (Aslam and Corrado 2012), financial security (Deryugina et al. 2018), physical safety (Hooghe et al. 2011), friendship (Victor and Pikhartova 2020), and political activity (Cho and Rudolph 2008). These place effects, however, differ between spatial scales. Place effects that operate through social interaction require people to be able to meet, see, and speak in order affect one another - they operate at a granular neighbourhood scale (Galster 2012). The benefits of living in a place with better labour market opportunities operate at a larger spatial scale as individuals commute longer distances to work (Chyn and Katz 2021; Petrović et al. 2022). How place effects differ between spatial scales is, however, mostly overlooked in the current place-effects literature that treats place as a homogeneous category (Cho and Rudolph 2008; Hooghe et al. 2011; Ludwig et al. 2011; Sharkey and Faber 2014; Sørensen 2016; Bernasco et al. 2017; Chetty and Hendren 2018a,b; MacDonald et al. 2020; Petrović et al. 2020), and this accounts for some of the literature's inconsistent findings (Chyn and Katz 2021).

The major contribution of this chapter is to analyse the effects of place-based prosperity at different spatial scales on a wide range of well-being outcomes (e.g. health, financial security, physical safety etc.) using individual-level data matched to places. This is, as far as I am aware, the first piece of work to do this.

Despite the long-standing recognition of the need to differentiate between spatial scales when analysing place effects, there is little work that does so in practice (Tunstall et al. 2004). The small but growing, literature that does analyse the effect of place at different scales usually does so for a single outcome such as health (Graif et al. 2016), happiness (Knies et al. 2021), or earnings (Petrović et al. 2022). This literature also mostly focuses on only analysing place effects at different granular spatial scales (population below 10,000), and so cannot differentiate between social-interactive mechanisms that operate at granular scales and labour market effects that operate at larger spatial scales (Galster 2012; Sharkey and Faber 2014; Chyn and Katz 2021).

Using individual fixed-effects regressions and event studies, I find that places have differing effects at different spatial scales. Living in a more prosperous local labour market has a substantive association with aspects of well-being associated with living in an area with greater employment prospects - better financial security, greater physical security, and (surprisingly) more friends. The effects on physical and financial security increase over time. Living near a more prosperous labour market also leads to significantly less leisure time. Living in a more prosperous labour market also indirectly improves other domains of well-being by increasing potential incomes. Living in a more prosperous neighbourhood, on the other hand, has little impact on one's potential incomes but does have a positive impact on overall well-being as well as better physical safety and a lower probability of dying.

How places affect well-being outcomes is important in both academic and policy terms. Less-educated middle aged people are dying in ever greater numbers from drugs, alcohol, and suicide in both the United States and United Kingdom as their individual economic prospects and the places they live have gone into relative economic decline (Case and Deaton 2017; Joyce and Xu 2019; Case and Deaton 2020). This has led to life expectancy falling overall in the United States as well as in the most deprived areas of the United Kingdom before the COVID-19 pandemic (Cooke 2020; Fleming 2020). Where place-based prosperity plays a role in deaths of despair, then the scale at which these effects take place matter for designing effective interventions at either the neighbourhood (e.g. investing in local community infrastructure) and/or labour market (e.g. public works programs) level. Here, I find that both individual and neighbourhood prosperity are linked to longer life expectancy, indicating that a mixture of individual and place-based policies at both the neighbourhood and labour market policies (that indirectly raise incomes) could help to reduce deaths of despair.

I use Sen's Capability Approach as an organising framework for selecting well-being outcomes in this chapter. This framework is useful for selecting a wide range of outcomes that we value in and of themselves as components of well-being (Sen 2001; Robeyns and Byskov 2020). The Capability Approach views the good life as made up of beings and doings (e.g. "being healthy, "doing" a good job) known as functionings. When an individual can substantively achieve a functioning (e.g. be able to do a good job), they have achieved a capability. Well-being is measured as the capabilities an individual possesses. While the precise list of capabilities varies somewhat between authors, the same substantive items are included across different lists (e.g. health, social life, financial security) (Nussbaum 2003; Decancq et al. 2015; Vizard and Speed 2016; Alkire and Kovesdi 2020). In this chapter, I select capability domains found in the LSE's Multidimensional Inequality Framework and indicators where data is available (McKnight et al. 2019). In practice, the list of domains differs little across multidimensional indices of well-being (e.g.Vizard and Speed (2016); Alkire and Kovesdi (2020)) and it would make little difference which list was chosen.

How places affect well-being outcomes has become more important in advanced economies where spatial inequality has risen due to high-valued economic production becoming concentrated in large cities while former manufacturing areas have gone into relative decline (Moretti 2013; Iversen and Soskice 2019; Kemeny and Storper 2020). The United Kingdom is one the most spatially unequal economies in the OECD, with London and the surrounding commuter belt constituting the economic, political and financial centre of the country (McCann 2016; Sandher 2018). The relationship between the various domains of well-being and spatial prosperity is not, however, uniformly positive. More prosperous regions have better health outcomes and higher disposable incomes, but also have lower levels of life satisfaction, social connections, and housing space (Zymek and Jones 2020). The urbanicity of an area also matters - people living in more urban areas experience more crime for a given level of prosperity. Alkire and Kovesdi (2020) find that London has the lowest well-being when constructing a Capability Index for the United Kingdom.

Less-skilled workers are less mobile than graduates and so are less likely to be able to move to and live in more prosperous areas (Amior 2015; Autor et al. 2015; Swinney and Williams

2016). I find that a given level of prosperity has no greater effect on well-being domains for less-educated people. Less-skilled workers still, however, gain an indirect "locational" surplus from living in more prosperous areas because they are less likely to be able to move to and live in more prosperous areas unlike graduates. These non-graduates have greater employment rates and higher wages in stronger local labour markets (Moretti 2013). They also possess fewer financial and emotional resources that would allow them to shield themselves from negative place effects (Sharkey and Faber 2014).

In order to estimate the separate effects of individual and place-level factors on well-being outcomes, I use Understanding Society data that is linked at the geographic level to local authorities as a measure of local labour markets (average population 180,000) and Middle Super Output Areas as a measure of neighbourhoods (average population 7,500). I control for the prosperity of the surrounding areas using a spatial lag variable, which has the added benefit of adjusting measures of prosperity for the differing sizes of administrative boundaries. I use the percentage deviation of the median wage from the average as the geographic measure of spatial prosperity at the local authority level. At the MSOA level, I use the percentage deviation of income-related social security claimant rates from the average. These percentage deviation measures show the impact that both spatial prosperity and spatial inequality have on well-being.

There is no perfect way to control for selection bias in where people choose to live and so perfectly estimate the causal impact of places on well-being outcomes. (Quasi-)experimental studies also have significant selection effects in which people choose to move and where they choose to move (Gallagher et al. 2019). Here, I use a range of different methods to analyse the impact of places on well-being. Individual fixed-effects regressions are used to show the association between personal incomes, place prosperity, and well-being. Models with fixed effects at the local authority level are also included to control for time-invariant characteristics of places. Event study regressions that exploit (quasi-) exogenous moves are also used to show the impact of moving to a better area as well as their impacts over time.

Finally, a logistic regression is used to show the association between the prosperity of places and the probability of dying.

The rest of this chapter proceeds as follows. First, I discuss how the gap in the literature regarding the differing effects of places at different spatial scales within this chapter. Following this, I describe the advantages of using Sen's Capability Approach to select well-being outcomes. I then move on to discuss how (spatial) income and well-being inequality has evolved in advanced economies and the United Kingdom. I then set out hypotheses, data, and the measurement of the key variables - the Capability Index of well-being and spatial prosperity. Results are then presented. Finally, I close with a discussion of the results, their policy implications, and directions for future research.

## 4.2 THE SCALE OF PLACE EFFECTS

More prosperous areas have positive effects on a wide range of well-being outcomes (Galster and Sharkey 2017) including physical health (Jivraj et al. 2020), happiness (Florida et al. 2013), educational attainment (Chetty et al. 2016), earnings (Deryugina et al. 2018) , physical safety (Hooghe et al. 2011), friendship (Victor and Pikhartova 2020) , and political participation (Cho and Rudolph 2008). However, place prosperity does not have constant effects at different spatial scales. (Quasi-) Experimental research shows that moving to a more prosperous neighborhood has little impact on employment or wages whereas moving to more prosperous places measured at a larger spatial scale (i.e. spatial scales that do capture the strength of the local labour market) does lead to higher employment and/or wages (Deryugina et al. 2018, 2020; Chyn and Katz 2021; Harding et al. 2021).

Place prosperity has differing effects at different spatial scales because the mechanisms by which they affect individuals also operate at different spatial scales. Social-interactive mechanisms operate at more granular levels (where individuals can see, hear, speak, and affect one another) whereas labour market mechanisms operate at larger spatial scales (where people can commute longer distances to work) (Lebel et al. 2007; Chyn and Katz 2021; Petrović et al. 2022). Other mechanisms, such as the effect of the natural/man-made environment and institutions operate at ambiguous spatial scales (Galster 2012; Galster and Sharkey 2017; Petrović et al. 2020). This is discussed in more detail in Section 4.4 below.

The current place-effects literature, however, rarely differentiates between the scale of places when estimating their effects on individual well-being outcomes (Cho and Rudolph 2008; Hooghe et al. 2011; Ludwig et al. 2011; Sharkey and Faber 2014; Sørensen 2016; Bernasco et al. 2017; Chetty and Hendren 2018a,b; MacDonald et al. 2020; Petrović et al. 2020). Chetty and Hendren (2018a), for example, *"conceptualise "neighbourhood effects" as the sum of place effects at different geographies, ranging from broad to narrow: CZ [population - 380,000], counties [average population - 105,000], ZIP codes [average population - 10,000],* *and census tracts [average population - 4,000]."* They report estimates at the commuting zone level as indicating the effects of "place". Chetty et al. (2016), by contrast, measure "place" effects at the census tract level. This is misleading as place effects are unlikely to be constant between these different spatial scales both because of the differing mechanisms by which places effect individuals, and the lack of a strong correspondence between place prosperity at different spatial scales (Cove et al. 2008). The place-effects literature, however, overlooks these distinctions and simply refers to "place" (or sometimes misleadingly "neighbourhood") effects when reporting results where it should refer to neighbourhood, labour market, and/or regional effects (Leventhal and Dupéré 2019; Petrović et al. 2020).

This is surprising, given there has been a long-standing recognition in the literature of the need to differentiate between different spatial scales when assessing place effects (Tunstall et al. 2004; Petrović et al. 2020). The place-effects literature that actually does differentiate between spatial scales is small but growing. This literature includes work on the effect of place-based prosperity at different scales on individual incomes (Bolster et al. 2007; Andersson and Musterd 2010; Petrović et al. 2022), youth access to tobacco (Duncan et al. 2014), educational attainment (Brattbakk 2014; Andersson and Malmberg 2015), life satisfaction and earnings (Knies et al. 2021), and mental health (Propper et al. 2005; Graif et al. 2016).

However, most of this work is limited by only examining spatial scales at granular neighbourhood levels with population numbers below 10,000 (Propper et al. 2005; Bolster et al. 2007; Brattbakk 2014; Duncan et al. 2014; Graif et al. 2016; Knies et al. 2021), most do not consider the characteristics of the surrounding areas (Petrović et al. 2022), and none consider a wide range of well-being outcomes. This paper fills these gaps in the literature by examining the effects of places on a wide range of well-being outcomes at different spatial scales that reflect differing place-effect mechanisms.

Which spatial scale matters for well-being outcomes is important in both academic and policy terms. In both the United States and the United Kingdom, there has been a rise in deaths of despair from drug, alcoholism, and suicide for non-university educated middle-aged people who are more concentrated in former industrial areas (Moretti 2013; Joyce and Xu 2019; Case and Deaton 2020; Zymek and Jones 2020). Life expectancy is now falling in the United States and the most deprived areas of the United Kingdom (Cooke 2020; Fleming 2020). Falling life expectancy and rising deaths of despair appear to be caused by both place-based (Deryugina et al. 2020; Jivraj et al. 2020) and individual prosperity (Dow et al. 2020). This chapter adds to this evidence base by providing evidence on how places affect life expectancy.

## 4.3 WHAT IS WELL-BEING?

I use Sen's Capability Approach as a method for choosing well-being outcomes in this chapter. This method uses a broad set of information intended to capture whether a person is able to achieve the multiple ends needed to live a good life, rather than arbitrarily equating the full breadth and richness of the human experience to some single mental state or income (Sen 2001; Robeyns and Byskov 2020). The Capability Approach is also a practical tool that, *"evaluates policies according to their impact on people's capabilities"* (Robeyns 2005, p.95). Knowing what influences each part of well-being is central to the purpose of the Capability Approach, and is therefore useful as an organising framework to identify the effect of place-based prosperity on well-being at different spatial scales.

Sen (2001) stated that, in order to assess an individual's well-being, we have to assess whether they have the substantive ability to live a *"life one has reason to value"* (Sen 2001, p.1774). The life one has reason to value is made up of *"beings"* and *"doings"* e.g. *"being healthy"*, *"doing"* a job etc., which are known as *"functionings"* The substantive ability to achieve a functioning (a *"beings"* or *"doing"*) is a capability and the different combinations of functionings that an individual can achieve is their Capability Set.

These beings and doings must be ends, and not means, of well-being. Capabilities must be valuable in and of themselves, and not solely as a means to gain other outcomes we may value (Streeten 1994; Robeyns 2005). The Capability Approach focuses on ends rather than means because people differ in their ability to convert means into the ends we value. For example, different people require different numbers of calories to achieve nourishment (due to e.g. pregnancy, disease etc.) (Cohen 1993). Being well-nourished is therefore a capability, having a certain amount of food is not. Food is a means to the end we value (being well-nourished).

It is possible for one to have a capability but not to achieve a functioning out of choice. For example, one could have the ability to, *" be well nourished,"* but choose to starve as a matter of protest (Cohen 1993; Nussbaum 2002). From the social scientists' perspective, functionings are used to evaluate well-being in practice as it is not possible to evaluate capabilities with precision from available datasets. While this may lead to some mismeasurement at the individual level, it is unlikely to do so at the group level. When a group does not achieve a particular functioning, it is safe to conclude that they did not possess the capability to achieve it in the first place (Alkire 2015). One can then compare whether one is "healthy" etc. in order to come to a ranking as to who has the greater well-being (Sen 2006). This is the common approach in the literature that operationalises the Capability Approach (Brandolini and D'Alessio 1998; Chiappero-Martinetti and Roche 2009).

These functionings, or "beings" and "doings" can be grouped into various domains that well-being is evaluated against (e.g. education, health etc.). There is no set list of capabilities or domains that make up a good life - Sen himself believed that this set should be determined by people through enlightened public reasoning (Nussbaum 2003; Sen 2005). In practice, however, most people come to similar views (and even similar rankings) about what they value in life - health, for example, is consistently ranked as one of the most important, if not the most important, capability (Benjamin et al. 2014; OECD 2021). Diverse lists of capabilities lists usually come to the same conclusions regarding the domains that should be included, *"Despite the large variety of approaches and the differences in opinion about the underlying logic, the specific proposals are strikingly similar."*(Decancq et al. 2015, p.81) .

The benefits of using Sen's Capability Approach as an organising framework for selecting well-being outcomes is best demonstrated by comparing it to two other commonly used measures of well-being - income and happiness. The major advantages of the Capability Approach when compared to these two accounts of well-being are: 1) it focuses on ends rather than instrumental means and, 2) it incorporates an appropriately broad set of information covering the breadth of a good life, recognising the essentially pluralistic nature of well-being (Streeten 1994; Sen 2001; Nussbaum 2002; Sen 2005; Robeyns and Byskov 2020)

Income has advantages as a measure of well-being. It is simple and easy to understand. It approximates the amount of material goods people can buy, and material goods are important for a well-lived life. At the individual level, higher incomes are positively associated with desirable outcomes such as happiness (Layard 2005), health (Marmot 2016; Marmot et al. 2020), and friendship (Victor and Pikhartova 2020).

Income is not, however, a suitable measure of well-being because it is a means to gain what we value rather than an end we value in and of itself. And because people differ in their ability to convert incomes into outcomes that are desirable, it is not a consistent indicator of how people can gain these well-being outcomes either. One who is disabled, for example, needs more money to achieve the same outcomes as a non-disabled person (Hick 2016). Sen stresses the unsuitability of income as an indicator of well-being in the foundational text of the Capability Approach (Sen 1979) and it is a core, consistent theme of the literature (Cohen 1993; Sen 1999, 2001; Nussbaum 2002). The relationship between income and desirable outcomes also changes through time. The rising importance of wealth in the United Kingdom means that income is no longer strongly related measures of economic insecurity (Green and de Geus 2022). A strength of the Capability Approach is that, by requiring us to choose outcomes we value in and of themselves, they are not susceptible to these conversion issues (Robeyns 2005; Decancq et al. 2015).

Using income as a measure of well-being also means not appropriately accounting for non-income dimensions of well-being (Nussbaum 2002; Stiglitz et al. 2009). This leads to perverse conclusions. Someone who is rich, but cripplingly lonely and sad, would *literally* be living a better life than someone else who had £1 less in income but lots of friends and/or happiness. Income is limited by its narrow informational base and only incidentally accounts for non-income dimensions of well-being. By contrast, Sen's Capability Approach asks us to consider a wide range of information when measuring well-being

Happiness (or Subjective Well-Being: SWB) is a more robust measure of well-being than income. It measures an end we value rather than a means to achieve it. Happiness is an exceedingly popular measure of well-being and has been widely used for thousands of years in the philosophical literature (Mill et al. 1985; Bentham 2014; Parry and Thorsrud 2021) and more recently in empirical studies (Layard 2005; Aslam and Corrado 2012).

The key drawback of using happiness as a measure of well-being is that its informational basis is too narrow (Robeyns and Byskov 2020). Happiness or SWB is an important component of a good life but it is not the only one. Similar to income, it is correlated with other desirable outcomes but this correlation differs across outcomes such as being healthy or well-educated (Veenhoven 2010; Boarini et al. 2012). As we desire other ends, it makes sense to measure them directly rather than use another indicator (in this case, happiness) that is imperfectly correlated with them.

Asking *only* whether someone is happy or satisfied with their life also falls prey to adaptive expectation problems - a person can have higher well-being than another because they are simply unaware of a better life and/or because they are congenitally disposed to have a more positive outlook (Sen 2001; Haidt 2006). For example, someone living in a poorer nation with a much lower life expectancy who said they were happier than someone in the United Kingdom, would literally be living a better life under the Subjective Well-Being view. This is not a mere theoretical curiosity. Measures of life satisfaction over the past 15 years has shown Costa Rica having higher values than the UK despite its lower life expectancy - prior to Hugo Chavez's death, the same was true for Venezuala (Max Roser and Ritchie 2013; Ortiz-Ospina and Roser 2013). When controlling for income across nations, levels of life expectancy have little impact on Subjective Well-Being whereas changes in life expectancy do - on the Subjective Well-Being view, a nation that had lower, stable life expectancy would *literally* provide a better life than another nation with a higher level of life expectancy that had recently fallen (Deaton 2008). This clashes with our own intuitions of what a good life is and leads to perverse policy objectives where maximising a subjective psychological state would take precedence over all others. The dystopian vision set out in *A Brave New World* would become the ultimate aim of government policy if Subjective Well-Being was the only criteria for a good life (Huxley 2006).

The *good life* is pluralistic and is not reducible to a single characteristic, such as happiness. Feeling happy at any given time cannot supersede the fact that, for example, one is not appropriately housed or fed (Streeten 1994). Sen's Capability Approach does not allow us to ignore these objective facts and requires one to use a broad set of information that incorporates the multiple ends we value (Sen 2001; Robeyns and Byskov 2020).

The Capability Approach provides a well-grounded organising framework for choosing different well-being outcomes. One does not, however, have to accept the the preeminence of Sen's approach to accept the results of how spatial scale affects different outcomes such as , *"being healthy"* etc.. The results below on the effects of place on different outcomes still stand irrespective of one's views of well-being. I now turn to how places affect these different domains of well-being.

## 4.4 HOW DO PLACES IMPACT WELL-BEING?

Places affect people through different mechanisms at different spatial scales. Prosperity can also differ for a place at different spatial scales. Prosperous neighbourhoods (with residents of less 10,000 or less) can exist in larger labour markets that are less prosperous with few job opportunities, especially for those with lower skills (Cove et al. 2008).

The clearest link between place effect mechanisms and spatial scales are: 1) labour market and 2) social-interactive mechanisms. Labour market mechanisms (the effect of the local labour market on an individual) operate at larger scales as people can commute longer distances to get to work (Sharkey and Faber 2014; Chyn and Katz 2021). Social-interactive mechanisms (that encompasses social processes such as peer effects, network effects, collective action, and social contagion), operate at a more granular level as they rely on people being able to talk, see and be affected by other's actions (Galster 2012).

By contrast, environmental mechanisms (the effect of the natural and man-made environment) has an ambiguous relationship with spatial scale, being able to take place at different levels from both granular neighbourhoods (e.g. a deprived tower block in a rich area such as Grenfell Tower in Kensington and Chelsea) and much larger areas (e.g. living in a town that is poorly connected due to substandard infrastructure) (Galster 2012; Petrović et al. 2020). Similarly, institutional mechanisms (the effect of outside actors on a given area) can also operate at ambiguous spatial scales from the micro (e.g. the under-provision of market goods in a neighbourhood) to the regional (e.g. discrimination against an entire region).

More prosperous labour markets have a positive impact on well-being domains through their greater employment opportunities and higher potential incomes. These areas provide higher potential incomes for all workers; even less skilled workers in the same occupation earn more when living in or near to more affluent areas (Moretti 2013). Higher individual incomes give people greater financial, emotional, and cognitive resources that lead to better physical and mental health, more friendships, greater financial security, as well as greater political participation (Layard 2005; Dolan et al. 2008; Mullainathan 2013; Marmot 2016; Mood and Jonsson 2016). By contrast, a lack of employment opportunities and lower incomes has been convincingly identified as a source of rising deaths of despair from alcohol, drugs, and suicide for men (Autor et al. 2019; Case and Deaton 2020; Eisen et al. 2020). Earlier work linked falling employment prospects to deaths for middle-aged men from alcoholism and suicide in post-Soviet Russia (Stewart et al. 1994). Crime also becomes a more attractive economic prospect in areas with weaker labour markets (i.e. where there are fewer formal economic opportunities) (Draca and Machin 2015).

Higher potential earnings in more prosperous areas will be somewhat offset by higher housing costs but, as residential mobility is less than perfect, and much lower for non-graduates, those who happen to live in more affluent areas may receive a locational surplus (and so be able to "buy") more well-being than a similarly skilled person who lives in a less affluent area (Amior 2015; Autor et al. 2015; Swinney and Williams 2016). This locational surplus is likely to be present for non-graduates who are less mobile whereas graduates are more willing and able to move to areas with greater well-being payoffs (Swinney and Williams 2016).

More prosperous labour markets are also likely to have some negative effects on well-being outcomes. Housing costs are higher near and within more prosperous areas reflecting both the higher potential incomes and other well-being benefits that come with living there (Florida et al. 2013; Ryan-Collins et al. 2017). Home size is subsequently smaller, overcrowding more frequent, and commuting times often longer, both near and within more prosperous areas (Eurostat 2020).

Spatial prosperity at the labour market level operates through increasing potential employment and wages. Measures of labour market prosperity should, therefore, reflect this in order to capture this mechanism.

More prosperous neighbourhoods improve well-being outcomes through social-interactive mechanisms. Residents in these areas are more likely to practice and so encourage positive behaviours (such as healthy eating and political participation (Cho and Rudolph 2008; Carrell et al. 2011; Ludwig et al. 2011)), act in concert to stop undesirable ones (like crime (Bernasco et al. 2017)), communicate opportunities to one another, as well as provide more social support (leading to greater friendship (Victor and Pikhartova 2020)) (Galster 2012; Leventhal and Dupéré 2019). Non-graduates are particularly affected by neighbourhood prosperity as they are less able to insulate themselves from the effects of their local neighbourhoods (Sharkey and Faber 2014).

These social-interactive mechanisms operate at the neighbourhood level rather than the local labour market level. The type of spatial prosperity that is important for social-intereactive effects, therefore, differs from local labour market effects. Social-interactive mechansims are more closely linked to measures of deprivation/advantage within a neighbourhood, which indicate how people who live in the area can act interact with one another (McCulloch 2003; Leventhal and Dupéré 2019). This is related to, but is not equivalent to, labour market prosperity. Wages can be high in areas where there is also high amounts of neighbourhood deprivation. In these areas, local labour market prosperity is high while neighbourhood prosperity is low. For example, Tower Hamlets (an East London local authority), has high wages (that are 10% higher than the London average and 45% higher than the UK average) *as well as* the highest child poverty rate in the country at 55.8% (Hirsch and Stone 2021; NOMIS 2021).

Areas also have other effects on well-being outcomes that are ambiguous with regard to spatial scale as they operate through institutional and environmental mechanisms. More prosperous areas are likely to have better public and private good provision. Pubs have been more likely to close in more deprived areas and the fall in social spaces has led to a consequent rise in support for radical right parties (Angus et al. 2017; Bolet 2021). Public good expenditure may be greater in more deprived areas, but its provision is more effective in more prosperous areas where there is less need. Within the UK, the most deprived areas receive the most funding, and then saw the largest cuts during the post-2010 fiscal retrenchment - this has been linked to falling life expectancy, falling mobility from less public transport, rising violent crime, and lower incomes in these deprived areas (Watkins et al. 2017; Gray and Barford 2018; Marmot et al. 2020).

The urbanicity of an area is a mediating factor between spatial prosperity and well-being outcomes. People living in urban areas have lower levels of intra-community social capital due to high residential turnover making it harder to form relationships and act collectively to stop undesirable behaviours (Layard 2005; Sørensen 2016). This lack of intra-community social capital means that, for a given level of prosperity, people living in urban areas have fewer friendships and experience more crime (Draca and Machin 2015; MacDonald et al. 2020). For adults, there is evidence that areas have a cumulative impact on health outcomes over time but this finding is not universal (Jivraj et al. 2020; Hagedoorn and Helbich 2021).

In summation, I would therefore expect more prosperous areas to have impacts on well-being outcomes but for these impacts to differ between spatial scales. More prosperous labour markets are likely to directly give higher potential incomes and safety outcomes. Indirectly, they are likely to improve other well-being outcomes by increasing potential income. They would also, however, lead to smaller houses and less leisure time due to congestion. More prosperous neighbourhoods are likely to give their residents better health outcomes, physical security, social lives, and political participation through their social-interactive effects. These impacts are mediated by urbanicity. For a given level of prosperity, we would expect urban areas to have more crime and fewer friendships due to the lower levels of intra-community social capital. Finally, I expect the less-educated to gain greater well-being benefits from more prosperous labour markets (as they are less able to move to areas with greater job opportunities) and neighbourhoods (as they are less able to insulate themselves from social-interactive effects).

## 4.5 SPATIAL INEQUALITY IN ADVANCED ECONOMIES

Rising interpersonal income inequality has been coupled with rising spatial inequality in the wake of technological change and globalisation. Spatial inequality has been rising in advanced economies as secular economic forces have led to the concentration of high-wage jobs, performed by graduates, in major cities. This represented a marked difference from the post-war era, when mass production manufacturing jobs with good wages were undertaken by men with few formal qualifications in factories and industrial plants across the country. Spatial inequality subsequently fell across advanced economies in *Les Trente Glorieuses* as rising growth provided good job opportunities for people across the country (Frey 2019; Iversen and Soskice 2019; Carrascal-Incera et al. 2020; Kemeny and Storper 2020; Zymek and Jones 2020).

The secular forces of technological change and globalisation that raised the return to graduate qualifications also destroyed mid-skill manufacturing jobs leading to a divided labour market with high and low-pay jobs. In today's knowledge economy, high-value production is now undertaken by highly skilled graduates working together in offices based in major cities while low-pay production takes place across the country (Iammarino et al. 2019; Kemeny and Storper 2020).

These secular economic forces have a self-reinforcing place-based nature. They encourage the concentration of both economic advantage and disadvantage in separate areas. High-value knowledge based production requires large numbers of graduates working in close proximity to other graduates within cities, which leads to high productivity firms locating in these areas, and then more graduates move to these areas, and so on (Florida and Mellander 2018; Haskel 2018; Iversen and Soskice 2019). These high productivity areas also provide higher wages and more employment for less-skilled workers in these cities as higher skill workers consume the services they work in. Economic disadvantage has become similarly concentrated in weaker economies that high-skilled workers have left, and where high productivity firms do not locate (Moretti 2013).

The benefits of high productivity cities are more than just pecuniary. High-skill graduates are mobile and fickle – they leave potentially high productivity areas that do not have the amenities to keep them satisfied. These include good infrastructure, public services as well as a vibrant cultural scene and nightlife (Florida and Mellander 2018). These areas have other non-pecuniary well-being benefits for those who live in them and near them. In the United Kingdom, life expectancy and broadband availability are higher, and crime lower, in regions that are more productive (Zymek and Jones 2020).

There is also, however, a divide within these high productivity cities. High-skilled people live in neighbourhoods of these cities that are most pleasant with the most amenities, including transport infrastructure, while low-skilled workers are pushed ever further away into relatively deprived and geographically isolated areas of the city where housing costs are lower (Florida 2017). Segregation replicates itself on the granular neighbourhood scale within the labour market of major cities, as well as between those major cities and other conurbations. Deprived neighbourhoods can and do exist within larger, prosperous labour markets. However, while low-income people within and near these cities are further away from well-being benefits than high-income people, they are still, obviously, closer to them than low pay individuals on the economic periphery of these nations.

The economic periphery of advanced economies are the former industrial areas, where the manufacturing sector has shrunk precipitously due to technological change and trade (Autor et al. 2015; Beatty and Fothergill 2017) . The decline in local employment opportunities has led to a self-reinforcing decline in these area where high-skilled people leave and concentrated disadvantage remains (Swinney and Williams 2016; Sandher and Innes 2020). These areas of concentrated disadvantage have subsequently seen large rises in the number of deaths of despair (Autor et al. 2019; Charles et al. 2019).

Given that places have an effect on a wide range of well-being outcomes, rising spatial inequality and the relative decline of former manufacturing areas is likely to have led to widening inequality well-being inequality within advanced democracies as well. In this chapter, I examine how these place effects operate.

## 4.6 SPATIAL INCOME AND WELL-BEING INEQUALITY IN THE UK

Spatial inequality has risen across advanced economies, and the UK is one of the most geographically unequal in the OECD - England contains both the richest (Inner London) and five of the ten poorest areas in Northern Europe (McCann 2016; Panjwani 2018). The UK is hyper centralised - London constitutes its major economic *and* political centre. The central government has control over most policy issues and funding decisions, while the level of sub-national expenditure is one of the lowest in the OECD (McCann 2016). London is where most high-pay jobs and industries are found - it is the political, financial, and technological centre in marked contrast to other large developed nations such as the United States, Germany, and Canada (Florida 2017).

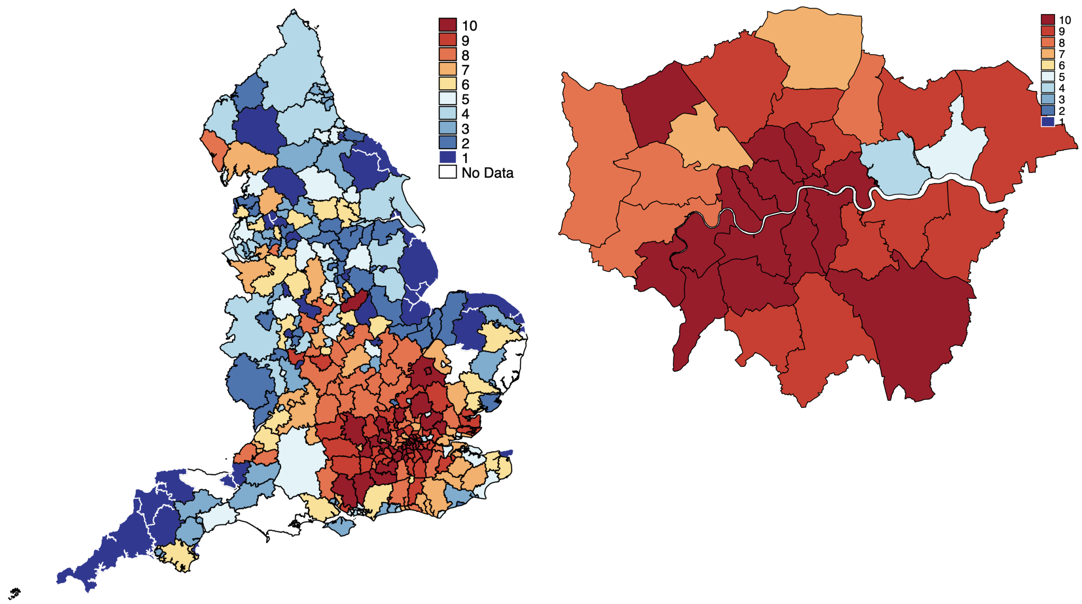
This centralisation of high-value economic activity and political power is reflected in the UK's spatial inequality. Over half of its spatial inequality is regional in nature (Zymek and Jones 2020). In particular, the United Kingdom has one large super-high productivity area that encompasses London and the surrounding commuter belt in the South East with dotted islands of prosperity around other major cities that can be seen in Figure 4.1[1] below (Florida 2017; Sandher 2018). Infrastructure spending has become similarly biased toward London (Raikes 2019). London's greater job and well-being opportunities are reflected in its higher housing costs - the house price to income ratio is around twice as high as it is in the rest of country (Ryan-Collins et al. 2017; ONS 2020).

London does not, however, provide uniformly high well-being to all of its citizens. London has both the UK's highest wage levels *and* its highest poverty levels due to both its status as a major world city and the higher housing costs that come with it (Agrawal and Phillips 2020). Within London, lower income households are pushed further away from transport

[1]Data on wages is unavailable for six local authorities - five due to boundary changes and one (the City of London) due to a tiny sample size

**Figure 4.1: Spatial Prosperity in England and London in 2017 by Median Wage Deciles**

(a) England (b) London




and other amenities - the commuting and congestion costs that come from living in one of the world's major city are felt by the capital's poorer citizens (Florida 2017).

Empirical work using Sen's Capability Approach found London had the country's lowest levels of well-being, while subjective life satisfaction and social connections are also lowest in the capital (Alkire and Kovesdi 2020; Zymek and Jones 2020). London's citizens do, however, still benefit in other ways from being closer to the nation's economic centre - intergenerational occupation-wage mobility is much higher in London and life expectancy in poorer areas of the capital is also comparatively higher than poorer areas elsewhere in the country (Buck and Maguire 2015; Authority 2018; Bell et al. 2018).

The former manufacturing areas of the country, on the other hand, provide uniformly lower levels of well-being for their citizens. These areas have the lowest life expectancy and proportion of graduates as well as the highest numbers on disability-related social security payments (Beatty and Fothergill 2017; Sandher and Innes 2020). These former manufacturing areas, which suffered the largest employment shocks from deindustrialisation in the

1970s, are the most deprived areas in the UK today (Rice and Venables 2021).

In this chapter, I describe and then analyse how living in the super-high productivity area of London and the deprived former industrial areas impact well-being for their residents. In particular, I analyse at what scale the effects operate for a wide range of well-being outcomes.

## 4.7 HYPOTHESES

I test the following hypotheses in this chapter.

**Hypothesis 1**: Labour market prosperity will have an effect on well-being outcomes associated with greater potential incomes (financial security, safety and living conditions) while neighbourhood prosperity will have an effect on outcomes that operate through social-interactive effects (health, social life, safety, and political participation)

Greater prosperity at the labour market level will have an impact on well-being outcomes related to living in areas with greater employment and wage levels (greater financial security and physical safety but less comfortable living conditions due to longer commutes and greater housing costs). Social-interactive mechanisms will operate at the neighbourhood level, where the interactions with those in your immediate vicinity affect your own well-being outcomes.

**Hypothesis 2**: Less-educated individuals will gain more well-being benefits than the highly-educated from living in a more prosperous area

Highly-educated individuals can both more easily choose where they live, and gain employment more easily wherever they are. They also have greater resources to insulate themselves from the negative impacts of their surroundings. Less-educated individuals will, on the other hand, find it harder to gain employment in more deprived areas and be more adversely affected by the negative impacts of places. I therefore expect that less-educated people will see relatively more positive well-being outcomes from living in a more prosperous area than highly educated individuals.

**Hypothesis 3**: Well-Being effects will increase the longer someone lives in a more prosperous area

Consistent with findings that places have a greater impact on health outcomes the longer one lives in an area, I expect that places will have a greater impact on other well-being outcomes the longer someone lives in a given area.

**Hypothesis 4**: People will die more quickly in less prosperous areas

As deaths of despair are more concentrated in more deprived areas due to a lack of employment opportunities, and more deprived neighbourhoods also negatively impact health outcomes, I expect life expectancy to be lower in less prosperous places.

## 4.8 DATA

I measure the domains of well-being using the UK Household Longitudinal Study (UKHLS) in England between 2010 and 2017 for working age adults (i.e. those aged 16 and over), which includes a rich variety of socioeconomic data. Spatial data on the urbanicity of an area, local prosperity, and population density is taken from the Office for National Statistics. Updated data on local authority expenditure per person in each year was kindly provided by David Phillips and Kate Ogden at the Institute of Fiscal Studies (Harris et al. 2019). This helps to control for measures of need in the local area that are not captured by local prosperity measures e.g. age and health needs.

## 4.9 METHODOLOGY

### 4.9.1 Measuring Well-Being

There is a growing literature that constructs capability indices using available data. Given that capabilities are difficult to observe, I will evaluate an individual's functioning set as is common in the literature (Alkire 2015). At the individual level, this may lead to some mismeasurement where individuals choose not to achieve a functioning despite the capability to do so. These individual idiosyncrasies are, however, unlikely to affect group level estimates - people will not generally choose to be deprived on some dimension that is desirable.

There are four steps I undertake to build a Capability Index. I use the example of the Life and Health domain below to illustrate how it is constructed.

More information on the construction of the Index is given in the Appendix.

1. **Identify Relevant Domains and Functionings** -

   Domains are broad areas of well-being that reflect broad areas of well-being while functionings reflect the indicators within those broad areas. I use a slightly modified list of domains from the LSE Multidimensional Inequality Framework (MIF) to select domains of Capabilities. The Education domain is excluded as the impacts of place and family largely have an impact on children who are excluded from this study (Heckman et al. 2006; Chetty et al. 2016).

The domains in the MIF are similar to other multidimensional well-being lists such as the OECD Better Life Index and Burchardt & Vizard's list of ten valued capabilites (Benjamin et al. 2014; OECD 2021). As is discussed above, Decancq et al. (2015) notes that capability lists often come to the same conclusions despite their differing approaches.

The MIF is designed to measure inequality within a society. However, that inequality is present in the indicators chosen (e.g. inequality in life expectancy) and not the domains of well-being. That is why domains are strikingly similar across the multidimensional indices. The choice of the MIF is, therefore, an appropriate one.

**Table 4.1: Comparison of Domains Across Multidimensional Well-Being indices**

| **LSE MIF Index Domains** | **Burchardt and Vizard's 10 Domains** | **Alkire MWI (2020)** | **OECD Better Life Index** |
|---|---|---|---|
| Life & Health | Life; Health | Personal well-being: Health | Health;<br>Life Satisfaction |
| Physical and Legal Security | Physical Security | | Safety |
| Education | Education and Learning | Education | Education |
| Financial Security and;<br>Dignified Work | Standard of Living | What We do;<br>Personal Finance | Income;<br>Jobs |
| Comfortable Living Conditions | Productive and Valued Activities;<br>Standard of Living | Living Standards | Work-Life Balance;<br>Housing;<br>Environment |
| Participation | Participation, Influence, and Voice | Governance | Civic Engagement |
| Social Life | Individual, Family, and Social Life | Our Relationships | Community |
| | Identity, Expression, Self-respect | | |
| | Legal Security | | |

**Table 4.2: Well-Being Domains and Data availability in the BHPS/Understanding Society**

| Domain | Variables | Years Data Available |
|---|---|---|
| **Life and Health** | Self-Reported Health, Life Satisfaction | 2009 - 2017 |
| **Individual, Family, and Social Life** | Number of Close Friends (up to 3) | 2011, 2014, 2017 |
| **Financial Security and Dignified Work** | Financial Situation, Employment Status, | 2009 - 2017 |
| **Comfortable Living Conditions** | Number of Rooms/Not Overcrowded, Leisure Time | 2009 - 2017 |
| **Participation, Influence, and Voice** | Have a Say In What Government Does | 2011, 2014, 2017 |
| **Physical and Legal Security** | Extent of People Attacked on Street | 2011, 2014, 2017 |

For indicators, I use variables that are available in Understanding Society that reflect each substantial component of domains. For example, physical and mental health indicators are used for the Life and Health domain. Where these are not markedly different, I combine these indicators into one measure.

Where indicators measure markedly different parts of a domain, I split these out in the results for the sake of comprehension. In practice, this means splitting the Comfortable Living Conditions domain into two sub-domains - housing and leisure time, as they reflect different aspects of well-being that are difficult to compare.

The full list of domains and the variables used to measure them are shown in Table 4.2. The first domain is Life and Health, and I use self reported health and life satisfaction to measure the functionings that fall within this domain.

2. **Measuring possession of a functioning** - I use the "Fuzzy Set Theory" where an individual can either possess a functioning, partly possess, or not possess it (Brandolini and D'Alessio 1998). For example, if an individual's life satisfaction is "Completely Satisfied" then I view them as fully functioning and the functioning is given a score of

1, if it is "Neither Satisfied nor Dissatisfied" then they are partly functioning and given a score of 0.5. If their Life Satisfaction is "Completely Unsatisfied" then they they are not functioning and given a score of zero. Each functioning in a domain is weighted, usually equally, and the domain overall is given a score between 0 and 1. For example, life satisfaction and self-rated health functioning scores are halved and summed to give the overall Life and Health domain score, which is bounded between 0 and 1.

3. **Weighting** - I calculate implied relative weights from survey experiment data where individuals were asked to choose between pairwise choices of well-being domains, and where the authors then use these choices to calculate the relative marginal utility for each domain (Benjamin et al. 2014). The weights assigned to each well-being domain reflect the marginal utility revealed by individual choices. This type of choice comes closest to Sen's idea of public reasoning, where the public is asked to weight their own choices rather than being imposed by the researcher.[2] From this experiment data, I take the highest relative marginal utility estimate for each domain. I compare this to equal weights. The weights are shown in Table 4.2.

   I also construct a composite well-being index using principal component analysis. I take the factor loadings from the first principal component to calculate a PCA-derived Capability Index (Alkire et al. 2015; Greco 2018). The PCA-derived composite index has a very high correlation with the Capability Index of 0.9845. This is then rescaled to take values between 0 and 1. The results for the PCA-derived Capability Index are almost identical to the weighted one and so is relegated from the main text to Appendix D.

4. **Aggregation** - I sum the domains together in a weighted index and also consider them separately in the analysis. As will be seen below, spatial prosperity has differ-

[2]This data includes 136 components of well-being and so I align each to a domain/sub-domain of well-being of well-being and then get an implied weighting. I exclude those that are exclusively other regarding and/or reflect personal choices/feelings

**Table 4.3: Well-Being Domains and Weighting**

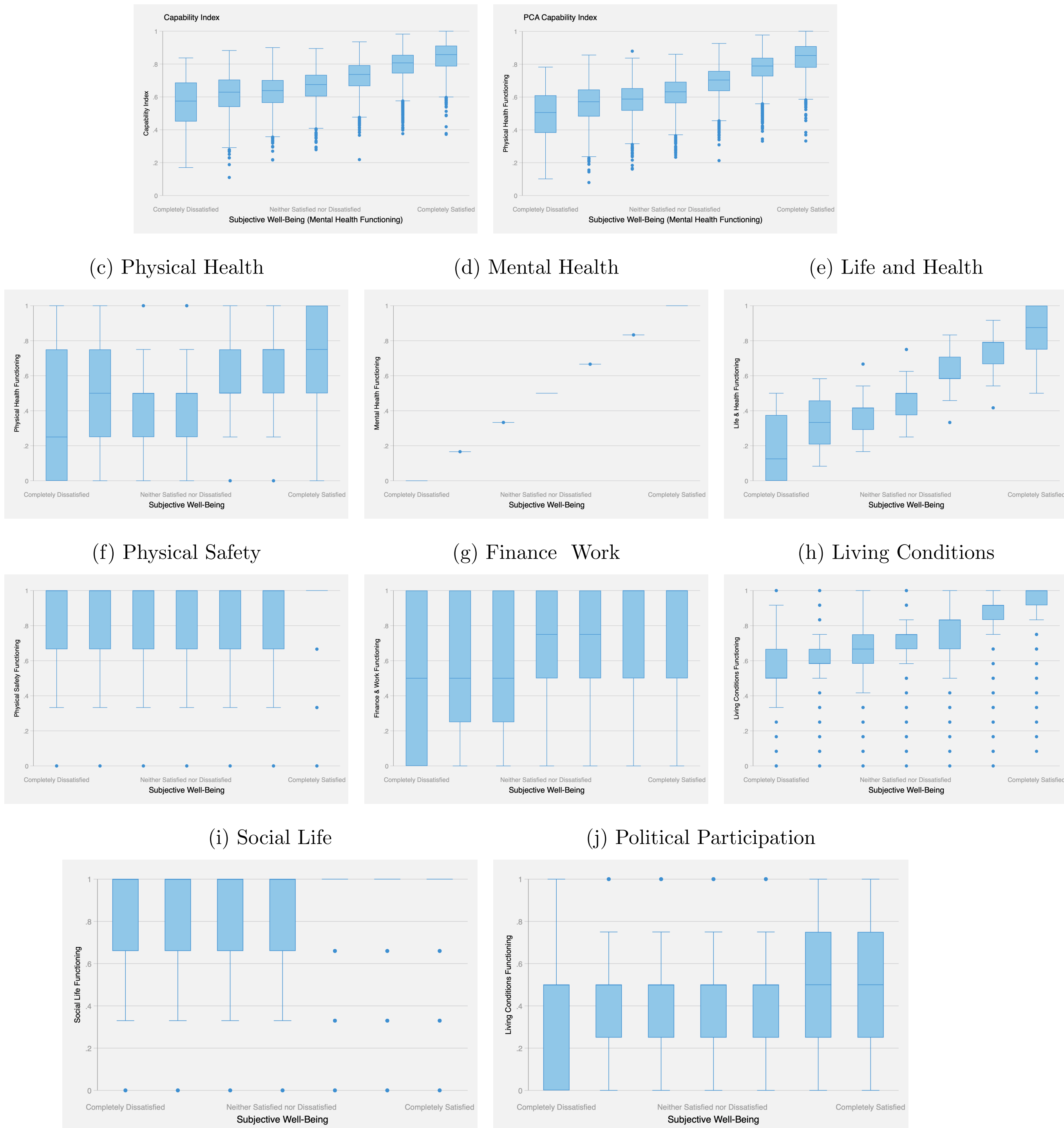
| Domain | Benjamin et al. (2014) Weight | Equal Weights |
|---|---|---|
| **Life and Health** | 21.11% | 14.3% |
| **Comfortable Living Conditions** | 18.47% | 14.3% |
| **Financial Security and Dignified Work** | 17.06% | 14.3% |
| **Physical and Legal Security** | 16.57% | 14.3% |
| **Individual, Family, and Social Life** | 14.99% | 14.3% |
| **Participation, Influence, and Voice** | 11.81% | 14.3% |

ing impacts on the various domains of well-being that are missed in the aggregated Capability Index.

Figure 4.2 below shows the association between the Subjective Well-Being measure more commonly used in the literature and each domain of well-being e.g. Dolan et al. (2008). This shows the wide variation in outcomes that is missed when only considering Subjective Well-Being - there are, for example, many people with poor physical health who are also completely satisfied with life. As the life satisfaction measure is used as our measure of mental health, this domain has a perfect one-to-one relationship with SWB.

The closest example in the literature to creating a Capability index as I do here is Alkire and Kovesdi (2020). They create a multidimensional Capability index using one wave of Understanding Society data in order to show how many people do not achieve an adequate standard of well-being and how far below an adequate threshold they fall. The analysis here differs from their work in two key respects. Firstly, I aim to show what determines well-being and its components, rather than who possesses adequate well-being. Secondly, the weights derived here are arguably more robust as they depend upon a public reasoning exercise as conceived by Sen.

**Figure 4.2: Association between Capability Index Domains and Subjective Well-Being in 2017**




(a) Capability Index (b) PCA Capability Index

(c) Physical Health (d) Mental Health (e) Life and Health

(f) Physical Safety (g) Finance Work (h) Living Conditions

(i) Social Life (j) Political Participation

### 4.9.2 Measuring Spatial Prosperity

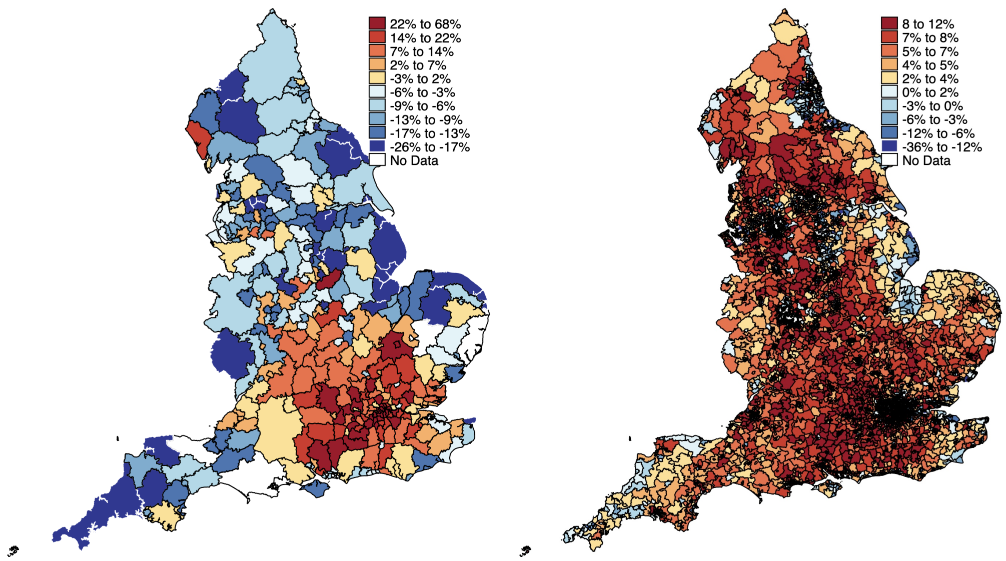
I use ONS data to measure spatial prosperity. Data is measured at two levels - the local authority (average population 180,000) and Middle Super Output Area (MSOA - average population approximately 7,500) level. The impacts of place at the local authority and MSOA level are taken to roughly approximate the size of local labour markets and neighbourhoods respectively. Local authorities are selected as a proxy for local labour markets due to data availability. There is, however, a wide variation in their size. Some local authorities, particularly in London, are close enough together for several local authorities to constitute a single labour market. Spatially lagged measures of local prosperity, that account for the prosperity of the surrounding area, control for these differential sizes.

Local prosperity is measured at the local authority level using median wages as it reflects the strength of the local labour market and so the impact that greater potential incomes has on well-being. At the MSOA level, the (negative) percentage claiming income-related social security payments is used as the measure of neighbourhood advantage to reflect the fact that it is harder to experience positive social-interactive effects in more deprived areas. These are positively but not perfectly related. Across local authorities, the correlation between these two measures is 0.29. This is unsurprising. As described above, these two measures reflect the different channels that spatial prosperity has at different spatial scales. Median wages measure local labour market opportunities and claimant rates measure neighbourhood social-interactive effects. We should not, therefore, expect them to necessarily be very strongly correlated with one another.

The main independent variables of interest are the percentage deviations from the average. These are used to incorporate both spatial prosperity and inter-place spatial inequality. At the local authority level, the key independent variable is the percentage deviation of the median wage in a local authority from the national median and at the MSOA the (negative) percentage deviation of the social security claimant rate from its national rate. For both

**Figure 4.3: Area Prosperity (%Deviation from Mean) in Local Authorities and MSOAs**

(a) Local Authorities (b) MSOAs




variables, higher values therefore represent more prosperous areas - and are shown in Figure 4.3 below.

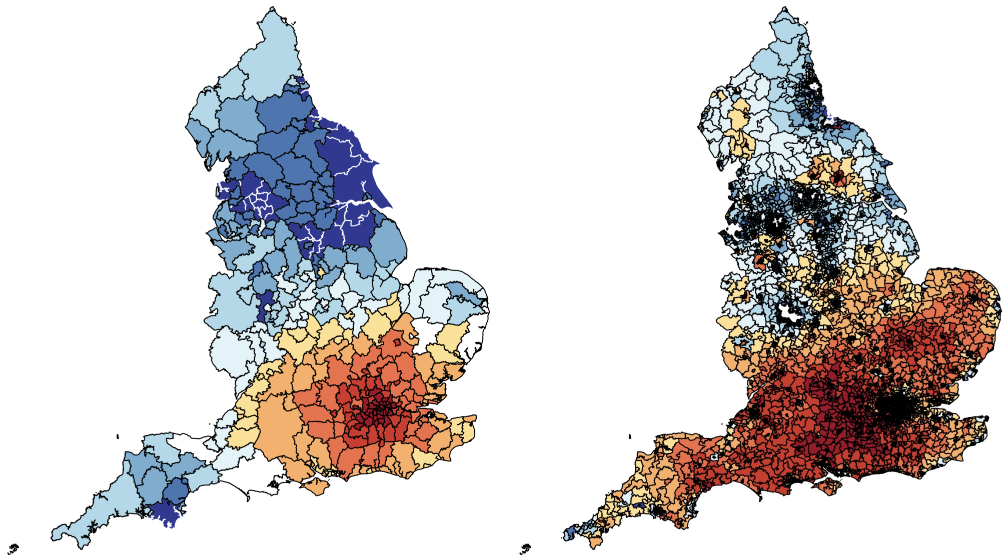
I also measure the impact of surrounding areas on an individual's well-being. As described above, living in more deprived areas in London appears to confer benefits on that are that are not available in equally deprived areas elsewhere in the country and, in addition, the local labour market in large cities like London will not fall within local authority boundaries. Not accounting for this spatial dependence would lead to biased and inconsistent estimates (Fischer and Wang 2011). In order to account for the spatial dependence between areas, I create spatially lagged versions of the spatial prosperity variables, which accounts for the prosperity of the surrounding areas. These spatially lagged variables weight the impact of other areas with respect to the distance from a given area, where nearby locations have more of an impact than far away ones (Grubesic and Rosso 2014)

The spatial lag variable is given by:

$$\text{Spatially lagged Prosperity}_i = \Sigma_{i \neq j} w_{ij} SpatialProsperity_j$$

**Figure 4.4: Spatially Lagged Prosperity in Local Authorities and MSOAs**

(a) Local Authorities (b) MSOAs



where $w_{ij}$ measures how much weight the outcome of variable in area $j$ is given in the calculation of the spatially lagged variable. In this chapter, I use the following weight matrix:

$$w_{ij} = d_{ij}^{-2}$$

Spatially lagged prosperity measures are shown in Figure 4.4.

There are limitations to a measure of spatially lagged prosperity. In particular, it assumes that the impact of distance is equal across the country. This is unlikely to be true. For a given place, the spatial prosperity of areas that are 10 miles away are likely to have a greater impact in London due its better transport infrastructure than they are in rural areas, for example.

## 4.10 DOES LIVING IN A MORE PROSPEROUS AREA IMPROVE YOUR WELL-BEING?

### 4.10.1 Association Between Spatial Prosperity and Well-Being - All Individuals

I use fixed effects specifications that control for individual level invariant characteristics, including their psychological dispositions, in this chapter unless otherwise stated.

I estimate the following equation to estimate the association between the various domains of well-being as well as individual and spatial prosperity at the local authority (LA) and MSOA level. For all regressions in this chapter, I also report separate results for functionings in the Life and Health domain (Physical and Mental Health) due to the importance of health for well-being. One cannot live a *"good life"* if one is dead.

$$\begin{aligned}\text{Well-Being}_{i,t} = a_i + c_t + \text{Equivalised Household Income}_{i,t} + \text{LA Prosperity}_{j,t} + \\ \text{Spatially Lagged LA Prosperity}_{j,t} + \text{MSOA Prosperity}_{j,t} + \\ \text{Spatially Lagged MSOA Prosperity}_{j,t} + \text{Area Characteristics}_{j,t} + \\ \text{Individual Characteristics}_{i,t} + \epsilon_{i,t}\end{aligned} \tag{4.1}$$

Where area characteristics include Local Authority Population Density, MSOA Population Density, Local Authority Expenditure, and a London Dummy. Individual characteristics include age, age-squared, and relationship status, which have been shown to have an impact on self-rated happiness, health outcomes, and financial security (Dolan et al. 2008). This is a deliberately parsimonious specification to avoid controlling for variables that could be intermediately impacted through place (Jivraj et al. 2020).

Regressions are shown with and without local authority fixed effects. Data is measured between 2010 and 2017 where variables are available. Including local authority fixed effects has the advantage of controlling for constant characteristics of local authorities that are not otherwise measured. However, this specification has the drawback of controlling for the level effects of local authority prosperity and only therefore estimating the impacts of within-local authority changes in prosperity in this period. There is considerable persistence in local authority prosperity over time - the standard deviation of Median Wage differences is 17.0 between local authorities but only 3.5 within them. The important changes in spatial inequality that occur as a result of the Great Recession are, therefore, absorbed by the specification with local authority fixed effects (Sandher 2018).

The results in Tables 4.3 and 4.4 below provide support for Hypothesis 1. After controlling for household income, there is a significant association between well-being and spatial prosperity, and this impact differed between spatial scales. Greater prosperity at the local labour market (local authority level) led to greater financial security, greater physical security, and worse living conditions in the specification without fixed effects. Surprisingly, living in more prosperous local authorities was also associated with a more active social life.

At the neighbourhood level (MSOA), greater prosperity led to greater overall well-being as well greater physical security. There was a lack of expected effects for health outcomes, social life, and political participation at the MSOA level, which may indicate the lack of social-interactive mechanisms for these well-being domains. As expected, denser and more urban neighbourhoods provide less physical security due to the lack of bonding social capital present but there was surprisingly little impact of population density on social life.

An increase in household income had a more consistent impact on almost all domains of well-being (with the exception of physical security, house size, and social life). Higher incomes also had a strong negative impact on living conditions, possibly due to the lower leisure time available richer in households. The most reliable way to raise personal well-being is still to increase personal incomes. However, the impact of living in more prosperous places was sometimes comparable to or greater than having an increase in monthly income of £1000, (Figure 4.5) even if the effects were less consistent across well-being domains.

While these results do provide some support for Hypothesis 1, they do not allow a causal claim to be made nor can they account for selection effects of where people choose to live. They do, however, provide plausible evidence that local prosperity could have an effect on well-being domains, and that these effects differ between the labour market and neighbourhood levels.

## Table 4.4: Association Between Individual/Spatial Prosperity and Well-Being

| | Well-Being Index/Domain | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Capability Index | | Physical Health | | Mental Health | | Life & Health | | Physical Security | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| **Personal Income** | | | | | | | | | | |
| Household Income | 0.0025** | 0.0025** | 0.0003 | 0.0003 | 0.0020*** | 0.0020*** | 0.0010*** | 0.0010*** | 0.0003 | 0.0004 |
| (£1000 increase in) | (0.0010) | (0.0010) | (0.0003) | (0.0003) | (0.0006) | (0.0006) | (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| **LA Prosperity** | | | | | | | | | | |
| Median Wage (10 % from Mean) | (0.0010) | (0.0010) | (0.0003) | (0.0003) | (0.0006) | (0.0006) | (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| Spatially Lagged Median Wage | 0.0028 | -0.0043* | 0.0018 | -0.0048* | -0.0079** | -0.0070*** | -0.0140*** | -0.0080*** | -0.0106*** | -0.0069*** |
| | 0.0028 | -0.0043* | -0.0079** | -0.0069*** | -0.0140*** | -0.0080*** | -0.0106*** | -0.0069*** | -0.0187*** | -0.0131*** |
| | (0.0037) | (0.0025) | (0.0039) | (0.0026) | (0.0046) | (0.0030) | (0.0033) | (0.0023) | (0.0065) | (0.0042) |
| **MSOA Prosperity** | | | | | | | | | | |
| Means-tests Social Security | 0.0099*** | 0.0094*** | -0.0000 | -0.0003 | 0.0003 | -0.0004 | 0.0000 | -0.0006 | 0.0303*** | 0.0310*** |
| Payment Rate (1 % point decline) | (0.0024) | (0.0023) | (0.0020) | (0.0020) | (0.0026) | (0.0025) | (0.0018) | (0.0018) | (0.0041) | (0.0040) |
| Spatially Lagged Means-Tested | -0.0071 | -0.0080 | -0.0056 | -0.0057 | 0.0068 | 0.0102 | 0.0013 | 0.0036 | 0.0002 | 0.0058 |
| Social Security Rate | (0.0077) | (0.0065) | (0.0058) | (0.0051) | (0.0075) | (0.0064) | (0.0053) | (0.0046) | (0.0133) | (0.0110) |
| **Area Characteristics** | | | | | | | | | | |
| London Dummy | -0.2613*** | 0.0021 | 0.1006* | 0.0238** | -0.0704 | 0.0211** | 0.0009 | 0.0208** | 0.3489*** | 0.0006 |
| | (0.1004) | (0.0097) | (0.0595) | (0.0098) | (0.1034) | (0.0107) | (0.0639) | (0.0081) | (0.1293) | (0.0164) |
| LA Population Density | -0.0034*** | -0.0028*** | -0.0009 | -0.0007 | -0.0008 | -0.0005 | -0.0009* | -0.0006 | -0.0079*** | -0.0079*** |
| | (0.0007) | (0.0007) | (0.0006) | (0.0006) | (0.0007) | (0.0007) | (0.0005) | (0.0005) | (0.0011) | (0.0011) |
| MSOA Population Density | -0.0034*** | -0.0028*** | -0.0009 | -0.0007 | -0.0008 | -0.0005 | -0.0009* | -0.0006 | -0.0079*** | -0.0079*** |
| | (0.0007) | (0.0007) | (0.0006) | (0.0006) | (0.0007) | (0.0007) | (0.0005) | (0.0005) | (0.0011) | (0.0011) |
| Constant | 0.8031*** | 0.6934*** | 0.4661*** | 0.5065*** | 0.6813*** | 0.6175*** | 0.5604*** | 0.5442*** | 0.8478*** | 0.8648*** |
| | (0.1091) | (0.0845) | (0.0737) | (0.0675) | (0.1099) | (0.0800) | (0.0715) | (0.0579) | (0.1657) | (0.1456) |
| Individual Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| LA Fixed Effects | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No |
| Individual Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Area Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Individuals | 33,963 | 33,963 | 56,964 | 56,964 | 50,660 | 50,660 | 50,651 | 50,651 | 46,009 | 46,009 |
| No. of Observations | 63,641 | 63,641 | 252,384 | 252,384 | 221,215 | 221,215 | 221,160 | 221,160 | 91,246 | 91,246 |
| Overall $R^2$ | 0.0136 | 0.0274 | 0.0278 | 0.0461 | 0.0075 | 0.0081 | 0.0094 | 0.0116 | 0.0690 | 0.0887 |

Robust standard errors calculated. Standard Errors in parentheses
Individual Characteristics include Marital Status, Age, and Age$^2$
Area Characteristics include LA Population Density, MSOA Population Density, Local Authority Expenditure per person, and a London Dummy
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## Table 4.5: Association Between Individual/Spatial Prosperity and Well-Being in Local Authorities

| | Well-Being Index/Domain | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Finance & Work | | Leisure Time | | House Size | | Social Life | | Participation & Voice | |
| | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) |
| **Personal Income** | | | | | | | | | | |
| Household Income | 0.0173*** | 0.0173*** | -0.0046*** | -0.0047*** | 0.0003* | 0.0002 | 0.0011 | 0.0011 | 0.0015*** | 0.0013** |
| (£1000 increase in) | (0.0037) | (0.0037) | (0.0005) | (0.0005) | (0.0002) | (0.0002) | (0.0008) | (0.0008) | (0.0006) | (0.0006) |
| **LA Prosperity** | | | | | | | | | | |
| Median Wage (10 % from Mean) | 0.0010 | 0.0030** | 0.0001 | -0.0012 | -0.0003 | -0.0009 | 0.0100*** | 0.0067*** | -0.0002 | -0.0001 |
| | (0.0016) | (0.0014) | (0.0018) | (0.0015) | (0.0013) | (0.0011) | (0.0029) | (0.0022) | (0.0032) | (0.0025) |
| Spatially Lagged Median Wage | -0.0048 | -0.0013 | -0.0120** | -0.0136*** | 0.0028 | 0.0046 | 0.0270*** | -0.0023 | 0.0106 | 0.0008 |
| | (0.0048) | (0.0036) | (0.0052) | (0.0036) | (0.0034) | (0.0037) | (0.0079) | (0.0049) | (0.0086) | (0.0054) |
| **MSOA Prosperity** | | | | | | | | | | |
| Means-tests Social Security | 0.0047 | 0.0045 | 0.0014 | 0.0018 | -0.0047 | -0.0062* | 0.0040 | 0.0027 | 0.0076 | 0.0060 |
| Payment Rate (1 % point decline) | (0.0029) | (0.0029) | (0.0029) | (0.0029) | (0.0031) | (0.0032) | (0.0043) | (0.0042) | (0.0048) | (0.0046) |
| Spatially Lagged Means-Tested | 0.0008 | 0.0049 | 0.0047 | 0.0035 | -0.0099 | -0.0119 | 0.0331** | 0.0107 | 0.0121 | 0.0033 |
| Social Security Rate | (0.0078) | (0.0070) | (0.0084) | (0.0075) | (0.0070) | (0.0079) | (0.0144) | (0.0122) | (0.0170) | (0.0142) |
| **Area Characteristics** | | | | | | | | | | |
| London Dummy | -0.1440* | 0.0006 | -0.0835 | -0.0064 | 0.0050 | 0.1173 | -0.1528 | -0.0253 | 0.1365 | -0.0188 |
| | (0.0825) | (0.0135) | (0.1216) | (0.0128) | (0.0178) | (0.1779) | (0.1335) | (0.0160) | (0.1507) | (0.0191) |
| LA Population Density | 0.0155*** | 0.0048*** | 0.0133** | 0.0038*** | -0.0076*** | -0.0088 | 0.0012 | 0.0041** | -0.0183** | 0.0012 |
| | (0.0057) | (0.0015) | (0.0062) | (0.0015) | (0.0022) | (0.0073) | (0.0084) | (0.0019) | (0.0089) | (0.0024) |
| MSOA Population Density | 0.0007 | 0.0005 | -0.0016* | -0.0009 | -0.0026** | -0.0028** | 0.0002 | -0.0002 | -0.0005 | 0.0009 |
| | (0.0009) | (0.0008) | (0.0008) | (0.0008) | (0.0012) | (0.0012) | (0.0012) | (0.0011) | (0.0013) | (0.0012) |
| Constant | 0.0730 | 0.0057 | 0.7424*** | 0.7299*** | 0.8729*** | 0.8238*** | 0.8924*** | 0.8511*** | 0.4508** | 0.3203 |
| | (0.1604) | (0.1560) | (0.1328) | (0.0948) | (0.0572) | (0.0861) | (0.2082) | (0.1852) | (0.2262) | (0.2055) |
| Individual Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| LA Fixed Effects | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No |
| Individual Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Area Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Individuals | 54,099 | 54,099 50,640 | 50,640.0000 | 50280.0000 | 50280.0000 | 42507.0000 | 42507.0000 | 42085.0000 | 42085.0000 | |
| No. of Observations | 244,116 | 244,116 | 221,157 | 221,157 | 215,540 | 215,540 | 84,228 | 84,228 | 83,347 | 83,347 |
| Overall $R^2$ | 0.0049 | 0.0056 | 0.0424 | 0.0686 | 0.1049 | 0.0316 | 0.0001 | 0.0004 | 0.0013 | 0.0023 |

Robust standard errors calculated. Standard Errors in parentheses

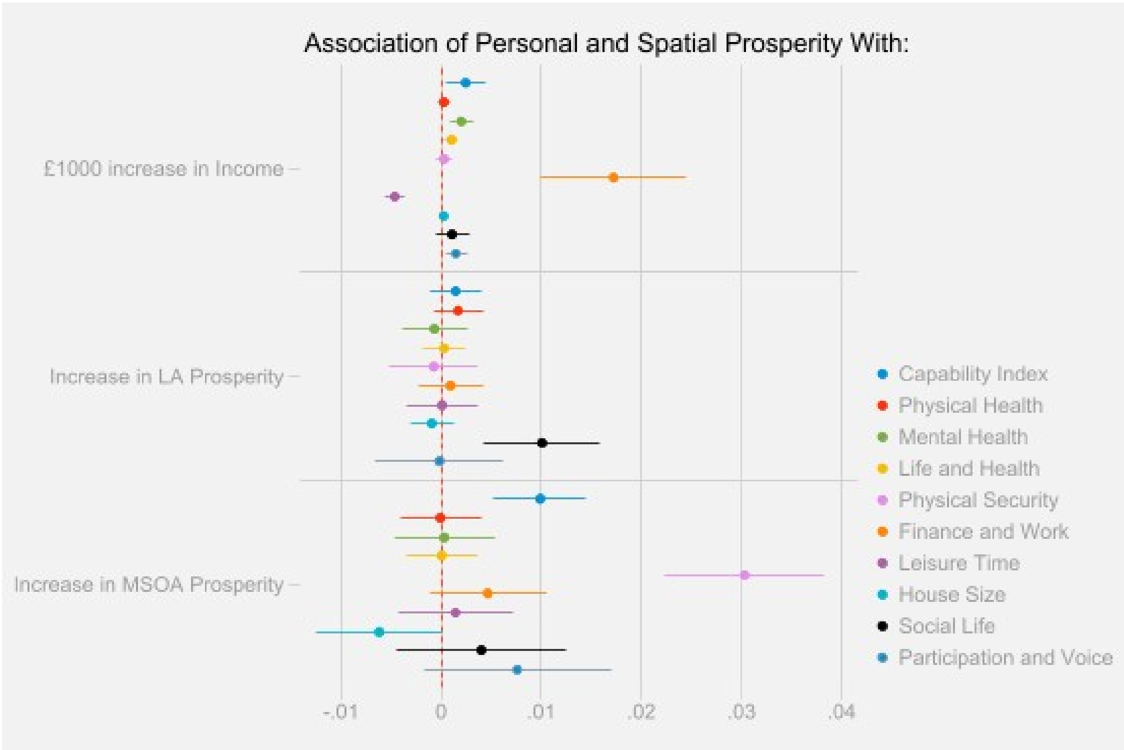
Individual Characteristics include Marital Status, Age, and Age$^2$

Area Characteristics include LA Population Density, MSOA Population Density, Local Authority Expenditure per person, and a London Dummy

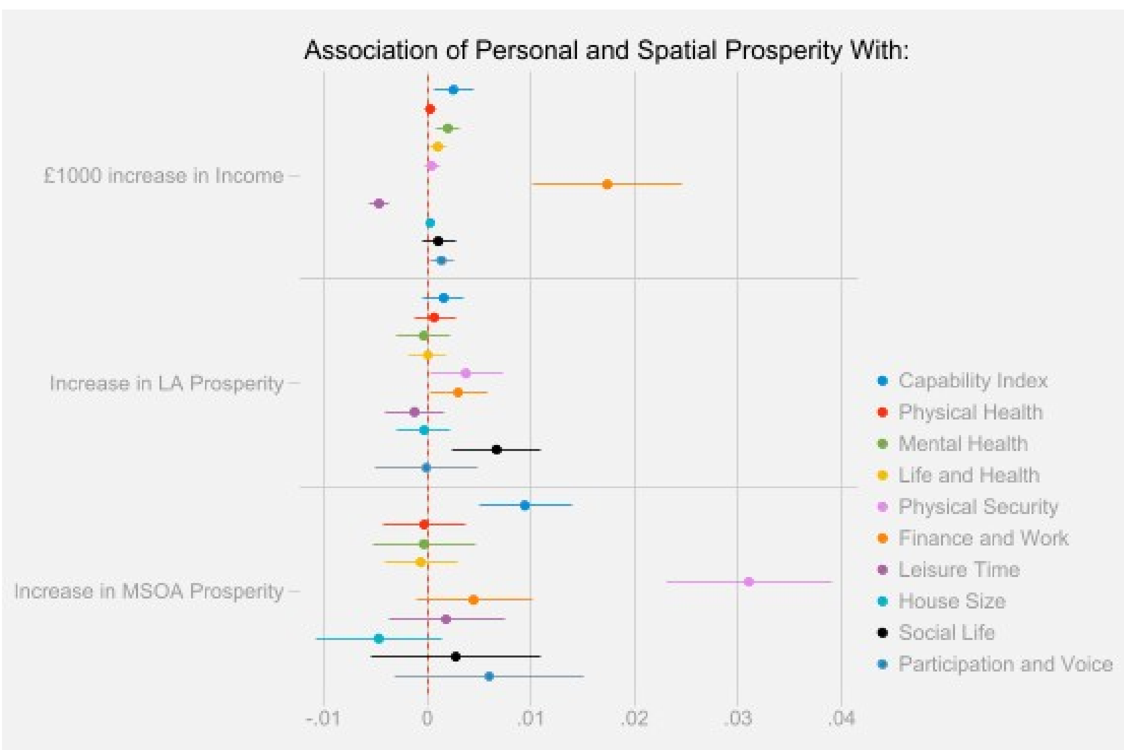
$^*p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Figure 4.5: Association of Household Income and Spatial Prosperity with Well-being with and Without Fixed Effects**

(a) With Fixed Effects




(b) No Fixed Effects



### 4.10.2 Places and the Less-Skilled

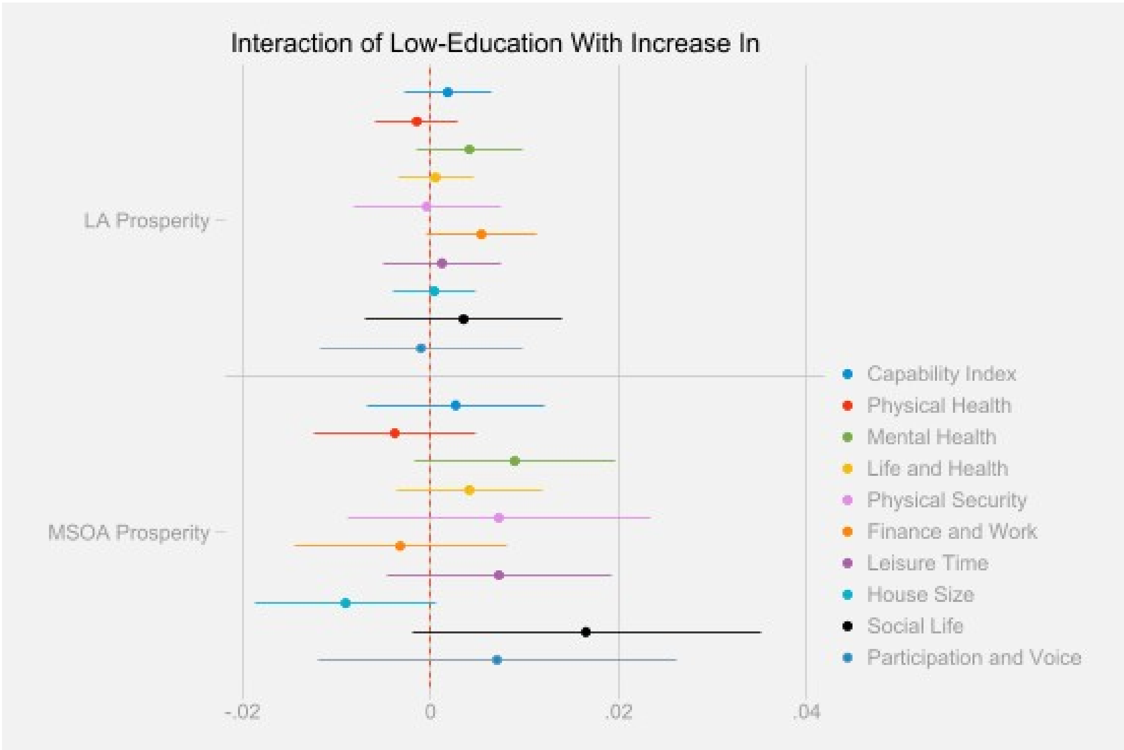
Equation 4.2 is estimated to measure the association between household income, spatial prosperity, and education. The Low Education Dummy indicates whether an individual has less than an A-Level Education. The interactions between spatial prosperity and the Low Education Dummy are the key variables that show whether the impact of places differs for the low-educated compared to everyone else. A Graduate Dummy is also included. I restrict the sample to those who are over 24 years of age to avoid the confounding of effects from gaining a degree.

$$\begin{aligned}
\text{Well-Being}_{i,t} = {} & a_i + c_t + \text{Equivalised Household Income}_{i,t} + \text{LA Prosperity}_{j,t} + \\
& \text{Spatially Lagged LA Prosperity}_{j,t} + \text{MSOA Prosperity}_{j,t} + \\
& \text{Spatially Lagged MSOA Prosperity}_{j,t} + \\
& + (\text{Low Ed Dummy}_{i,t} \times \text{LA Prosperity}_{j,t}) + (\text{Low Ed Dummy}_{i,t} \times \text{MSOA Prosperity}_{j,t}) \\
& + (\text{Low Ed Dummy}_{i,t} \times \text{Spatially Lagged LA Prosperity}_{j,t}) \\
& + (\text{Low Ed Dummy}_{i,t} \times \text{Spatially Lagged MSOA Prosperity}_{j,t}) \\
& + \text{Low Ed Dummy} + \text{Grad Dummy} \\
& + \text{Individual Characteristics}_{i,t} + \text{Area Characteristics}_{j,t} + \epsilon_{i,t}
\end{aligned} \tag{4.2}$$

There is little support for Hypothesis 2 with spatial prosperity appearing to have no direct extra benefit for the less-educated. Almost none of the interaction terms are significant with the somewhat notable exception of Finance & Work in more prosperous local authorities, which is marginally significant. This is surprising, given that less-educated people have fewer financial and emotional resources to shield themselves from negative place effects (Sharkey and Faber 2014). It is particularly surprising that there is a lack of place-based effects for health outcomes, given that deaths of despair are concentrated within the less educated group as well as the consistent finding that neighbourhoods have an impact on health outcomes (Case and Deaton 2020; Jivraj et al. 2020).

**Figure 4.6: Association of Spatial Prosperity with Well-being for the Less-Skilled in Local Authorities and MSOAs**

(a) Fixed Effects




(b) Without Fixed Effects

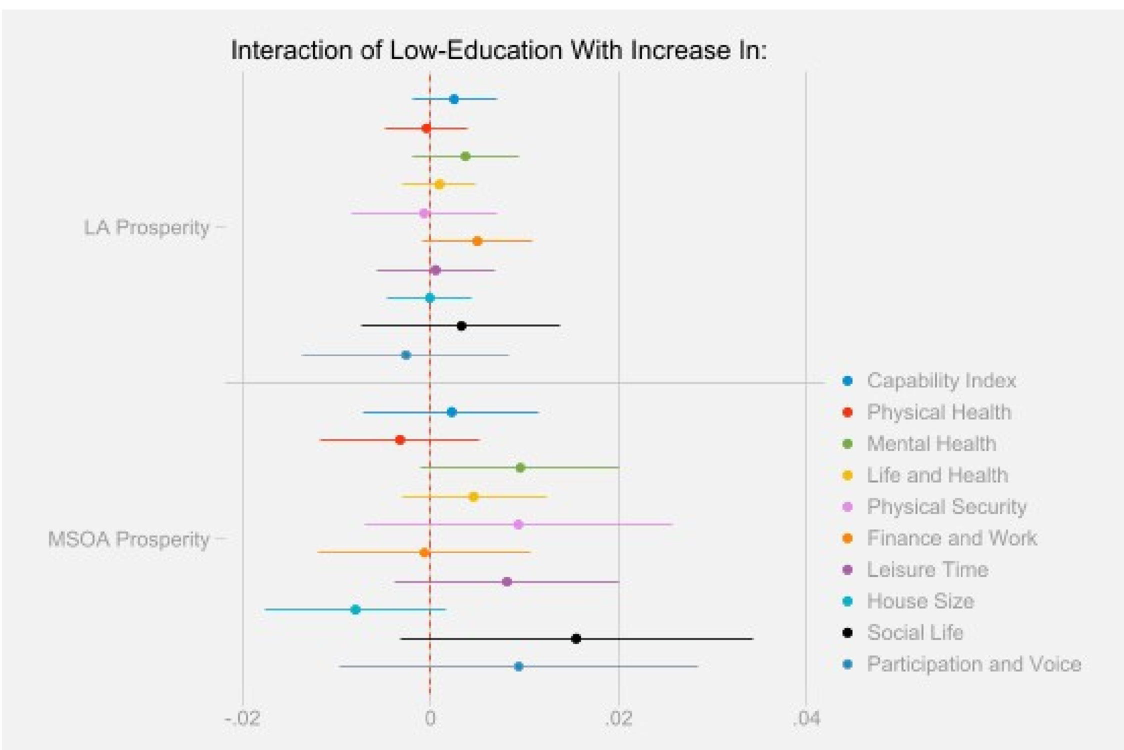



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**Table 4.6: Association Between Individual/Spatial Prosperity and Well-Being by Education Status in Local Authorities**

| | Well-Being Index/Domain | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Capability Index | | Physical Health | | Mental Health | | Life & Health | | Physical Security | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| **Personal Income** | | | | | | | | | | |
| Household Income | 0.0023** | 0.0023** | 0.0004 | 0.0004 | 0.0019*** | 0.0019*** | 0.0010*** | 0.0010*** | 0.0003 | 0.0004 |
| (£000's) | (0.0009) | (0.0009) | (0.0003) | (0.0003) | (0.0006) | (0.0006) | (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| **LA Prosperity** | | | | | | | | | | |
| Median Wage Difference | 0.0011 | 0.0012 | 0.0019 | 0.0006 | -0.0010 | -0.0006 | 0.0007 | 0.0002 | -0.0001 | 0.0036 |
| | (0.0015) | (0.0012) | (0.0016) | (0.0013) | (0.0020) | (0.0016) | (0.0014) | (0.0012) | (0.0027) | (0.0022) |
| Spatial Lag | 0.0070* | -0.0023 | -0.0071 | -0.0077** | -0.0106** | -0.0069* | -0.0087** | -0.0071** | -0.0203*** | -0.0177*** |
| Wage Difference | (0.0042) | (0.0030) | (0.0046) | (0.0034) | (0.0053) | (0.0038) | (0.0039) | (0.0029) | (0.0074) | (0.0050) |
| **MSOA Prosperity** | | | | | | | | | | |
| Claimant Rate Difference | 0.0081*** | 0.0068** | -0.0001 | -0.0007 | -0.0035 | -0.0042 | -0.0023 | -0.0030 | 0.0252*** | 0.0268*** |
| | (0.0029) | (0.0027) | (0.0028) | (0.0028) | (0.0034) | (0.0034) | (0.0025) | (0.0024) | (0.0052) | (0.0053) |
| Spatial Lag | -0.0032 | -0.0024 | -0.0096 | -0.0065 | 0.0103 | 0.0134* | 0.0018 | 0.0052 | -0.0087 | -0.0005 |
| | (0.0088) | (0.0074) | (0.0075) | (0.0066) | (0.0090) | (0.0080) | (0.0066) | (0.0058) | (0.0161) | (0.0138) |
| **LA Education Interaction** | | | | | | | | | | |
| Low-Ed Dummy × | 0.0018 | 0.0025 | -0.0014 | -0.0004 | 0.0041 | 0.0037 | 0.0005 | 0.0009 | -0.0004 | -0.0007 |
| Median Wage Difference | (0.0023) | (0.0023) | (0.0022) | (0.0023) | (0.0029) | (0.0029) | (0.0020) | (0.0020) | (0.0040) | (0.0039) |
| **MSOA Education Interaction** | | | | | | | | | | |
| Low-Ed Dummy × | 0.0027 | 0.0022 | -0.0038 | -0.0033 | 0.0089 | 0.0095* | 0.0041 | 0.0046 | 0.0073 | 0.0093 |
| Claimant Rate Difference | (0.0048) | (0.0048) | (0.0044) | (0.0044) | (0.0054) | (0.0054) | (0.0039) | (0.0039) | (0.0082) | (0.0083) |
| **Education** | | | | | | | | | | |
| Low-Education Dummy | 0.0045 | 0.0024 | -0.0145* | -0.0140* | 0.0010 | -0.0004 | -0.0086 | -0.0091 | 0.0044 | 0.0041 |
| | (0.0073) | (0.0073) | (0.0077) | (0.0077) | (0.0097) | (0.0097) | (0.0073) | (0.0072) | (0.0127) | (0.0127) |
| Graduate Dummy | 0.0160* | 0.0141 | -0.0069 | -0.0076 | 0.0046 | 0.0011 | 0.0003 | -0.0019 | 0.0008 | 0.0041 |
| | (0.0086) | (0.0089) | (0.0086) | (0.0087) | (0.0106) | (0.0106) | (0.0076) | (0.0076) | (0.0148) | (0.0146) |
| Constant | 0.9213*** | 0.7501*** | 0.4351*** | 0.4410*** | 0.6821*** | 0.5095*** | 0.5574*** | 0.4637*** | 0.8801*** | 0.7675*** |
| | (0.1165) | (0.0934) | (0.0986) | (0.0927) | (0.1381) | (0.1187) | (0.0897) | (0.0810) | (0.1843) | (0.1667) |
| Individual Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| LA Fixed Effects | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No |
| Individual Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Area Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Individuals | 29,480 | 29,480 | 45,717 | 45,717 | 41,239 | 41,239 | 41,231 | 41,231 | 38,198 | 38,198 |
| No. of Observations | 57,069 | 57,069 | 215,032 | 215,032 | 190,794 | 190,794 | 190,747 | 190,747 | 78,503 | 78,503 |
| Overall $R^2$ | 0.0137 | 0.0538 | 0.0258 | 0.0392 | 0.0128 | 0.0153 | 0.0029 | 0.0040 | 0.0535 | 0.0700 |

Robust standard errors calculated. Standard Errors in parentheses

Individual Characteristics include Marital Status, Age, and Age$^2$

Area Characteristics include LA Population Density, MSOA Population Density, LA Expenditure per person, and a London Dummy

$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

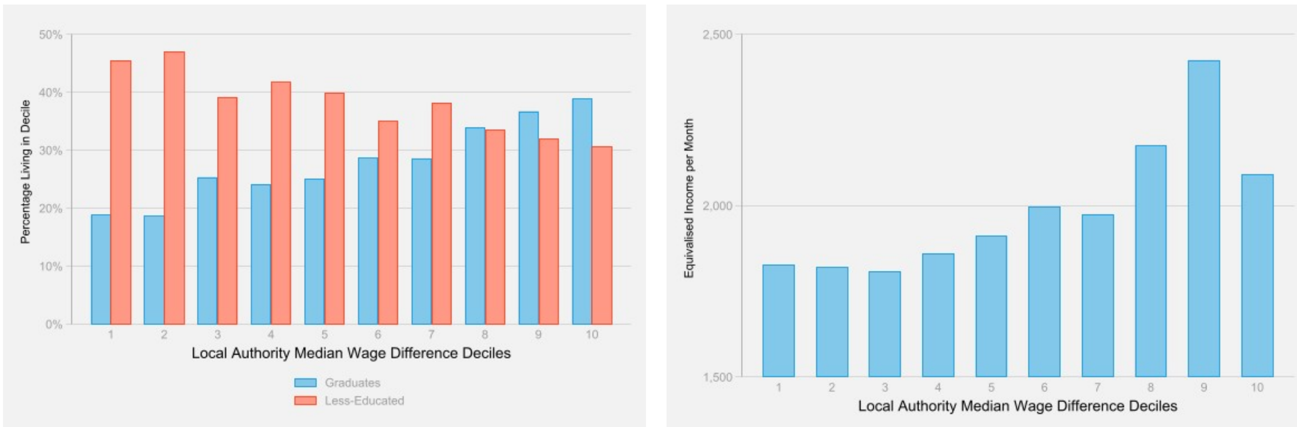
## Table 4.7: Association Between Individual/Spatial Prosperity and Well-Being by Education Status

| | Well-Being Index/Domain | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Finance & Work | | Leisure Time | | House Size | | Social Life | | Participation & Voice | |
| | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) |
| Household Income | 0.0156*** | 0.0156*** | -0.0047*** | -0.0047*** | 0.0003 | 0.0003 | 0.0011 | 0.0011 | 0.0017*** | 0.0016*** |
| (£000's) | (0.0036) | (0.0036) | (0.0005) | (0.0005) | (0.0002) | (0.0002) | (0.0009) | (0.0009) | (0.0006) | (0.0006) |
| **LA Prosperity** | | | | | | | | | | |
| Median Wage Difference | -0.0023 | 0.0005 | 0.0014 | -0.0000 | -0.0010 | -0.0008 | 0.0081** | 0.0060** | 0.0005 | 0.0013 |
| | (0.0020) | (0.0016) | (0.0022) | (0.0019) | (0.0016) | (0.0014) | (0.0034) | (0.0026) | (0.0039) | (0.0030) |
| Spatial Lag | 0.0001 | 0.0001 | -0.0093 | -0.0141*** | -0.0039 | -0.0001 | 0.0384*** | 0.0066 | 0.0150 | 0.0051 |
| Wage Difference | (0.0054) | (0.0042) | (0.0061) | (0.0045) | (0.0032) | (0.0038) | (0.0089) | (0.0062) | (0.0098) | (0.0066) |
| **MSOA Prosperity** | | | | | | | | | | |
| Claimant Rate Difference | 0.0075** | 0.0053 | -0.0064* | -0.0067* | -0.0036 | -0.0038 | 0.0007 | -0.0015 | 0.0038 | -0.0001 |
| | (0.0038) | (0.0036) | (0.0039) | (0.0038) | (0.0033) | (0.0035) | (0.0054) | (0.0053) | (0.0062) | (0.0060) |
| Spatial Lag | -0.0146 | -0.0055 | 0.0077 | 0.0075 | -0.0058 | -0.0090 | 0.0291 | 0.0064 | 0.0207 | 0.0190 |
| | (0.0094) | (0.0085) | (0.0101) | (0.0092) | (0.0072) | (0.0084) | (0.0178) | (0.0150) | (0.0202) | (0.0170) |
| **LA Education Interaction** | | | | | | | | | | |
| Low-Ed Dummy × | 0.0054* | 0.0050* | 0.0012 | 0.0005 | -0.0001 | 0.0004 | 0.0035 | 0.0033 | -0.0010 | -0.0026 |
| Median Wage Difference | (0.0030) | (0.0030) | (0.0032) | (0.0032) | (0.0023) | (0.0022) | (0.0053) | (0.0054) | (0.0055) | (0.0056) |
| **MSOA Education Interaction** | | | | | | | | | | |
| Low-Ed Dummy × | -0.0032 | -0.0006 | 0.0073 | 0.0081 | -0.0080 | -0.0090* | 0.0165* | 0.0155 | 0.0071 | 0.0094 |
| | (0.0058) | (0.0058) | (0.0060) | (0.0061) | (0.0049) | (0.0049) | (0.0095) | (0.0095) | (0.0098) | (0.0097) |
| **Education** | | | | | | | | | | |
| Low-Education Dummy | -0.0236** | -0.0264** | 0.0081 | 0.0074 | 0.0034 | 0.0035 | 0.0214 | 0.0196 | -0.0283 | -0.0314* |
| | (0.0103) | (0.0103) | (0.0108) | (0.0108) | (0.0069) | (0.0068) | (0.0162) | (0.0160) | (0.0178) | (0.0177) |
| Graduate Dummy | 0.0810*** | 0.0789*** | -0.0166 | -0.0185 | 0.0149** | 0.0156** | 0.0139 | 0.0098 | 0.0236 | 0.0224 |
| | (0.0130) | (0.0129) | (0.0129) | (0.0129) | (0.0074) | (0.0073) | (0.0172) | (0.0177) | (0.0199) | (0.0199) |
| Constant | 0.0447 | -0.0160 | 0.8868*** | 0.7319*** | 0.9863*** | 0.8865*** | 0.8925*** | 0.7739*** | 0.5497** | 0.3706 |
| | (0.1223) | (0.1158) | (0.1770) | (0.1341) | (0.0705) | (0.1231) | (0.2282) | (0.2150) | (0.2475) | (0.2334) |
| Individual Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | |
| LA Fixed Effects | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No |
| Individual Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Area Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Individuals | 43,605 | 43,605 | 41,217 | 41,217 | 41,467 | 41,467 | 35,571 | 35,571 | 35,396 | 35,396 |
| No. of Observations | 209,420 | 209,420 | 190,728 | 190,728 | 189,207 | 189,207 | 73,111 | 73,111 | 72,689 | 72,689 |
| Overall $R^2$ | 0.0003 | 0.0003 | 0.0035 | 0.0069 | 0.0361 | 0.0111 | 0.0001 | 0.0002 | 0.0000 | 0.0002 |

Individual Characteristics include Marital Status, Age, and Age$^2$
Area Characteristics include LA Population Density, MSOA Population Density, LA Expenditure per person, and a London Dummy
$^*p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Figure 4.7: Education and Local Authority Prosperity**

(a) Percentage of Graduates/Less Educated in Places (b) Average Monthly Income for Less-Educated in Places




However, places do still have an indirect impact on well-being domains for the less-educated through their impact on potential incomes. Personal income is still positively associated with most domains of well-being. As discussed above (and described below), the less-educated are less likely to move. They are also less likely to live in more prosperous places than graduates (Figure 4.7a), and when they do live in more prosperous places, their personal incomes are higher (Figure 4.7b). As less-educated workers are less able to move to more prosperous places, this suggests that more prosperous places have an indirect impact on their well-being outcomes by increasing their personal incomes (Moretti 2013; Amior 2015). The specification used in this section cannot account for these kinds of selection effects - that people may live in more prosperous areas based upon unobserved characteristics. It is to this which I now turn.

## 4.11 MOVERS

Spatial prosperity has a significant association with some aspects of well-being, these effects are sometimes more pronounced for those with less education, and differ between the local labour market and neighbourhood spatial scales. However, it is difficult to assess the effect of places using these specifications. There is likely to be selection effects in where people have chosen to live - namely, they may have unobserved characteristics that leads them to live in more prosperous places, confounding the point estimates above. Fixed effects specifications do help to control for some of these effects when they are invariant over time.

Here I go further to correct for this selection effect and analyse whether moving to a more prosperous area is associated with subsequent changes in well-being outcomes. There is a selection bias present here too, as those who choose to move are substantially different from those who do not. It is difficult to overcome this selection bias completely as we cannot randomly assign and then enforce moves for different families. Even the impressive literature that uses experimental housing vouchers as a form of random assignment suffers from this selection bias - only 40 - 48% of those offered vouchers in the Moving to Opportunity program actually moved and movers are significantly different from non-movers (Chetty et al. 2016; Chetty and Hendren 2018a; Leventhal and Dupéré 2019; Gallagher et al. 2019). One advantage of the specification used here is that it considers everyone who moves rather than just those on low incomes who are offered housing vouchers.

Movers are subject to a selection bias in the Understanding Society data - 31% of movers are graduates compared to 20% of the sample. Data limitations do not permit an examination of common trends prior to moves. In order to help attenuate this selection bias, I control for household income, age, and education status (that would allow individuals to move). Individual fixed effects (that account for time invariant characteristics such as ability) are used. As before, results are shown with and without local authority fixed effects.

I also estimate equation (5) below for quasi-exogenous movers - those who moved because the council offered them alternative accommodation or because their employer moved location. While this is not truly random, it does help to reduce selection bias. The number of cases for these quasi-exogenous moves is, however, low reducing the precision of these estimates - only 0.15% of the sample for MSOAs (528 cases) and .09% of the sample for LAs (214 cases) are quasi-exogenous movers compared to 17,463 in MSOAs (5.0% of the sample) and 6,982 in Local Authorities (2.4% of the sample) that were movers.

I calculate the difference in area prosperity for those move and interact this with a (Quasi-Exogenous) Mover dummy. For those who do not move, the Difference in Area Prosperity and the (Quasi-Exogenous) Mover Dummy is therefore zero and they constitute the comparison group. The estimated equation is shown in 4.3 below. For local authorities, I estimate this with and without fixed effects. For MSOAs, it is not possible to estimate these regressions with place fixed effects due to the low numbers of individuals in each MSOA cell.

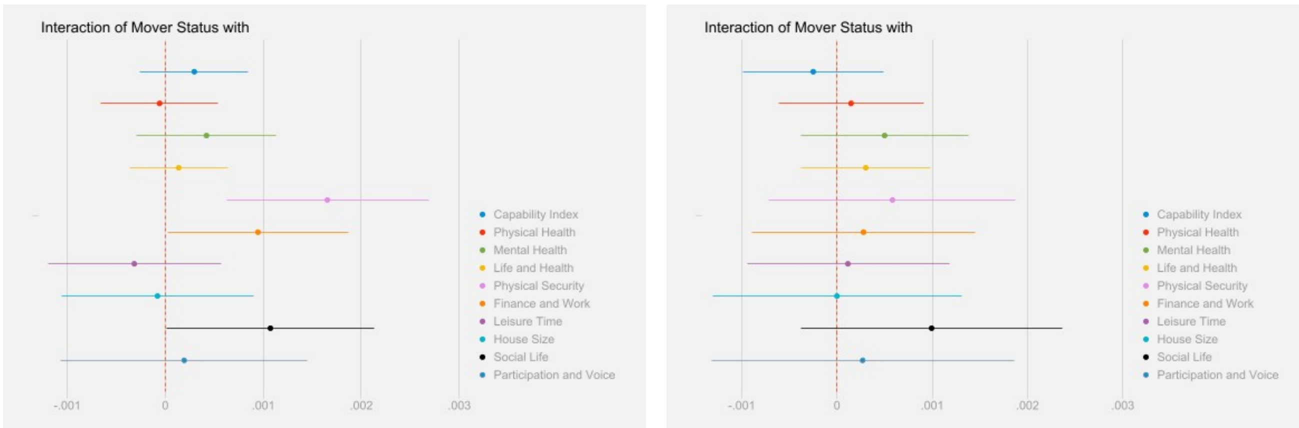
$$\begin{aligned}\text{Well-Being}_{i,t} = a_i + c_t &+ \text{Equivalised Household Income}_{i,t}\\ &+\ \text{Difference in Area Prosperity}_{j,t} \times \text{(Quasi-Exogenous)Mover Dummy}_{i,t}\\ &+ \text{Difference in Spatially Lagged Prosperity Decile}_{j,t} \times \text{(Quasi-Exogenous)Mover Dummy}_{i,t}\\ &+ \text{Individual Characteristics}_{i,t} + \text{Area Characteristics}_{j,t} + \epsilon_{i,t}\end{aligned} \tag{4.3}$$

Figures 4.8 to 4.11 below show the coefficient on the interaction of *Difference in Area Prosperity*$_{j,t}\times$ *(Quasi-Exogenous)Mover Dummy*$_{i,t}$ term. Full regression tables are shown in Appendix Tables 4A.3 to 4A.6 below. I find evidence in support of Hypotheses 1 and 2 from these specifications - moving to more prosperous places has some impact on well-being outcomes and these effects differ between the labour market and neighbourhood spatial scales.

At the local labour market level, moving to a more prosperous area has a positive impact on physical security, financial security and social life but this disappears when controlling for local authority fixed effects. For quasi-exogenous movers, there are no significant impacts.

**Figure 4.8: Impact of Moving to a More Prosperous Area on Well-Being Domains in LAs**

(a) Without LA Fixed Effects (b) With LA Fixed Effects




At the neighbourhood level, moving to a more prosperous area is associated with greater overall well-being as well as greater physical safety. These are the same domains of well-being that are significant in the association regressions, providing support for that specification. For quasi-exogenous movers, mental health and social outcomes improve when moving to more prosperous neighbourhoods, which may indicate the positive impact of social-interactive effects may exist for these domains.

These results provide support for places having an effect on, rather than being associated with, some domains of well-being. The lack of impacts for quasi-exogenous LA mover regressions may simply be an artifact of there being relatively few movers within the Understanding Society data used here.

It may seem surprising that the effect of moving to a more prosperous local authority is not more strongly associated with the Finance and Work domain of well-being. However, this is likely due to these effects being partially absorbed by increases in equivalised income and a greater probability of employment for (quasi-exogenous) movers. People are more likely to move to an area there is a job available, and high-skilled people are the most likely to move toward higher wages. By contrast, non-movers benefit passively when living in an area where there is a stronger labour market - they gain a locational surplus from living in

**Figure 4.9: Impact of Quasi-Exogenous Moves to a More Prosperous Area on Well-Being Domains in LAs**

(a) Without LA Fixed Effects (b) With LA Fixed Effects

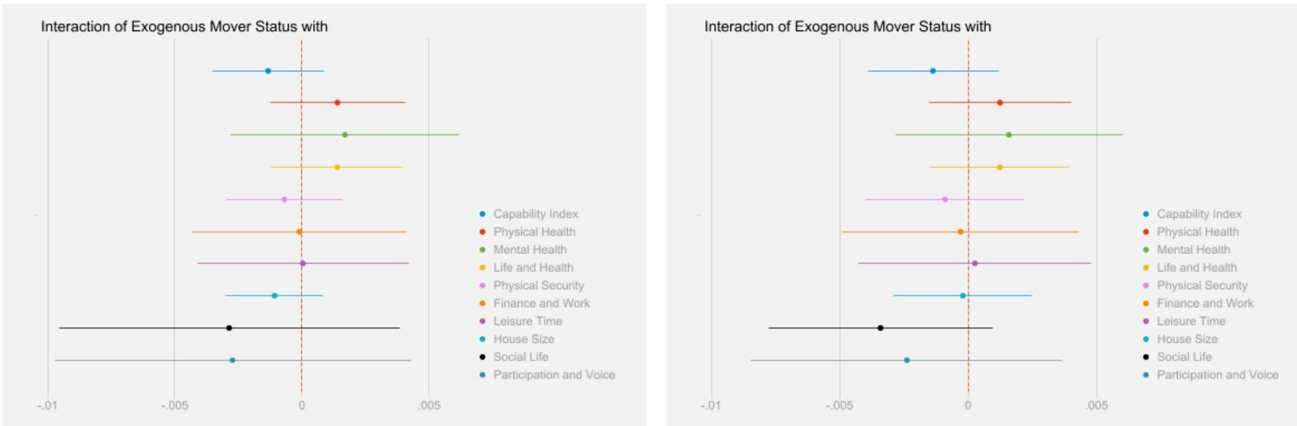



**Figure 4.10: Impact of Moving to a More Prosperous Area on Well-Being Domains in MSOAs**

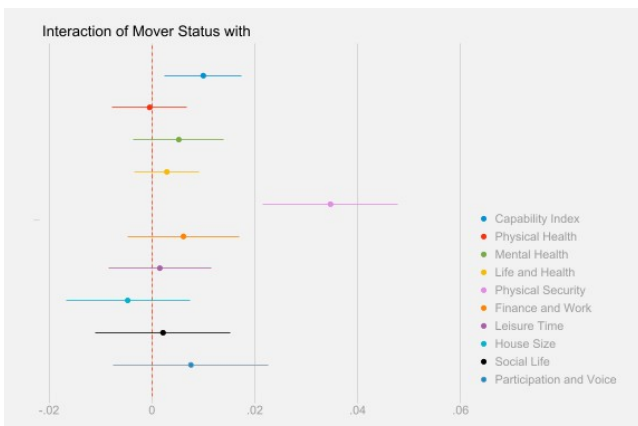
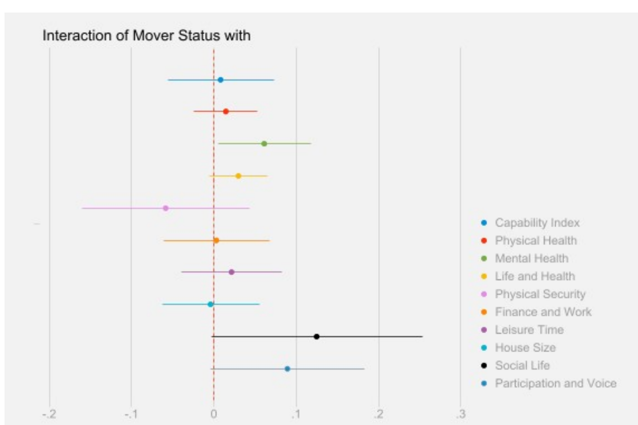



**Figure 4.11: Impact of Quasi-Exogenous Moves to a More Prosperous MSOA**



a more prosperous area.

I test whether movers gain extra income and employment opportunities by estimating equations 4.4 and 4.5 below for those below 60 years of age. I estimate these equations for movers and quasi-exogenous movers (for housing reasons). Including those who moved for employment reasons would somewhat defeat the purpose of trying to assess whether moving to a more prosperous area led to greater employment prospects.

$$\begin{aligned}\text{Household Income}_{i,t} = a_i + c_t +& \\ &\text{Difference in Area Prosperity}_{j,t} \times \text{Mover Dummy}_{i,t} \\ &+ \text{Difference in Spatially Lagged Prosperity Decile}_{j,t} \times \text{Mover Dummy}_{i,t} + \text{age} + \\ &+ \text{Graduate Dummy}_{i,t} + \text{Low Education Dummy}_{i,t} + \\ &\text{Individual Characteristics}_{i,t} + \text{Area Characteristics}_{j,t} + \epsilon_{i,t}\end{aligned} \tag{4.4}$$

$$\begin{aligned}\text{Employment Indicator}_{i,t} = a_i + c_t +& \\ &\text{Difference in Area Prosperity}_{j,t} \times \text{Mover Dummy}_{i,t} \\ &+ \text{Difference in Spatially Lagged Prosperity Decile}_{j,t} \times \text{Mover Dummy}_{i,t} + \\ &\text{age} + \text{Graduate Dummy}_{i,t} + \text{Low Education Dummy}_{i,t} + \\ &\text{Individual Characteristics}_{i,t} + \text{Area Characteristics}_{j,t} + \epsilon_{i,t}\end{aligned} \tag{4.5}$$

Moving to more prosperous local authorities has a significant positive effect on employment and a weaker effect on income as shown in Table 4.7 below. For quasi-exogenous movers for housing related (and not employment reasons) to a more prosperous area leads to a greater probability of employment. In line with other findings in the literature, moving to an area with stronger labour markets leads to higher potential incomes, which would then help to increase well-being (Deryugina et al. 2018; Chyn and Katz 2021). These results do not hold at the neighbourhood/MSOA level, which again indicates that this is not a suitable measure for labour markets as shown (Table 4.8).

**Table 4.8: Impact of Moving on Education and Employment Incomes in Local Authorities**

| | Movers | | Quasi-Exogenous Movers (Housing) | |
|---|---|---|---|---|
| | Household Income | Employment | Household Income | Employment |
| | (1) | (2) | (3) | (4) |
| **Mover Interactions** | | | | |
| Mover Flag × | 0.0056* | 0.0023*** | | |
| Median Wage Difference | (0.0033) | (0.0007) | | |
| Mover Flag × | 0.0014 | 0.0006 | | |
| Spatial Lag Median Wage | (0.0060) | (0.0015) | | |
| **Quasi-Mover Interactions** | | | | |
| Quasi-Exogenous Mover Flag × | | | -0.0363 | 0.0373* |
| Median Wage Difference | | | (0.0413) | (0.0224) |
| Quasi-Exogenous Mover Flag × | | | 0.0585 | -0.0167 |
| Spatial Lag Median Wage | | | (0.0400) | (0.0159) |
| **Mover Dummies** | | | | |
| Mover Flag | -0.220*** | -0.0404*** | | |
| | (0.0299) | (0.0079) | | |
| Quasi-Mover Flag | | | 0.186 | -0.335** |
| | | | (0.376) | (0.170) |
| Individual Fixed Effects | Yes | Yes | Yes | Yes |
| LA Fixed Effects | No | No | No | No |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Individual Characteristics | Yes | Yes | Yes | Yes |
| Area Characteristics | Yes | Yes | Yes | Yes |
| Education Controls | Yes | Yes | Yes | Yes |
| No. of Individuals | 45998 | 46220 | 47970 | 48171 |
| No. of Observations | 197295 | 198937 | 205579 | 207326 |
| Overall $R^2$ | 197295 | 198937 | 205579 | 207326 |

Robust standard errors calculated. Standard Errors in parentheses
Individual Characteristics include Marital Status, Age, Age$^2$, $GraduateDummy$
Area Characteristics include LA Population Density,
MSOA Population Density Local Authority Expenditure per person, and a London Dummy
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## Table 4.9: Impact of Moving on Education and Employment Incomes in MSOAs

| | Movers | | Quasi-Exogenous Movers (Housing) | |
|---|---|---|---|---|
| | Household Income | Employment | Household Income | Employment |
| | (1) | (2) | (3) | (4) |
| **Mover Interactions** | | | | |
| Mover Flag × | -0.0338 | 0.0124 | | |
| Claimant Difference | (0.0407) | (0.0086) | | |
| Mover Flag × | -0.0102 | 0.0259 | | |
| Lagged Claimant Difference | (0.129) | (0.0261) | | |
| **Quasi-Mover Interactions** | | | | |
| Quasi-Exogenous Mover Flag × | | | -0.179 | -0.0852 |
| Claimant Difference | | | (0.249) | (0.0663) |
| Quasi-Exogenous Mover Flag × | | | 0.417 | 0.215* |
| Spatial Lag Claimant Difference | | | (0.727) | (0.116) |
| **Mover Dummies** | | | | |
| Mover Flag | -0.158*** | -0.0279*** | | |
| | (0.0241) | (0.00583) | | |
| Quasi-Mover Flag | | | 0.252** | 0.0296 |
| | | | (0.125) | (0.0440) |
| Individual Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Individual Controls | Yes | Yes | Yes | Yes |
| Education Controls | Yes | Yes | Yes | Yes |
| Population Density Controls | Yes | Yes | Yes | Yes |
| No. of Individuals | 44,803 | 45,002 | 44,803 | 45,002 |
| No. of Observations | 187,218 | 188,900 | 187,218 | 188,900 |
| Overall $R^2$ | 0.0805 | 0.0846 | 0.0861 | 0.0881 |

Robust standard errors calculated. Standard Errors in parentheses
Individual Characteristics include Marital Status, Age, Age$^2$, $GraduateDummy$
Area Characteristics include LA Population Density,
MSOA Population Density Local Authority Expenditure per person, and a London Dummy
$^*p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## 4.12 LIVING TIME

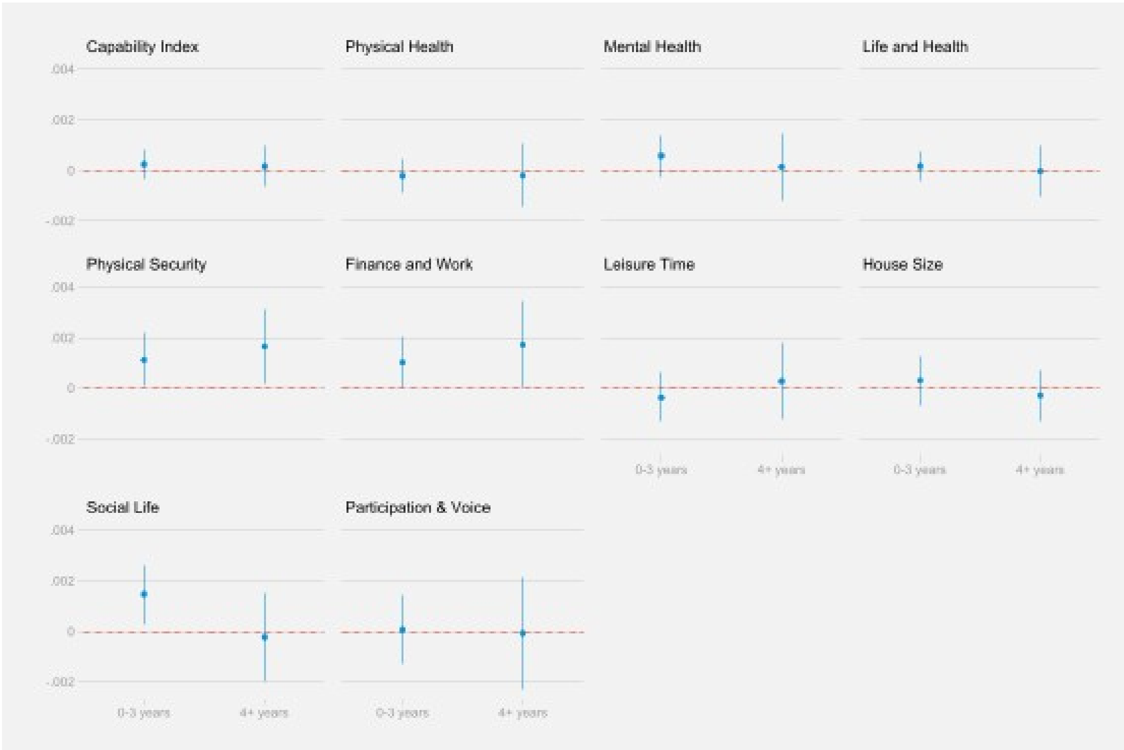
I estimate equation (4.6) below to analyse whether the length of time after moving to an area has a significant impact on well-being outcomes. The Living Time Category consists of 0 - 3 years, and 4 years plus, with the reference category being the year before moves, as well as never movers. The Living Time categories are selected so that each variable is measured at least once in each category. Selection bias may be present as not all domains of well-being are measured in all years. I restrict the sample to those who remain in the study in every between 2010 and 2017 to help attenuate attrition bias. The coefficient on the interaction between local prosperity and living time are shown graphically below.

$$\begin{aligned}
\text{Well-Being}_{i,t} = \; & \\
& a_i + c_t + \text{Equivalised Household Income}_{i,t} + \text{Difference in LA Prosperity}_{j,t} \\
& + \text{Difference in Spatially Lagged Area LA Prosperity}_{j,t} \\
& + (\text{Difference in LA Prosperity}_{j,t} \times \text{Living Time Category}_{i,t}) \\
& + (\text{Difference in Spatially Lagged Area LA Prosperity}_{j,t} \times \text{Living Time Category}_{i,t}) \\
& + \text{Difference in MSOA Prosperity}_{j,t} \\
& + \text{Difference in Spatially Lagged Area MSOA Prosperity}_{j,t} \\
& + (\text{Difference in MSOA Prosperity}_{j,t} \times \text{Living Time Category}_{i,t}) \\
& + (\text{Difference in Spatially Lagged Area MSOA Prosperity}_{j,t} \times \text{Living Time Category}_{i,t}) \\
& + \text{Individual Characteristics}_{i,t} + \text{Area Characteristics}_{j,t} + \epsilon_{i,t}
\end{aligned} \tag{4.6}$$

Overall, there is little evidence in support of Hypothesis 3 - places do not generally have a stronger impact on most well-being outcomes over time. However, the effect of local authority prosperity on physical and financial security does increase somewhat over time.

**Figure 4.12: Living Time Categories with Well-Being Domains in Local Authorities and MSOAs**

(a) Local Authorities




(b) MSOAs

## 4.13 DEATH

I estimate a logit regression model to test whether living in a more deprived area is associated with lower life expectancy. Around 0.61% of the sample die in the sample period. This is an underestimate of deaths - around 40% fewer deaths are recorded than would be expected in the general population (even when accounting for population weights). Specifically, it is those living alone who would be least likely to be non-identified after death (Lynn 2011). Deprived communities with lower wages and less-skilled individuals also tend to have lower marriage rates, which has a negative impact on health outcomes and leads to lower life expectancy (Autor et al. 2019). The effects identified here are, therefore, likely to be downwardly biased.

The equation to be estimated is shown below and is similar to the framework in Sullivan and Von Wachter (2009). Education, relationship status, age, and sex are included as controls given their significant impact on mortality rates as are dummy variables for those who are employed when under the age of 60 and those who become non-employed when under 60 (Cubbin et al. 2000; Sullivan and Von Wachter 2009; Olfson et al. 2021). I also include indicators for whether individuals were employed prior to the age of 60 as well as whether they became non-employed before the age of 60. As before, specifications are shown with and without LA fixed effects.

$$\begin{aligned} \ln\left(\frac{p_{i,t}}{1-p_{i,t}}\right) = & a_i + \text{Equivalised Household Income}_{i,t} + \text{Area Prosperity}_{j,t} + \\ & \text{Spatially Lagged Prosperity}_{j,t} + \text{Male Dummy}_{i,t} \\ & \text{Individual Characteristics}_{i,t} + \text{Area Characteristics}_{j,t} + \\ & \text{Employed Under-60}_{i,t} + \text{Lose Employment Under-60}_{i,t} \\ & + \text{Year}_t \end{aligned} \tag{4.7}$$

In support of Hypothesis 4, I find that place-based prosperity does have an effect on mortality. Surprisingly, however, neighbourhood but not local labour market prosperity, has

**Table 4.10: Association Between Place-Based Prosperity and Probability of Death**

| | No Fixed Effects | Fixed Effects |
|---|---|---|
| | (1) | (2) |
| **Personal Income** | | |
| Equivalised Household Income | -0.0896*** | -0.0873*** |
| (£1000 increase in) | (0.0251) | (0.0261) |
| **Area Prosperity** | | |
| Median Wage (10 % from Mean) | 0.00932 | 0.134 |
| | (0.0280) | (0.103) |
| Spatially Lagged Median Wage | -0.0262 | -0.0261 |
| | (0.0485) | (0.276) |
| Claimant Rate (10 % from Mean) | -0.107** | -0.105** |
| | (0.0456) | (0.0496) |
| Spatially Lagged Claimant Rate | -0.0532 | -0.0224 |
| | (0.113) | (0.152) |
| **Individual-level Controls** | | |
| Age | 0.0869*** | 0.0792*** |
| | (0.0168) | (0.0168) |
| $Age^2$ | 0.0001 | 0.0002 |
| | (0.0001) | (0.0001) |
| Male Dummy | 0.609*** | 0.620*** |
| | (0.0580) | (0.0606) |
| Grad Dummy | -0.135 | -0.144 |
| | (0.108) | (0.112) |
| Low Ed Dummy | 0.198*** | 0.213*** |
| | (0.0715) | (0.0738) |
| Relationship Dummy | -0.425*** | -0.407*** |
| | (0.0623) | (0.0658) |
| Employed Under-60 | -0.587*** | -0.601*** |
| | (0.127) | (0.129) |
| Lost Job Under-60 | 0.416* | 0.428* |
| | (0.231) | (0.233) |
| **Area Characteristics** | | |
| LA Population Density | -0.0042 | -0.227 |
| | (0.0229) | (0.309) |
| MSOA Population Density | 0.0236* | 0.0279* |
| | (0.0134) | (0.0157) |
| Constant | -10.49*** | -9.021*** |
| | (0.605) | (1.349) |
| Time Fixed Effects | Yes | Yes |
| LA Fixed Effects | Yes | Yes |
| No. of Observations | 233,286 | 225,937 |
| Pseudo $R^2$ | .22 | .24 |

Robust standard errors calculated. Standard Errors in parentheses
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

a significant impact on death rates (Cubbin et al. 2000). This is in contrast to other findings in the literature that do find that labour market prosperity does have an impact on death rates (Deryugina et al. 2020). This could be due to the underidentification of deaths in the data and/or the inclusion of personal income as a control. I do find that being employed under the age of 60 is negatively related to death rates while becoming non-employed under the age of 60 is positively related to death rates. Local labour market prosperity does, therefore, have an indirect impact on death by increasing the probability of employment and reducing redundancy probabilities.

## 4.14 DISCUSSION AND CONCLUSION

In this chapter, I have shown that places have a differing impact on well-being outcomes at different spatial scales. More prosperous local labour markets improve well-being outcomes associated with having more job opportunities, namely financial security and physical security as well as friendships. Stronger local labour markets also have an indirectly improve other well-being outcomes by increasing personal incomes. Neighbourhoods improve well-being outcomes associated with social-interactive mechanisms, namely physical safety as well as overall well-being.

The major contribution of this chapter is to show that places have a differing impact on a wide range of well-being outcomes at different spatial scales. This is mostly overlooked in the current place effects literature that often treats place as a homogeneous category that has a consistent effect at different spatial scales (e.g. Chetty and Hendren (2018a,b)). Unlike the current literature that does analyse the effect of place at different scales, I also analyse effects at larger labour market and granular neighbourhood scales on a wide range of well-being outcomes and consider the characteristics of the surrounding areas. This is, as far as I am aware, the first piece of work to do this (Propper et al. 2005; Bolster et al. 2007; Andersson and Musterd 2010; Petrović et al. 2020, 2022).

The findings here have one overarching important policy implication - that increasing place prosperity at different spatial scales is important for improving well-being. The more nuanced policy implications are as follows.

Firstly, labour market prosperity has both a direct *and* indirect impact on well-being by providing higher potential incomes. Direct employment creation in deprived areas will help people live better lives across most well-being domains. This benefit will be felt most strongly by the less-educated (men) who have been left behind by technological change and automation (Sandher 2021).

Secondly, more prosperous neighbourhoods have an effect on well-being domains, which is distinct from the strength of their labour market. Improving job opportunities while not reducing neighbourhood deprivation is not sufficient for raising well-being across all domains. Crucially, more prosperous neighbourhoods significantly reduce the probability of death. It is therefore plausible that reducing deaths of despair will require both local labour market and neighbourhood improvement policies.

Finally, personal income tends to have a stronger and more consistent impact on well-being than spatial prosperity. Therefore, measures that increase incomes through, for example, increasing universal social security payments or improving individual productivity through training could help to increase outcomes across a range of well-being domains.

This chapter does suffer from some limitations that could be addressed through future research. Firstly, the estimates here cannot fully account or control for selection bias. I do make an attempt to control for this using individual fixed effects, local authority fixed effects, covariate controls, and the use of quasi-exogenous place assignment. None of these methods are perfect although such selection biases are also present in work using experimental methods such as housing vouchers, albeit to a much lesser degree (Gallagher et al. 2019). It is, however, encouraging that the results here are consistent with work that exploits exogenous moves, which shows that moving to more prosperous areas leads to better labour market outcomes (Deryugina et al. 2018, 2020).

Secondly, other measures of local labour markets and neighbourhoods could be used. I use local authorities as a measure of labour markets due to data availability at this level and control for the differential size of these places using both population density and spatial lags. An added benefit is the availability of other covariates such as urbanicity. Future work may consider spatial scales that are more closely tied to labour market size, even where other place-based data is not available, to assess whether the results found here are robust. Relatedly, I also MSOA as a measure of neighbourhoods (population 7,500) due to data availability. Future work could consider more granular spatial scales, where data is available, to assess whether the results differ from those presented her.

Thirdly, while this work can examine the impact on death, and provides plausible evidence that increasing personal incomes and neighbourhood conditions will improve life expectancy, it cannot examine deaths from alcohol, suicide, and drug overdoses in isolation. Deaths are also undercounted within the Understanding Society Dataset used here. Work that uses administrative data and links health outcomes to geographic identifiers is needed to provide a greater understanding of what *place-based* characteristics are associated with deaths of despair. Previous work has already convincingly linked rising personal income with falling deaths of despair (Dow et al. 2020).

Finally, this work does not examine, in detail, how the place-based labour market and social-interactive mechanisms that affect each well-being outcome operate. A more detailed understanding of these mechanisms, and how they differ for each outcome, would assist in policy design. I leave detailed work on the exact operation of these mechanisms on well-being outcomes to future research.

## 4.15 APPENDIX A: CONSTRUCTION OF CAPABILITY INDEX WELL-BEING DOMAINS

Scores for each domain are as follows:

**Life and Health**

Life and health = (0.5 x Physical Health) + (0.5 x Mental Health)

Physical Health = 1 if General Health = Excellent

Physical Health = 0.75 if General Health = Very Good

Physical Health = 0.5 if General Health = Good

Physical Health = 0.25 if General Health = Fair

Physical Health = 0 if General Health = Poor

Mental Health = 1 if "Satisfaction with Life Overall" = Completely Satisfied

Mental Health = 0.833 if "Satisfaction with Life Overall" = Mostly Satisfied

Mental Health = 0.666 if "Satisfaction with Life Overall" = Somewhat Satisfied

Mental Health = 0.5 if "Satisfaction with Life Overall" = Neither Satisfied nor Dissatisfied

Mental Health = 0.333 if "Satisfaction with Life Overall" = Somewhat Dissatisfied

Mental Health = 0.166 if "Satisfaction with Life Overall" = Mostly Dissatisfied

Mental Health = 0 if "Satisfaction with Life Overall" = Completley Dissatisfied

**Physical Safety**

Physical Safety = 1 if "Extent of People Attacked on Street" = Not at all Common

Physical Safety = 0.66 if "Extent of People Attacked on Street" = Not Very Common

Physical Safety = 0.33 if "Extent of People Attacked on Street" = Fairly Common

Physical Safety = 0 if "Extent of People Attacked on Street" = Very Common

**Financial Security**

EITHER Financial Security = 1 if "Current Subjective Financial Situation" = "Living comfortably"

IF "Current Subjective Financial Situation ≠ "Living comfortably" THEN Financial Security = (0.5 x Employment Flag) + (0.5 x Subjective Financial Situation)

Employment Flag = 1 if "Current Economic Activity" = Paid Employment

Employment Flag = 1 if "Current Economic Activity" = Self Employed

Employment Flag = 0 if "Current Economic Activity" = Not Paid Employment or Self Employed

Financial Situation = 0.5 if Current Subjective Financial Situation = "Doing Alright"

Financial Situation = 0.25 if Current Subjective Financial Situation = "Finding it quite difficult"

Financial Situation = 0.0 if Current Subjective Financial Situation = "Finding it very difficult"

**Comfortable Living Conditions**

Living Conditions = (0.5 x House Size) + (0.5 x Leisure Time)

House Size = 1 if number of bedrooms > number of adults 14 - number of couples

House Size = 0 if number of bedrooms < number of adults 14 - number of couples

Leisure Time = 1 if "Satisfaction with Amount of Leisure Time" = Completely Satisfied

Leisure Time = 0.833 if "Satisfaction with Amount of Leisure Time" = Mostly Satisfied

Leisure Time = 0.666 if "Satisfaction with Amount of Leisure Time" = Somewhat Satisfied

Leisure Time = 0.5 if "Satisfaction with Amount of Leisure Time" = Neither Satisfied nor Dissatisfied

Leisure Time = 0.333 if "Satisfaction with Amount of Leisure Time" = Somewhat Dissatisfied

Leisure Time = 0.166 if "Satisfaction with Amount of Leisure Time" = Mostly Dissatisfied

Leisure Time = 0 if "Satisfaction with Amount of Leisure Time" = Completley Dissatisfied

**Political Participation and Voice**

Participation = 1 if "Don't have a say in what government does" = "Strongly Disagree"

Participation = 0.75 if "Don't have a say in what government does" = " Disagree"

Participation = 0.5 if "Don't have a say in what government does" = "Neither Agree nor Disagree"

Participation = 0.25 if "Don't have a say in what government does" = "Agree"

Participation = 0 if "Don't have a say in what government does" = "Strongly Agree"

**Social Life**

Social life =1 if "How Many Close Friends" =>3

Social life =0.66 if "How Many Close Friends" = 2

Social life =0.33 if "How Many Close Friends" = 1

Social life =0 if "How Many Close Friends" = 0

## 4.16 APPENDIX B: MOVER STATUS REGRESSIONS

**Table 4A.1: Association Between Individual/Spatial Prosperity and Well-Being by Mover Status in Local Authorities with LA Fixed Effects**

| | Well-Being Index/Domain | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Capability Index | Physical Health | Mental Health | Life Health | Physical Security | Finance & Work | Leisure Time | House Size | Social Life | Participation & Voice |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| **Personal Income** | | | | | | | | | | |
| Household Income | 0.0025** | 0.0003 | 0.0020*** | 0.0010*** | 0.0004 | 0.0169*** | -0.0046*** | 0.0003 | 0.0010 | 0.0015*** |
| (£000's) | (0.0010) | (0.0003) | (0.0006) | (0.0004) | (0.0004) | (0.0037) | (0.0005) | (0.0002) | (0.0008) | (0.0006) |
| **Mover Interactions** | | | | | | | | | | |
| Mover Flag × | -0.0002 | 0.0001 | 0.0005 | 0.0003 | 0.0006 | 0.0003 | 0.0001 | 0.0000 | 0.0010 | 0.0003 |
| Median Wage | (0.0004) | (0.0004) | (0.0004) | (0.0003) | (0.0007) | (0.0006) | (0.0005) | (0.0007) | (0.0007) | (0.0008) |
| Mover Flag × | 0.0010* | 0.0009 | 0.0004 | 0.0007 | -0.0001 | -0.0000 | 0.0015* | 0.0002 | -0.0009 | -0.0001 |
| Spatial Lag Wage | (0.0006) | (0.0007) | (0.0008) | (0.0006) | (0.0009) | (0.0009) | (0.0009) | (0.0013) | (0.0010) | (0.0013) |
| **Mover Categories** | | | | | | | | | | |
| Mover Flag | 0.0024 | -0.0031 | 0.0034 | 0.0010 | 0.0039 | -0.0038 | -0.0051 | -0.0000 | -0.0156** | -0.0093 |
| | (0.0036) | (0.0036) | (0.0043) | (0.0031) | (0.0059) | (0.0053) | (0.0050) | (0.0055) | (0.0062) | (0.0076) |
| Constant | 0.8003*** | 0.4225*** | 0.6409*** | 0.5215*** | 0.8543*** | -0.0363 | 0.7552*** | 0.8131*** | 0.8117*** | 0.4452** |
| | (0.1089) | (0.0843) | (0.1270) | (0.0821) | (0.1661) | (0.1097) | (0.1452) | (0.0949) | (0.2041) | (0.2250) |
| Individual Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| LA Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Area Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Individuals | 33,580 | 55,319 | 49,559 | 49,551 | 45,262 | 52,435 | 49,539 | 48,838 | 41,877 | 41,547 |
| No. of Observations | 63,188 | 248,237 | 218,620 | 218,566 | 90,342 | 239,743 | 218,559 | 212,014 | 83,478 | 82,696 |
| Overall $R^2$ | 0.0154 | 0.0482 | 0.0061 | 0.0115 | 0.0572 | 0.0072 | 0.0366 | 0.0452 | 0.0005 | 0.0007 |

Individual Characteristics include Marital Status, Age, Age$^2$, $LowEducationDummy, GraduateDummy$
Area Characteristics include LA Population Density, MSOA Population Density, LA Expenditure per person, and a London Dummy
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 4A.2: Association Between Individual/Spatial Prosperity and Well-Being in Local Authorities without LA Fixed Effects**

| | Well-Being Index/Domain | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Capability Index | Physical Health | Mental Health | Life Health | Physical Security | Finance & Work | Leisure Time | House Size | Social Life | Participation & Voice |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| **Personal Income** | | | | | | | | | | |
| Household Income | 0.0025** | 0.0022** | 0.0003 | 0.0019*** | 0.0010*** | 0.0004 | 0.0170*** | -0.0022*** | 0.0011 | 0.0014** |
| (£000's) | (0.0010) | (0.0009) | (0.0003) | (0.0006) | (0.0004) | (0.0004) | (0.0037) | (0.0003) | (0.0009) | (0.0005) |
| **Mover Interactions** | | | | | | | | | | |
| Mover Flag × | 0.0003 | -0.0001 | 0.0004 | 0.0001 | 0.0017*** | 0.0009** | -0.0003 | -0.0001 | 0.0011** | 0.0002 |
| Median Wage | (0.0003) | (0.0003) | (0.0004) | (0.0003) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0006) |
| Mover Flag × | -0.0003 | 0.0005 | 0.0004 | 0.0005 | -0.0021*** | -0.0003 | 0.0007 | -0.0002 | -0.0026*** | -0.0012 |
| Spatial Lag Wage | (0.0005) | (0.0005) | (0.0007) | (0.0005) | (0.0008) | (0.0008) | (0.0008) | (0.0011) | (0.0008) | (0.0011) |
| **Mover Categories** | | | | | | | | | | |
| Mover Flag | 0.0037 | -0.0008 | 0.0064* | 0.0039 | 0.0029 | -0.0072 | 0.0020 | 0.0019 | -0.0040 | -0.0052 |
| | (0.0031) | (0.0033) | (0.0039) | (0.0028) | (0.0052) | (0.0048) | (0.0046) | (0.0045) | (0.0059) | (0.0067) |
| Constant | 0.7037*** | 0.4441*** | 0.5824*** | 0.5009*** | 0.8755*** | -0.1002 | 0.7254*** | 0.8371*** | 0.8432*** | 0.3476* |
| | (0.0847) | (0.0791) | (0.1009) | (0.0692) | (0.1464) | (0.1035) | (0.1161) | (0.0684) | (0.1860) | (0.2060) |
| Individual Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| LA Fixed Effects | No | No | No | No | No | No | No | No | No | No |
| Individual Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Area Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Individuals | 33,580 | 55,319 | 49,559 | 49,551 | 45,262 | 52,435 | 49,539 | 48,838 | 41,877 | 41,547 |
| No. of Observations | 63,188 | 248,237 | 218,620 | 218,566 | 90,342 | 239,743 | 218,559 | 212,014 | 83,478 | 82,696 |
| Overall $R^2$ | 0.0333 | 0.0598 | 0.0065 | 0.0127 | 0.0652 | 0.0074 | 0.0625 | 0.1244 | 0.0057 | 0.0014 |

Individual Characteristics include Marital Status, Age, Age$^2$, $LowEducationDummy, GraduateDummy$
Area Characteristics include LA Population Density, MSOA Population Density, LA Expenditure per person, and a London Dummy
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 4A.3: Association Between Individual/Spatial Prosperity and Well-Being in Local Authorities with LA Fixed Effects**

| | Well-Being Index/Domain | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Capability Index | Physical Health | Mental Health | Life Health | Physical Security | Finance & Work | Leisure Time | House Size | Social Life | Participation & Voice |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| **Personal Income** | | | | | | | | | | |
| Household Income | 0.0025** | 0.0003 | 0.0019*** | 0.0010*** | 0.0004 | 0.0169*** | -0.0046*** | 0.0003 | 0.0011 | 0.0015*** |
| (£000's) | (0.0010) | (0.0003) | (0.0006) | (0.0004) | (0.0004) | (0.0037) | (0.0005) | (0.0002) | (0.0009) | (0.0006) |
| **Mover Interactions** | | | | | | | | | | |
| Quasi-Exogenous Mover Flag × | -0.0014 | 0.0013 | 0.0016 | 0.0012 | -0.0009 | -0.0003 | 0.0003 | -0.0002 | -0.0034 | -0.0024 |
| Median Wage | (0.0013) | (0.0014) | (0.0023) | (0.0014) | (0.0016) | (0.0024) | (0.0023) | (0.0014) | (0.0022) | (0.0031) |
| Quasi-Exogenous Mover Flag × | 0.0052* | -0.0058 | -0.0023 | -0.0040 | -0.0018 | -0.0029 | 0.0060 | -0.0001 | 0.0195*** | 0.0039 |
| Spatial Lag Wage | (0.0027) | (0.0036) | (0.0047) | (0.0035) | (0.0027) | (0.0033) | (0.0052) | (0.0035) | (0.0050) | (0.0063) |
| **Mover Categories** | | | | | | | | | | |
| Quasi-Exogenous Mover Flag | -0.0477** | 0.0129 | -0.0160 | 0.0022 | 0.0290 | 0.0081 | -0.0607 | -0.0032 | -0.1556*** | -0.0414 |
| | (0.0234) | (0.0229) | (0.0347) | (0.0230) | (0.0313) | (0.0387) | (0.0437) | (0.0247) | (0.0504) | (0.0545) |
| Constant | 0.7989*** | 0.4169*** | 0.6327*** | 0.5144*** | 0.8484*** | -0.0378 | 0.7481*** | 0.8120*** | 0.8172*** | 0.4469** |
| | (0.1091) | (0.0844) | (0.1272) | (0.0823) | (0.1661) | (0.1097) | (0.1453) | (0.0948) | (0.2037) | (0.2246) |
| Individual Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| LA Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Area Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Individuals | 33,580 | 55,319 | 49,559.0000 | 49,551.0000 | 45,262 | 52,435 | 49,539 | 48,838 | 41,877 | 41,547 |
| No. of Observations | 63,188 | 248,239 | 218,622 | 218,568 | 90,342 | 239,745 | 218,561 | 212,016 | 83,478 | 82,696 |
| Overall $R^2$ | 0.0150 | 0.0476 | 0.0061 | 0.0114 | 0.0572 | 0.0072 | 0.0377 | 0.0452 | 0.0004 | 0.0007 |

Individual Characteristics include Marital Status, Age, Age$^2$, $LowEducationDummy, GraduateDummy$
Area Characteristics include LA Population Density, MSOA Population Density, LA Expenditure per person, and a London Dummy
$^*p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 4A.4: Association Between Individual/Spatial Prosperity and Well-Being in Local Authorities with No LA Fixed Effects**

| | Well-Being Index/Domain | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Capability Index | Physical Health | Mental Health | Life Health | Physical Security | Finance & Work | Leisure Time | House Size | Social Life | Participation & Voice |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| **Personal Income** | | | | | | | | | | |
| Household Income | 0.0025** | 0.0003 | 0.0019*** | 0.0010*** | 0.0004 | 0.0170*** | -0.0047*** | 0.0005* | 0.0011 | 0.0014** |
| (£000's) | (0.0010) | (0.0003) | (0.0006) | (0.0004) | (0.0004) | (0.0037) | (0.0005) | (0.0002) | (0.0009) | (0.0006) |
| **Mover Interactions** | | | | | | | | | | |
| Quasi-Exogenous Mover Flag × | -0.0013 | 0.0014 | 0.0017 | 0.0014 | -0.0007 | -0.0001 | 0.0001 | -0.0011 | -0.0029 | -0.0027 |
| Median Wage | (0.0011) | (0.0014) | (0.0023) | (0.0013) | (0.0011) | (0.0022) | (0.0021) | (0.0010) | (0.0034) | (0.0036) |
| Quasi-Exogenous Mover Flag × | 0.0048** | -0.0068 | -0.0023 | -0.0044 | -0.0020 | -0.0038 | 0.0045 | 0.0011 | 0.0193*** | 0.0014 |
| Spatial Lag Wage | (0.0024) | (0.0043) | (0.0047) | (0.0039) | (0.0024) | (0.0031) | (0.0052) | (0.0024) | (0.0071) | (0.0065) |
| **Mover Categories** | | | | | | | | | | |
| Quasi-Exogenous Mover Flag | -0.0279 | 0.0164 | -0.0044 | 0.0086 | 0.0282 | 0.0123 | -0.0507 | 0.0140 | -0.1601*** | -0.0088 |
| | (0.0208) | (0.0225) | (0.0336) | (0.0230) | (0.0291) | (0.0385) | (0.0414) | (0.0187) | (0.0498) | (0.0441) |
| Constant | 0.6988*** | 0.4418*** | 0.5715*** | 0.4935*** | 0.8749*** | -0.1008 | 0.7212*** | 0.8378*** | 0.8491*** | 0.3557* |
| | (0.0847) | (0.0791) | (0.1009) | (0.0692) | (0.1464) | (0.1034) | (0.1160) | (0.0685) | (0.1858) | (0.2059) |
| Individual Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| LA Fixed Effects | No | No | No | No | No | No | No | No | No | No |
| Individual Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Area Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Individuals | 33,580 | 33,580 | 55,319 | 49,559 | 49,551 | 45,262 | 52,435 | 43,020 | 41,877 | 41,547 |
| No. of Observations | 63,188 | 63,188 | 248,239 | 218,622 | 218,568 | 90,342 | 239,745 | 180,365 | 83,478 | 82,696 |
| Overall $R^2$ | 0.0314 | 0.0462 | 0.0601 | 0.0063 | 0.0129 | 0.0657 | 0.0074 | 0.0937 | 0.0049 | 0.0013 |

Individual Characteristics include Marital Status, Age, Age$^2$, $LowEducationDummy$, $GraduateDummy$
Area Characteristics include LA Population Density, MSOA Population Density, LA Expenditure per person, and a London Dummy
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## Table 4A.5: Association Between Individual/Spatial Prosperity and Well-Being in MSOAs

| | Well-Being Index/Domain | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Capability Index | Physical Health | Mental Health | Life Health | Physical Security | Finance & Work | Leisure Time | House Size | Social Life | Participation & Voice |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| **Personal Income** | | | | | | | | | | |
| Household Income | 0.0025** | 0.0003 | 0.0020*** | 0.0010*** | 0.0005 | 0.0170*** | -0.0047*** | 0.0005** | 0.0011 | 0.0013** |
| (£000's) | (0.0010) | (0.0003) | (0.0006) | (0.0004) | (0.0004) | (0.0037) | (0.0005) | (0.0002) | (0.0009) | (0.0006) |
| **Mover Interactions** | | | | | | | | | | |
| Mover Flag × | 0.0100*** | -0.0005 | 0.0052 | 0.0030 | 0.0347*** | 0.0061 | 0.0015 | -0.0047 | 0.0021 | 0.0076 |
| Claimant Rate Difference | (0.0038) | (0.0037) | (0.0045) | (0.0032) | (0.0067) | (0.0055) | (0.0051) | (0.0062) | (0.0067) | (0.0077) |
| Mover Flag × | -0.0120 | 0.0162 | -0.0069 | 0.0045 | 0.0127 | -0.0091 | -0.0042 | -0.0040 | 0.0119 | -0.0318 |
| Spatial Lag Wage | (0.0115) | (0.0105) | (0.0130) | (0.0093) | (0.0174) | (0.0155) | (0.0147) | (0.0189) | (0.0214) | (0.0267) |
| **Mover Categories** | | | | | | | | | | |
| Flag | 0.0054** | -0.0023 | 0.0107*** | 0.0045** | -0.0022 | 0.0013 | -0.0014 | 0.0128*** | -0.0038 | 0.0020 |
| | (0.0025) | (0.0026) | (0.0031) | (0.0022) | (0.0041) | (0.0037) | (0.0036) | (0.0036) | (0.0050) | (0.0056) |
| Constant | 0.7097*** | 0.4494*** | 0.5759*** | 0.4998*** | 0.8781*** | -0.0949 | 0.7151*** | 0.8683*** | 0.8454*** | 0.3554* |
| | (0.0846) | (0.0789) | (0.1006) | (0.0690) | (0.1464) | (0.1033) | (0.1157) | (0.0682) | (0.1859) | (0.2056) |
| Individual Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| LA Fixed Effects | No | No | No | No | No | No | No | No | No | No |
| Individual Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Area Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Individuals | 33,871 | 55,913 | 50,128 | 50120 | 45,652 | 53006 | 50,108 | 49,342.0000 | 42,254 | 41,921 |
| No. of Observations | 63,496 | 249,542 | 219,866 | 219,812 | 90,753 | 241,014 | 219,806 | 213,093 | 83,875 | 83,090 |
| Overall $R^2$ | 0.0347 | 0.0589 | 0.0063 | 0.0129 | 0.0640 | 0.0075 | 0.0631 | 0.1257 | 0.0054 | 0.0014 |

Robust standard errors calculated. Standard Errors in parentheses
Individual Characteristics include Marital Status, Age, Age$^2$, $LowEducationDummy, GraduateDummy$
Area Characteristics include LA Population Density, MSOA Population Density, LA Expenditure per person, and a London Dummy
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 4A.6: Association Between Individual/Spatial Prosperity and Well-Being in MSOAs**

| | Well-Being Index/Domain | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Capability Index | Physical Health | Mental Health | Life Health | Physical Security | Finance & Work | Leisure Time | House Size | Social Life | Participation & Voice |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| **Personal Income** | | | | | | | | | | |
| Household Income | 0.0024** | 0.0003 | 0.0019*** | 0.0010*** | 0.0004 | 0.0170*** | -0.0047*** | 0.0005* | 0.0011 | 0.0014** |
| (£000's) | (0.0010) | (0.0003) | (0.0006) | (0.0004) | (0.0004) | (0.0036) | (0.0005) | (0.0002) | (0.0009) | (0.0006) |
| **Mover Interactions** | | | | | | | | | | |
| Quasi-Exogenous Mover Flag × | 0.0083 | 0.0144 | 0.0615** | 0.0298 | -0.0587 | 0.0032 | 0.0213 | -0.0039 | 0.1251* | 0.0892* |
| Claimant Rate Difference | (0.0329) | (0.0199) | (0.0287) | (0.0183) | (0.0519) | (0.0326) | (0.0310) | (0.0300) | (0.0653) | (0.0476) |
| Quasi-Exogenous Mover Flag × | -0.1064* | -0.0444 | -0.0956* | -0.0601 | 0.0922 | 0.0190 | -0.0087 | 0.0317 | -0.2138** | -0.0779 |
| Spatial Lag Wage | (0.0617) | (0.0425) | (0.0534) | (0.0367) | (0.1216) | (0.0748) | (0.0731) | (0.0637) | (0.0970) | (0.0974) |
| **Mover Categories** | | | | | | | | | | |
| Quasi-Exogenous Mover Flag | 0.0375* | -0.0136 | 0.0203 | 0.0076 | 0.0377 | 0.0231 | -0.0350 | 0.0021 | -0.0032 | -0.1029*** |
| | (0.0203) | (0.0168) | (0.0206) | (0.0142) | (0.0345) | (0.0224) | (0.0242) | (0.0315) | (0.0418) | (0.0368) |
| Constant | 0.6961*** | 0.4505*** | 0.5588*** | 0.4913*** | 0.8571*** | -0.0979 | 0.7167*** | 0.8534*** | 0.8495*** | 0.3556* |
| | (0.0845) | (0.0789) | (0.1006) | (0.0689) | (0.1465) | (0.1032) | (0.1157) | (0.0685) | (0.1856) | (0.2055) |
| Individual Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| LA Fixed Effects | No | No | No | No | No | No | No | No | No | No |
| Individual Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Area Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Individuals | 33,871 | 55,913 | 50,128 | 50,120 | 45,652 | 53,006 | 50,108 | 49,342 | 42,254 | 4,1921 |
| No. of Observations | 63,496 | 249,542 | 219,866 | 219,812 | 90,753 | 241,014 | 219,806 | 213,093 | 83,875 | 83,090 |
| Overall $R^2$ | 0.0312 | 0.0587 | 0.0061 | 0.0129 | 0.0641 | 0.0074 | 0.0630 | 0.1247 | 0.0050 | 0.0013 |

Robust standard errors calculated. Standard Errors in parentheses
Individual Characteristics include Marital Status, Age, Age$^2$, $LowEducationDummy, GraduateDummy$
Area Characteristics include LA Population Density, MSOA Population Density, LA Expenditure per person, and a London Dummy
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## 4.17 APPENDIX C: LIVING TIME REGRESSIONS

**Table 4A.7: Association Between Individual/Spatial Prosperity and Well-Being by Living Time in Local Authorities**

| | Well-Being Index/Domain | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Capability Index | Physical Health | Mental Health | Life Health | Physical Security | Finance & Work | Leisure Time | House Size | Social Life | Participation & Voice |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| **Personal Income** | | | | | | | | | | |
| Household Income | 0.0023** | 0.0020** | 0.0002 | 0.0013** | 0.0006* | 0.0004 | 0.0153*** | -0.0025*** | 0.0008 | 0.0014** |
| (£000's) | (0.0009) | (0.0008) | (0.0003) | (0.0005) | (0.0003) | (0.0004) | (0.0038) | (0.0003) | (0.0008) | (0.0006) |
| **Living Time Interactions** | | | | | | | | | | |
| 0-3 Years × | 0.0002 | 0.0001 | -0.0002 | 0.0006 | 0.0002 | 0.0011** | 0.0010* | -0.00018 | 0.0015** | 0.0001 |
| Median Wage Difference | (0.0003) | (0.0003) | (0.0003) | (0.0004) | (0.0003) | (0.0005) | (0.0005) | (0.0004) | (0.0006) | (0.0007) |
| 4+ years × | 0.0002 | 0.0002 | -0.0002 | 0.0002 | 0.0000 | 0.0017** | 0.0017* | -0.0004 | -0.0002 | -0.0001 |
| Median Wage Difference | (0.0004) | (0.0005) | (0.0006) | (0.0007) | (0.0005) | (0.0008) | (0.0009) | (0.0005) | (0.0009) | (0.0011) |
| **Living Time Categories** | | | | | | | | | | |
| 0-3 years | 0.0040 | 0.0050 | 0.0018 | 0.0068 | 0.0056* | 0.0071 | -0.0069 | 0.0046 | -0.0049 | -0.0065 |
| | (0.0033) | (0.0036) | (0.0038) | (0.0043) | (0.0031) | (0.0055) | (0.0053) | (0.0040) | (0.0062) | (0.0073) |
| 4+ years | 0.0038 | 0.0042 | -0.0045 | 0.0072 | 0.0024 | -0.0083 | -0.0195** | 0.0061 | 0.0037 | -0.0108 |
| | (0.0044) | (0.0048) | (0.0058) | (0.0069) | (0.0050) | (0.0075) | (0.0078) | (0.0052) | (0.0092) | (0.0103) |
| Individual Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| LA Fixed Effects | No | No | No | No | No | No | No | No | No | No |
| Individual Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Area Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Individuals | 22718 | 22718 | 27191 | 26871 | 26870 | 27037 | 27044 | 24526 | 26348 | 26094 |
| No. of Observations | 49419 | 49419 | 168941 | 157490 | 157454 | 66034 | 168060 | 132773 | 62932 | 62257 |
| Overall $R^2$ | 0.0336 | 0.0523 | 0.0392 | 0.0098 | 0.00578 | 0.0544 | 0.0048 | 0.0003 | 0.0044 | 0.0016 |

Robust standard errors calculated. Standard Errors in parentheses
Individual Characteristics include Marital Status, Age, Age$^2$, $LowEducationDummy, GraduateDummy$
Area Characteristics include LA Population Density, MSOA Population Density, LA Expenditure per person, and a London Dummy
$^*p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 4A.8: Association Between Individual/Spatial Prosperity and Well-Being by Living Time in MSOAs**

| | Well-Being Index/Domain | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Capability Index | Physical Health | Mental Health | Life Health | Physical Security | Finance & Work | Leisure Time | House Size | Social Life | Participation & Voice |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| **Personal Income** | | | | | | | | | | |
| Household Income | 0.0023** | 0.0002 | 0.0014** | 0.0006* | 0.0004 | 0.0153*** | -0.0054*** | 0.0006** | 0.0008 | 0.0014** |
| (£000's) | (0.0009) | (0.0003) | (0.0005) | (0.0003) | (0.0004) | (0.0038) | (0.0007) | (0.0003) | (0.0008) | (0.0006) |
| **Living Time Interactions** | | | | | | | | | | |
| 0-3 Years × | 0.0002 | -0.0002 | 0.0006 | 0.0002 | 0.0011** | 0.0010* | -0.0004 | 0.0003 | 0.0015** | 0.0001 |
| Claimant Rate Difference | (0.0003) | (0.0003) | (0.0004) | (0.0003) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0006) | (0.0007) |
| 4+ years × | 0.0002 | -0.0002 | 0.0001 | -0.0000 | 0.0017** | 0.0017* | 0.0003 | -0.0003 | -0.0002 | -0.0001 |
| Claimant Rate Difference | (0.0004) | (0.0006) | (0.0007) | (0.0005) | (0.0008) | (0.0009) | (0.0008) | (0.0005) | (0.0009) | (0.0011) |
| **Living Time Categories** | | | | | | | | | | |
| 0-3 years | 0.0040 | 0.0018 | 0.0068 | 0.0056* | 0.0071 | -0.0069 | 0.0081 | 0.0001 | -0.0049 | -0.0065 |
| | (0.0033) | (0.0037) | (0.0043) | (0.0031) | (0.0055) | (0.0053) | (0.0051) | (0.0050) | (0.0062) | (0.0073) |
| 4+ years | 0.0037 | -0.0045 | 0.0072 | 0.0024 | -0.0083 | -0.0195** | 0.0012 | 0.0096* | 0.0037 | -0.0108 |
| | (0.0044) | (0.0058) | (0.0069) | (0.0050) | (0.0075) | (0.0078) | (0.0078) | (0.0053) | (0.0092) | (0.0103) |
| Individual Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| LA Fixed Effects | No | No | No | No | No | No | No | No | No | No |
| Individual Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Area Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Individuals | 22,718 | 27,191 | 26,871 | 26,870 | 27,037 | 27,044 | 26,871 | 25,234 | 26,348 | 26,094 |
| No. of Observations | 49419 | 168941 | 157490 | 157454 | 66034 | 168060 | 157479 | 146941 | 62932 | 62257 |
| Overall $R^2$ | 0.0336 | 0.0392 | 0.0098 | 0.0058 | 0.0544 | 0.0048 | 0.0030 | 0.1050 | 0.0044 | 0.0016 |

Robust standard errors calculated. Standard Errors in parentheses
Individual Characteristics include Marital Status, Age, $Age^2$
Area Characteristics include LA Population Density, MSOA Population Density, LA Expenditure per person, and a London Dummy
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

## 4.18 APPENDIX D: PCA CAPABILITY RESULTS

### Table 4.9: Association Between Individual/Spatial Prosperity and Well-Being

| | No Fixed Effects (1) | Fixed Effects (2) |
|---|---|---|
| **Personal Income** | | |
| Household Income | 0.00221** | 0.00219** |
| (£1000 increase in) | (0.000934) | (0.000912) |
| **LA Prosperity** | | |
| Median Wage (10 % from Mean) | 0.00107 | 0.00110 |
| | (0.00142) | (0.00111) |
| Spatially Lagged | 0.00184 | -0.00479* |
| Median Wage | (0.00405) | (0.00277) |
| **MSOA Prosperity** | | |
| Means-tests Social Security | 0.00876*** | 0.00850*** |
| Payment Rate (1 % point decline) | (0.00257) | (0.00247) |
| Spatially Lagged | -0.00889 | -0.00965 |
| Social Security Payment | (0.00832) | (0.00702) |
| Constant | 0.810*** | 0.694*** |
| | (0.121) | (0.0916) |
| Individual Fixed Effects | Yes | Yes |
| Time Fixed Effects | Yes | Yes |
| LA Fixed Effects | No | Yes |
| Individual Characteristics | Yes | Yes |
| Area Characteristics | Yes | Yes |
| No. of Individuals | 33,963 | 33,963 |
| No. of Observations | 63,641 | 63,641 |
| $R^2$ | 0.0142 | 0.0402 |

Robust standard errors calculated. Standard Errors in parentheses
Individual Characteristics include Marital Status, Age, Age$^2$
Area Characteristics include LA Population Density,
MSOA Population Density, LA Expenditure per person, and a London Dummy
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 4.10: Association Between Individual/Spatial Prosperity and Well-Being by Education Status**

| | No Fixed Effects (1) | Fixed Effects (2) |
|---|---|---|
| **Personal Income** | | |
| Household Income | 0.0020** | 0.0020** |
| (£1000 increase in) | (0.0009) | (0.0008) |
| **LA Prosperity** | | |
| Median Wage (10 % from Mean) | 0.0011 | 0.0010 |
| | (0.0017) | (0.0013) |
| Spatially Lagged | 0.0055 | -0.0033 |
| Median Wage | (0.0045) | (0.0032) |
| **MSOA Prosperity** | | |
| Means-tests Social Security | 0.0073** | 0.0062** |
| Payment Rate (1 % point decline) | (0.0031) | (0.0030) |
| Spatially Lagged | -0.0055 | -0.0043 |
| Social Security Payment | (0.0095) | (0.0080) |
| **LA Education Interaction** | | |
| Low-Ed Dummy × | 0.0010 | 0.0018 |
| Median Wage Difference | (0.0025) | (0.0025) |
| **MSOA Education Interaction** | | |
| Low-Ed Dummy × | 0.0003 | -0.0004 |
| Claimant Rate Difference | (0.0052) | (0.0051) |
| Constant | 0.810*** | 0.694*** |
| | (0.121) | (0.0916) |
| Individual Fixed Effects | Yes | Yes |
| Time Fixed Effects | Yes | Yes |
| LA Fixed Effects | No | Yes |
| Individual Characteristics | Yes | Yes |
| Area Characteristics | Yes | Yes |
| No. of Individuals | 33,963 | 33,963 |
| No. of Observations | 63,641 | 63,641 |
| $R^2$ | 0.0142 | 0.0402 |

Robust standard errors calculated. Standard Errors in parentheses
Individual Characteristics include Marital Status, Age, Age$^2$
Area Characteristics include LA Population Density,
MSOA Population Density, LA Expenditure per person, and a London Dummy
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 4.11: Association Between Individual/Spatial Prosperity and Well-Being by Mover Status in Local Authorities**

| | No Fixed Effects (1) | Fixed Effects (2) | No Fixed Effects (3) | Fixed Effects (4) |
|---|---|---|---|---|
| **Personal Income** | | | | |
| Household Income | 0.00218** | 0.00221** | 0.00217** | 0.00220** |
| (£1000 increase in) | (0.000909) | (0.000933) | (0.000905) | (0.000933) |
| **Mover Interactions** | | | | |
| Mover Flag × | 0.000212 | -0.000238 | | |
| Median Wage Difference | (0.000301) | (0.000402) | | |
| Exogenous Mover Flag × | | | -0.000875 | -0.000717 |
| Median Wage Difference | | | (0.00144) | (0.00150) |
| Mover Flag × | -0.0000235 | 0.00106 | | |
| Spatially Lagged Wage Difference | (0.000596) | (0.000664) | | |
| Exogenous Mover Flag × | | | 0.00378 | 0.00400 |
| Spatially Lagged Wage Difference | | | (0.00295) | (0.00305) |
| **Mover Categories** | | | | |
| Mover Flag | 0.00463 | 0.00303 | | |
| | (0.00340) | (0.00397) | | |
| Exogenous Mover Flag | | | -0.0260 | -0.0487* |
| | | | (0.0258) | (0.0278) |
| Constant | 0.810*** | 0.694*** | | |
| | (0.121) | (0.0916) | | |
| Individual Fixed Effects | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| LA Fixed Effects | No | Yes | No | Yes |
| Individual Characteristics | Yes | Yes | Yes | Yes |
| Area Characteristics | Yes | Yes | Yes | Yes |
| No. of Individuals | 33,580 | 33,580 | 33,580 | 33,580 |
| No. of Observations | 63,188 | 63,188 | 63,188 | 63,188 |
| $R^2$ | 0.020 | 0.035 | 0.020 | 0.035 |

Robust standard errors calculated. Standard Errors in parentheses
Individual Characteristics include Marital Status, Age, Age$^2$
Area Characteristics include LA Population Density,
MSOA Population Density, LA Expenditure per person, and a London Dummy
$^*p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 4.12: Association Between Individual/Spatial Prosperity and Well-Being by Mover Status in MSOAs**

| | (1) | (2) |
|---|---|---|
| **Personal Income** | | |
| Household Income | 0.0022** | 0.0022** |
| (£1000 increase in) | (0.0009) | (0.0009) |
| **Mover Interactions** | | |
| Mover Flag × | 0.0097** | |
| Claimant Rate Difference | (0.0042) | |
| Quasi-Exogenous Mover Flag × | | 0.0050 |
| Claimant Rate Difference | | (0.0348) |
| Mover Flag × | -0.0147 | |
| Spatially Lagged Claimant Rate Difference | (0.0123) | |
| Quasi-Exogenous Mover Flag × | | -0.1049 |
| Spatially Lagged Claimant Rate Difference | | (0.0645) |
| **Mover Flags** | | |
| Mover Flag | 0.0070** | |
| | (0.0028) | |
| Quasi-Exogenous Mover Flag | | 0.0362 |
| | | (0.0224) |
| Constant | 0.7090*** | 0.6931*** |
| | (0.0917) | (0.0916) |
| Individual Fixed Effects | Yes | Yes |
| Time Fixed Effects | Yes | Yes |
| LA Fixed Effects | No | No |
| Individual Characteristics | Yes | Yes |
| Area Characteristics | Yes | Yes |
| No. of Individuals | 33,871 | 33,871 |
| No. of Observations | 63,496 | 63,496 |
| $R^2$ | 0.0529 | 0.0460 |

Robust standard errors calculated. Standard Errors in parentheses
Individual Characteristics include Marital Status, Age, Age$^2$
Area Characteristics include LA Population Density,
MSOA Population Density, LA Expenditure per person, and a London Dummy
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

**Table 4.13: Association Between Individual/Spatial Prosperity and Well-Being by Living Time**

| | Local Authority (1) | MSOA (2) |
|---|---|---|
| **Personal Income** | | |
| Household Income | 0.0020** | 0.0020** |
| (£1000 increase in) | | (0.0008) |
| (0.0008) | | |
| | | |
| **Living Time Interactions** | | |
| 0-3 Years × | 0.0002 | |
| Median Wage Difference | (0.0003) | |
| | | |
| 4+ Years × | 0.0002 | 0.0050 |
| Median Wage Difference | (0.0005) | (0.0348) |
| | | |
| 0-3 Years × | | -0.0093 |
| Claimant Rate Difference | | (0.0130) |
| 4+ Years × | | 0.0007 |
| Claimant Rate Difference | | (0.0174) |
| | | |
| **Living Time Categories** | | |
| 0-3 Years | 0.0050 | 0.0058** |
| | (0.0036) | (0.0029) |
| 4+ Years | 0.0042 | 0.0059 |
| | (0.0048) | (0.0042) |
| | | |
| Constant | 0.7130*** | 0.7211*** |
| | (0.0968) | (0.0969) |
| Individual Fixed Effects | Yes | Yes |
| Time Fixed Effects | Yes | Yes |
| LA Fixed Effects | No | No |
| Individual Characteristics | Yes | Yes |
| Area Characteristics | Yes | Yes |
| No. of Individuals | 22,718 | 22,718 |
| No. of Observations | 49,419 | 49,419 |
| $R^2$ | 0.0523 | 0.0541 |

Robust standard errors calculated. Standard Errors in parentheses
Individual Characteristics include Marital Status, Age, Age$^2$
Area Characteristics include LA Population Density,
MSOA Population Density, LA Expenditure per person, and a London Dummy
$^{*}p < 0.10$ , $^{**}p < 0.05$, $^{***}p < 0.01$

# Chapter 5

# Conclusion

In this thesis, I analysed a political and economic cause of income inequality as well as its impact on well-being within the United Kingdom. In particular, I focused on who governments redistribute to and why (a political cause of inequality), why non-graduate men were less adept at performing job tasks demanded in the post-industrial economy (an economic cause of inequality), and the relative roles of local labour market and neighbourhood prosperity on well-being (its impact). These three chapters filled important gaps within the literature.

Here I summarise the findings and contributions made in each chapter. I then move on to the limitations that apply to this thesis as a whole.

## Findings and Contributions

Chapter 2, *"Mo' Votes, Mo' Money"* filled a gap in the literature of who governments redistribute to and why. The current literature focuses on redistribution from the rich to the poor (Meltzer and Richard 1981; Iversen and Soskice 2006; Pontusson and Rueda 2008; Lupu and Pontusson 2011; Georgiadis and Manning 2012; Margalit 2013; Alt and Iversen 2017; Elkjær and Iversen 2020). But this perspective overlooks the more nuanced types of redistribution that take place today. Across the OECD, social security payments for pensioners have seen a relative increase while poverty has shifted from pensioners to the young (Scruggs et al. 2017; OECD 2019). This includes the United Kingdom, where child poverty has recently begun to rise while pensioner poverty has remained stable (Bourquin et al. 2019a; DWP 2021).

At the same time as redistribution has become more nuanced, voter coalitions have also become more complex. They are no-longer solely about the rich vs. the poor - dimensions such as age now also play a role (Dalton 2014; Bell and Gardiner 2019). I use the insight from the distributive politics literature, that governments redistribute more to the voters that can give them victory at the next election (Dixit and Londregan 1996; Cox and McCubbins 2010). Using detailed microdata on voting patterns and information on which groups politicians targeted for redistribution, I constructed groups along the dimensions of income, age, and parental status. A microsimulation model is used to isolate the impacts of redistribution on people, abstracting from behavioural and demographic changes.

I find, between 2005 and 2019, that governments redistribute more to groups that are electorally important to them *and* that accounting for these more complex voter coalitions provides a better explanation of redistribution than the standard rich vs. poor account. As the post-2010 Conservative-led government generally had richer people supporting them, they did redistribute more to those on high-incomes. But, crucially, some low-income groups did support them - in particular, pensioners. Whereas others, such as low income non-pensioners, did not. Conducting an indicative back-of-the-envelope calculation, I find that pensioner poverty would have, therefore, remained stable regardless of who was in power after 2010 but child poverty would have been much lower had New Labour won.

By showing that governments redistribute to groups defined by more than just income, I fill a gap in the redistribution literature that hitherto had only empirically tested accounts of redistribution of rich to poor (Meltzer and Richard 1981; Georgiadis and Manning 2012; Iversen and Soskice 2006; Pontusson and Rueda 2008; Lupu and Pontusson 2011; Elkjær and Iversen 2020). Here, for the first time, I test a more nuanced view of the evolution of redistribution and voter coalitions (Iversen and Goplerud 2018). This chapter could be the beginning of an exciting stream of research in this area.

Another methodological contribution of this chapter was that it constitutes the first robust empirical test of the distributive politics literature within an advanced economy. Unlike current tests, which analyse which areas rather than which people benefit from distributive transfers, this chapter was able to track the individuals that the government chose to reward (Golden and Min 2013; Albertus 2019). This could be a promising method that could be used in future empirical tests of theoretical distributive politics literature.

In Chapter 3, *"No Country for Non-Graduate Men,"* the major gap in the literature I address regards why non-graduate men are less adept at performing the job tasks that are more greatly demanded in the post-industrial labour market (Black and Spitz-Oener 2010; Gregory 2011). A small literature links some childhood/adolescent skills to some job tasks, but this work has yet to link a wide range of skills with a full set of job tasks (Borghans et al. 2014; Weinberger 2014).

Non-graduate men being unable to perform job tasks that are more highly demanded in the post-industrial era has led to a large fall in their employment rates (Olivetti and Petrongolo 2016; Cortes et al. 2017; Binder and Bound 2019; Abraham and Kearney 2020). Automation and globalisation increased demand for analytical and interactive job tasks, which non-graduate men are less adept at performing, while reducing the demand for manual job tasks that they used to undertake in the post-war era (Autor et al. 2003; Autor 2015; Górka et al. 2017).

I find that childhood cognitive and emotional-health skills have a positive effect on the proportion of high-pay analytical and interactive job tasks that people perform as adults. I also find that cognitive, emotional-health, perseverance, and social skills in childhood and adolescence have a positive effect on employment outcomes. As the least-skilled boys have lower skills levels than the least skilled girls, I show that gendered differences in childhood and adolescent skills led to a significant (relative) fall in the analytical and interactive job tasks men perform as well as their employment rates.

Using a wider range of skills and job tasks allows me to fill an important omission in the literature. I show when and how child/adolescent skills affect future job tasks. In particular, I find by only examining certain skills (and its impact on certain tasks), the current finding that social skills are important for interactive and analytical job tasks in adulthood may suffer from an omitted variable bias (Borghans et al. 2014; Weinberger 2014). Including emotional-health and perseverance skills drives the effect of social skills on these tasks to zero. Ensuring a child is happy may be more important than ensuring they are sociable for their future labour market outcomes.

Finally, in Chapter 4 *"Familiar Faces, Worn out Places,"*, I analyse the role that place-based prosperity at different spatial scales plays in determining a wide range of well-being outcomes such as health, friendship, and physical safety. The current literature that considers the impact of places rarely differentiates between spatial scales (Sharkey and Faber 2014; Leventhal and Dupéré 2019; Jivraj et al. 2020; Petrović et al. 2020; Chyn and Katz 2021; Petrović et al. 2022). The small literature that does differentiate between spatial scales usually analyses these impacts at the granular scale (population less than 10,000) and rarely analyses more than one well-being outcome at a time (Propper et al. 2005; Anderson 2007; Bolster et al. 2007; Brattbakk 2014; Duncan et al. 2014; Graif et al. 2016; Knies et al. 2021; Petrović et al. 2022)

Places affect well-being outcomes through different mechanisms at different spatial scales. Larger local labour markets affect well-being outcomes through better employment prospects and higher potential incomes. Granular neighbourhoods affect well-being through social-interactive effects, where people can see, hear, and speak with one another (McCulloch 2003; Galster 2012; Leventhal and Dupéré 2019; Petrović et al. 2020). Crucially, prosperous neighbourhoods can exist in areas with depressed labour markets (Cove et al. 2008).

Using linked individual-area data at different spatial scales as well as controlling for the prosperity of the surrounding areas, I find that place prosperity does have differing effects on well-being outcomes at different scales. This shows that the current place-effects literature, which refers to homogeneous *"place"* effects but does not differentiate between spatial scales, could be misleading (e.g.Chetty and Hendren (2018a,b))

I select a wide range of well-being outcomes using Sen's Capability Approach (Sen 1979, 2001; Alkire and Kovesdi 2020). I find that labour market prosperity directly improves financial security, friendship, and physical security. It also indirectly helps to improve most well-being domains by increasing potential incomes. Neighbourhood prosperity directly raises overall well-being as well as physical security. Deaths are also lower if your incomes are higher, you were employed under the age of 60, and if your neighbourhood was more prosperous. Personal income also, unsurprisingly, improves most well-being domains. Improving personal, labour market, and neighbourhood prosperity is important for creating a *good life*.

**Limitations and directions for future research**

As the limitations for each chapter are given within them, I focus here on limitations that apply across chapters as well as directions for future research.

The major limitation of this thesis is that it focuses on changes within only one advanced economy, United Kingdom. There is a trade-off regarding specificity and generalisability. Examining the causes and consequences of inequality within one country allows a more detailed, thorough analysis using microdata that is not available at the cross-country level. But this comes with a cost in that I can only examine outcomes within one country. However, while I cannot be certain, I believe, on balance, these findings will hold across advanced economies. That is because the the forces described here - more complex voter coalitions and redistributive policies (Dalton 2014; OECD 2019), changing job task demands leading to falling non-graduate male employment (Olivetti and Petrongolo 2016; Abraham and Kearney 2020), and rising spatial inequality (Iversen and Soskice 2019; Carrascal-Incera et al. 2020) - are common across advanced economies. There are, of course, differences across advanced economies that could mediate the forces analysed in this thesis - different electoral systems could affect the impact of Relative Electoral Importance on redistribution (Iversen and Soskice 2006), more powerful unions could affect skill and task demands in a given labour market (Iversen and Soskice 2015), and less centralised governing systems could reduce the effect of spatial inequality on well-being (McCann 2016). A fruitful area of future research would be to analyse whether the findings in this thesis do, in fact, hold in different advanced economies. In particular, I look forward to research that analyses to what degree these findings hold and the circumstances that determine when they hold.

A second, related limitation is that the time periods and cohorts analysed are relatively limited. Chapters 2 & 4 cover 15 and 10 years respectively while Chapter 3 follows one cohort through time. In Chapters 2 and 4, this is due to data limitations. Future work could extend the analysis further back in time with less data - this work would be less comprehensive but would give an indication if the forces described in this thesis hold in earlier time periods. For example, there is not to my knowledge a publicly available microsimulation model that extends back to the 1997 election. However, future work could consider the outcomes of significant taxation and social security measures (such as income tax and pensions) to analyse whether my account of multidimensional redistribution holds. Similarly, the analysis in Chapter 4 could be extended backward in time with fewer indicators of well-being and place-based prosperity. Chapter 3 does not suffer from this drawback and could be replicated with other cohort studies, such as the British Cohort Study.

A third limitation is that none of the estimates in this thesis can be considered truly causal. While the research designs in each chapter all attempt to control for confounding factors in order to estimate the effect of the dependent variable of interest, the research designs cannot rule out other factors that could affect outcomes (Cunningham 2021). Future work that utilises natural experiments could test whether these findings are replicated in robust causal research designs. Regarding the findings in Chapter 2, a possible test could be to analyse whether different city/state governments that are controlled by the same party and were elected on the same manifesto, but that differ in their voter coalitions, also implement different policies to reward their respective voter coalitions. Regarding Chapter 4, a rich literature has exploited exogenous moves to estimate the casual effects of places, and this could be applied to consider a wide range of well-being domains as well as differentiating between spatial scales (Chetty et al. 2016; Deryugina et al. 2018).

There are other promising directions for future work that do not depend on the limitations of the chapters in this thesis.

Firstly, future work could examine in detail the mechanisms by which Relative Electoral Importance, childhood/adolescent skills, and place-based prosperity affect outcomes. Qualitative work, in particular, could be of use to describe how these mechanisms operate. Regarding Relative Electoral Importance and redistribution, research regarding what politicians think and say about targeting groups could be of use. Chapter 3 shows that emotional-health skills are important for Non-routine Analytical and Non-routine Interactive tasks. What is less clear is exactly why these skills are important for these tasks. In Chapter 4, the exact mechanisms by which labour market and neighbourhood prosperity operate could help in designing policy interventions. Job opportunities may not be sufficient if there are other barriers in the way of employment. Similarly, analysing when and how the social-interactive mechanisms of neighbourhoods effect other residents could prove useful.

Secondly, there are important measurement advances made in this thesis that could be applied elsewhere. The use of static microsimulation models for questions of distributive politics could be used to more precisely test who politicians actually reward when they come to office. The Capability Index constructed in Chapter 4 can, and I hope will, be used in future work as a simple measurement tool to both measure well-being across a range of domains as well as analyse its determinants.

Thirdly, this thesis has important political implications are worth examining. Specifically, regarding how the key variables in each chapter affects political outcomes. Falling redistribution (Fetzer 2019), falling non-graduate male employment (Baccini and Weymouth 2021), and rising spatial inequality have all led to increased support of populism (Becker et al. 2017; Zymek and Jones 2020). Tests could measure how changes in Relative Electoral Importance, childhood skills, and well-being domains affect support for populist parties. These tests should examine whether these variables have an independent effect on populist support or whether they are fully mediated by the mechanisms examined in this thesis. For example, falls in Relative Electoral Importance could lead to a rise in populist support, and this could be entirely due to its effect on redistribution. Or it could have an effect separate from its impact on redistribution, which may indicate that Relative Electoral Importance has an impact on other political choices that affect these voters. I look forward to future research in this area.

The chapters in this thesis make new contributions regarding the causes and consequences of income inequality. They provide some answers as to why all citizens in advanced economies do not live the *good life* as well as, I hope, some ideas on how to ensure that they do.

# Chapter 6

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