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From Homo Economicus to Homo Relaxus: Universal Basic Income and the Future of Work

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Abstract

In this thesis, I evaluate the labor market effects of means-tested transfers and explore the potential implications of introducing a universal basic income (UBI) as an alternative in the UK. Using empirical analysis and lifecycle simulations, I investigate the trade-offs between these two welfare approaches. The empirical analysis shows that means-tested transfers are associated with lower employment (12.6%) and weekly working hours (2.7 hours), particularly among lower-income groups. Simulations indicate that implementing a UBI further reduces hours worked by 14.9%, highlighting the trade-offs between financial security and labor participation incentives. By integrating grounded evidence with modeling, this thesis provides insights into welfare design and labor market impacts, offering a UK perspective to global debates.

Keywords: Universal Basic Income (UBI); Means-Tested Transfers; Labor Supply; UK Welfare Policy; Lifecycle Models

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Chapter 1

Introduction

"haha money printer go brrrr" (Screen Slate, 2020) —a meme that captured the internet during the announcement of the CARES act in the United States, captures an ongoing economic debate about the optimal welfare system. As stimulus checks ranging from $600 to $1,200 reached the pockets of households, questions of the effectiveness of the design and whether such programs affect incentives to work during a time of economic uncertainty. One such question raised was: should cash transfers be universal? These discussions resonate globally, particularly in the United Kingdom, where welfare reforms have undergone its most significant change since the post-war Beveridge Report.

In this thesis, I evaluate the labor market effects of means-tested transfers and explore the potential implications of introducing a universal basic income (UBI) as an alternative in the UK. By combining a grounded empirical analysis with a lifecycle model simulation, I intend to investigate the trade-offs between these two welfare approaches. Specifically, I examine the impacts on the intensive margin - hours worked by employed individuals.

The UK's current system centers around Universal Credit (UC). This is a means-tested benefit designed to streamline administration and incentivize work, which is expected to support 8.2 million households by 2028, or 29% of working-age households in the UK (Institute for Fiscal Studies, 2024). However, means-tested programs often face challenges such as low take-up rates and high administrative costs, which can

reduce effectiveness in supporting labor supply. As UC replaces six older benefits in the UK, 21% of recipients thus far have not successfully made the transition, leaving questions about the complexity and strictness of the program.

In contrast, Universal Basic Income (UBI) offers an alternative approach: an unconditional, lump-sum transfer which potentially can reduce these inefficiencies at the microeconomic level. First, it does not distort individual decisions and avoids threshold traps that might be induced by any means testing. Secondly, it can yield a 100% take-up rate as it avoids stigma or other frictions related to eligibility. However, UBI programs involve significant drawbacks that raise skepticism about its effectiveness (Kearney and Mogstad, 2019; Ravaillon, 2019). Concerns about its potential to discourage labor supply through large income effects, particularly at the bottom of the income distribution.

At the core of these debates lies the relationship between welfare policies and labor supply. This thesis contributes to the literature by investigating the research questions: *What are the labor supply effects of existing means-tested programs in the UK, particularly on the intensive margin?* and *How do these effects compare to those of a Universal Basic Income program?*

I address these questions through a two-part analysis, combining empirical evidence with lifecycle modelling. First, the empirical analysis establishes baseline labor supply effects of means-tested programs using data from the *Understanding Society* database. The lifecycle model simulates labor supply responses under a UBI scheme, enabling a direct comparison between these two systems. I investigate specifically intensive margin as studies within UBI tend to focus more on the intensive margin. This also allows me for a rigorous analysis within this field. I also argue that the UK is specifically interesting to investigate, since most studies within UBI has been made on the US, which provides an interesting contribution. With over 50% of UK

benefits currently being means-tested (Coady et al., 2021), one of the highest levels in Europe, UBI represents a radical shift from the UK's system today, making it especially interesting to look at.

Empirical Analysis: I quantify the labor supply effects of existing means-tested programs with an individual fixed-effects model. This analysis suggests that receiving any form of transfer is associated with a negative effect on average weekly hours, a reduction by 2.7. Further analysis reveals that this correlation in hours worked is more pronounced among lower-income households, consistent with stronger income effects in this group.

Lifecycle Model: I investigate the effects of a UBI by comparing a current scheme with a UBI scheme in lifecycle models. My findings show that the introduction of a UBI further reduces hours worked by 14.9%, suggesting that individuals choose to work fewer hours per week and opt for part-time work. These findings highlight the trade-offs between financial security and labor market incentives in welfare design.

This thesis makes three distinct contributions. First, I integrate an empirical analysis with lifecycle modeling to provide a comprehensive examination of the labor supply effects. I quantify the effects of current means-tested programs in the UK, which is particularly is relevant given the recent policy changes. Secondly, I address a gap in the literature by focusing on the UK, an underrepresented context in UBI research that often centers on the US. Third, I add to current literature on UBI modelling by incorporating a partial equilibrium approach, complementing existing studies that primarily rely on general equilibrium frameworks. Together, these contributions provide a robust framework for evaluating how these welfare policies influence labor market behavior.

The rest of the paper is structured as follows. Section 2 reviews the literature on Universal Basic Income and means-tested welfare programs. Section 3 provides an

institutional framework for the UK welfare system. Section 4 introduces the theoretical labor-leisure model underpinning this analysis. Section 5 outlines the empirical methodology, followed by data descriptions in Section 6. Section 7 reports descriptive statistics and Section 8 empirical results. Section 9 discusses robustness. Section 10 introduces the lifecycle model followed by parameter calibrations in Section 11. Section 12 reports results followed by a Universal Basic Income model in Section 13. Section 14 concludes.

Chapter 2

Literature Review

The literature on labor supply is vast: over the past 60 years, there has been a large volume of research by economists on labor supply (Blundell and MaCurdy, 1999; Heim, 2015). At the core of this research lies a fundamental trade-off: while tax and transfer policies aim to redistribute income or raise revenue, they often create disincentives for work, investment, and other productive activities. Since labor is of of the most important factors in production, the elasticity of labor supply is a crucial ingredient. Much attention has been devoted to modeling the institutional features of tax and transfer systems.[1]

This thesis is related to the literature on transfers and its relation to labor supply. Much of the discussion in this area has focused on tax and transfer system and its relation to labor supply. Specifically, the optimal shape the optimal income tax schedule, where Diamond (1998) and Saez (2001) find that U-shaped marginal tax rates, where proceeds should finance lump-sump transfers (essentially an UBI). This finding has been robust in separate contexts, such as savings models (Golosov et al., 2016), and for human capital accumulation (Stantcheva, 2017). While this paper does not provide an optimal tax analysis, I nonetheless show that cash transfers lead to differences in labor supply. Moffitt (2015) provide an overview the research within means-tested

[1]Classical work on optimal taxation, dating back to Ramsey (1927) and Mirrlees (1971) asks how government can raise a required level of revenue or achieve a desired degree of income redistribution in a way that minimizes the negative impact of taxes on economic activity.

programs. These programs have mainly focused on participation determinants, work incentives, and potential beneficial effects. While program design matters, transfers have negative effects on labor supply at the intensive margin (Moffitt and Zahn, 2024).

Within the field of labor supply, this thesis also focuses on universal basic income (UBI). While UBI is not a new concept - dating back to Friedman's discussion of a Negative Income Tax - it contrasts sharply with current targeted welfare transfers, have gained attention in policy and academic debates (Stern, 2016; Yang, 2018). Parijs and Vanderborght (2017) and Hoynes and Rothstein (2019) provide reviews of the policy idea. While economists such as Atkinson evaluated UBI using public finance tools in 1991, there empirical evidence on UBI is scarce due to the absence of programs that fulfill the criteria - being universal and also significant enough in size to study.[2]

This thesis is also related to the literature on aggregate effects of transfers and taxes in dynamic, general equilibrium models, given that UBI can be interpreted as a change in the tax and transfer system. Three contemporaneous papers - Conesa et al. (2023), Luduvice (2021), and Guner et al. (2023)) - study the effects in the US using a quantitative general-equilibrium framework, finding that welfare gains are difficult to achieve by replacing current transfers with a UBI. Similarly, Jaimovich et al. (2024) use search- and matching models that suggest welfare losses, while Santos and Rauh (2022) show potential welfare gains if UBI replaces unemployment benefits. Daruich and Fernández (2024) add intergenerational links and look at skill and educational

[2]Studies of analogous policies, such as the Income Maintenance Experiments in the 1970s, the Alaska Permanent Fund and the Indian tribe payments give insights into labor responses to UBI-like programs (Banerjee et al., 2019; Gentilini et al., 2020; Hanna and Olken, 2018; Hoynes and Rothstein, 2019). Jones and Marinescu (2022) investigate the macro labor supply effects.

outcomes. Lopez-Daneri (2016) finds that NTI transfers about 11% of mean income leads to a large, 2.1% welfare gain despite sharp output losses.

This thesis makes several contributions to the literature within transfers and labor supply. First, I calibrate my analysis using UK data, providing a complement to the US-focused studies mentioned above. Secondly, I incorporate a partial equilibrium framework, less common in research of UBI, to better isolate the labor market effects of policy changes. This approach offers a valuable complement to general equilibrium studies, to better understand individual labor supply responses. Thirdly, I contribute to the literature on means-tested transfers by examining labor market effects on the UK's recent welfare reforms, relevant given that Universal Credit is still on rollout before full implementation. Finally, by a grounded empirical analysis before I simulate a lifecycle model, this thesis aims to provide a holistic understanding to how different welfare policies influence labor supply.

Chapter 3

Institutional Framework

In this section, I describe the features of means-tested programs in the UK, the primary channels it can have affected the labor market, its economic scope and eligibility rules. These details provide context in the UK welfare system, giving a basis for evaluating existing policies and their effects on labor supply.

Universal credit goal and scope

The UK welfare system provides monetary transfers in several ways: state pension, tax credits, child benefits and more. This paper focuses on Universal Credit (UC), announced in 2010 and rolled out starting in 2013. When fully implemented, Universal credit will replace six "legacy" benefits: income-related employment and support allowance (ESA), income-based jobseeker's allowance (JSA), income support. Child tax credit (CTC), working tax credit (WTC) and housing benefit.

In 2023, the program had 6.3 million claimants. When fully rolled out, Universal Credit is estimated to provide 8.2 million households at any given time, or 29% of all working-age households in the UK (Institute for Fiscal Studies, 2024). UC is mainly targeting working-wage household with low income or earnings. The department of work and pensions (DWP) estimated the UC will provide net benefit of a £10.4

billion per year by increasing employment and by simplifying the system of means-tested benefits.[1]

The policy aims to create a system that incentivizes return to work, and align payments to monthly salaries, while simplify the system by reducing high marginal deducation rates to a single taper rate - ensuring financial rewards for even small amounts of work.

Eligibility requirements

The Department of Work and Pensions (DWP) administer and select recipients based on eligibility rules defined by the government. In order to be eligible, claimants must:

1. Be UK residents aged 18 or older and under the State Pension Age.

2. Have total capital less than £16,000. Capital under £6,000 are disregarded in the monthly tariff income calculation. For each additional £250 above this, £4.35 is added as tariff income (Revenue Benefits, 2024b).

Unlike older benefits such as income support, which had 100% withdrawal rate, the universal credit is designed to gradually taper away, allowing claimants to retain benefits while working part-time.

Generosity

Universal Credit benefit levels are subject to annual uprating. The standard allowance ranges from £311.68-617.60 depending age and partner status, equation to 16-32% of the mean wage in the UK.[2] Additional allowances are available for those with

[1] DWP expects implementing UC to cost £900 million or more, and to be completed at least by 2028

[2] £1950 monthly or £29,600 per year

children, disabilities, housing situation etc. The benefit cap limits weekly payments to: (Revenue Benefits, 2024a).

1. £486.89 (couples) and £326.26 (single) in Greater London
2. £423.46 (couples) and £283.71 (single) outside Greater London.

DWP estimates that 51% of ESA claimants, will gain an average of £130 per month with UC. However, organizations such as the Institute of Fiscal Studies project that 2.1 million households will lose benefits, compared to 1.8 who gain.

Take up rates

While Universal Credit began rolling out in 2013, full implementation is expected by 2028. Although take-up rates for Universal Credit are difficult to determine due to its recent implementation, Ko and Moffitt (2022) provide an overview of the take-up rates for the UKs six legacy benefits. These range from 50% to 96%, with the lowest rates observed for Jobseekers Allowance (50%) and Working Tax Credit (65%).[3]

As of 2024, a significant challenge with Universal Credit is that 21% of individuals notified to switch from their legacy benefit (most commonly tax credits) to Universal Credit failed to do so, resulting in the loss of both their legacy benefit and Universal Credit entitlements (National Audit Office, 2024).

One implementation challenge is the initial five-week waiting period for payments, which can cause financial strain and lead to rent arrears for Housing Benefit claimants. While emergency loans are available, 60% of claimants faced deductions due to loan repayments in 2019, which reduced their monthly entitlement.

[3]Take-up rates are estimated as follows: Income Support: 86% to 95%, Housing Benefit: 76%, Income Support Employment and Support Allowance: 82%, Child Tax Credit: 86%, Working Tax Credit: 65%, and Jobseekers Allowance: 50%.

The groups of people required to seek work has also broadened. Individuals previously exempt under Housing Benefit rules, such as full-time caregivers with working partners, are now required to job-search. Between 2015-2019, these changes increased claimants by 420,000. Additionally, it was announced in 2022 that jobseekers under Universal Credit would need to search more widely for suitable jobs starting from the fourth week of unemployment, rather than up to three months as was previously permitted (Department of Work and Pensions, 2022).

Table 3.1: Summary Table for Universal Credit Eligibility and Benefits

Criteria	**Details**
Age Requirement	Claimants must be aged 18 or older and under the State Pension Age.
Capital Limit	Total capital or joint capital must be less than £16,000. Capital below £6,000 is disregarded.
Tariff Income from Capital	For every £250 above £6,000, £4.35 is added to the monthly tariff income calculation.
Standard Allowance (Monthly)	Ranges from £311.68 to £617.60, depending on age and partner status.
Additional Allowances	Extra amounts are available for: • Children • Disabilities • Housing costs
Benefit Cap (Weekly)	Greater London: £486.89 (couples), £326.26 (single). Outside London: £423.46 (couples), £283.71 (single).
Waiting Period	At least 5 weeks before receiving the first payment; emergency loans are available.
Income Taper Rate	Benefits are reduced by £0.55 for every £1 earned above the Work Allowance.
Work Allowance	Rates depend on whether the claimant gets help with housing costs: • Higher rate: £673/month • Lower rate: £404/month

Chapter 4

Theoretical Framework

How much an individual works over their lifetime depends on two things: their demand for private consumption, and their demand for leisure. In this section I examine how changes in non-wage income affects labor supply through the intensive (hours worked) margin. Understanding how non-wage income affects labor supply will provide insights into the driving mechanisms under means-tested programs and Universal Basic Income - both non-wage transfers. Using a typical labor-leisure model as the theoretical framework (Cahuc et al., 2004), I derive optimal labor supply decisions through utility maximization and analyze the income effects. Finally, I propose my hypothesis linking non-wage income changes to labor supply behavior.

The Choice Problem of the Individual

Individuals choose to to allocate their total time between consumption C and leisure L. However, there is a trade-off: allocating time to work increases income for consumption, but reduces leisure which the individual also values. The individual needs to balance these competing priorities to maximize their utility.

The individuals total time is given by (L_0), which they then allocate between work (h) and leisure $(L = L_0 - h)$, to maximize utility:

$$U = U(C, L),$$

The individual's budget constraint i given by:

$$C + wL \leq R + wL_0,$$

shows that non-wage income R and wages w determine how much someone can spend. The potential income R_0 is given by $R_0 = wL_0 + R$. In this setup, the wage serves as both the price of consumption and the opportunity cost of leisure.

The individual's choice problem can then be summarized as:

$$\max_{C,L} U(C, L) \quad \text{s.t.} \quad C + wL \leq R + wL_0.$$

Under the assumptions of convex indifference curves and an interior solution, the optimal allocation of consumption and leisure satisfies:

$$\frac{U_L(C^*, L^*)}{U_C(C^*, L^*)} = w^*, \quad C^* + wL^* = R + wL_0.$$

These optimality conditions ensure that the marginal rate of substitution for leisure and consumption equals the real wage. For detailed derivations of the Lagrangian formulation and first-order conditions, see Appendix A1.

How much to work

In this section I use the optimality condition to analyze how working hours is affected following a non-wage transfer. While the substitution effect encourages individuals to work more as wages rise, I focus on the income effect, which reflects how non-wage income alters an individual leisure choice.

From the optimality condition I can see how leisure (L^*) responds to changes in wage (w) and non-wage income (R_0):

$$\frac{U_L(C^*, L^*)}{U_C(C^*, L^*)} = w^*,$$

Differentiating the above condition with respect to L^*, w, and R_0, the effects are expressed as follows:

Income Effect (Λ_1):

$$\Lambda_1 = \frac{\partial L^*}{\partial R_0} = \frac{\frac{U_{CL}U_C - U_{CC}U_L}{U_L}}{\left[2U_{CL} - U_{LL}\left(\frac{U_C}{U_L}\right) - U_{CC}\left(\frac{U_L}{U_C}\right)\right]}.$$

This expression captures the income effect: higher non-wage income R_0 allows individuals to consume more leisure without working as much. Leisure increases ($\Lambda_2 > 0$) reducing labor supply at the intensive margin. From the quasi-concavity of utility (convex indifference curves), the denominators in Λ_1 are positive, so the signs of this effects are determined by its numerator.

Implication: Higher non-wage income reduces labor supply at the intensive margin by increasing leisure

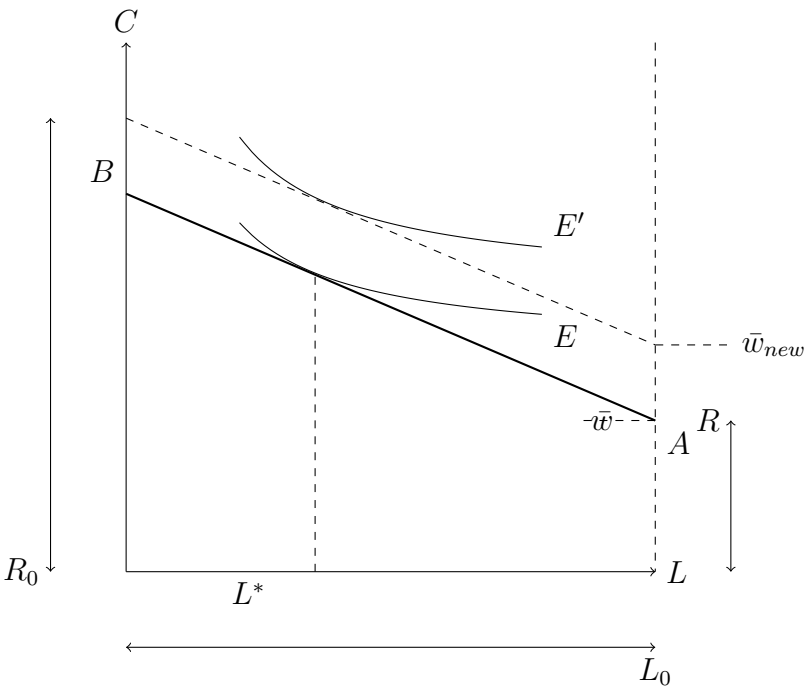
Effects of an Increase in Non-Wage Income (R)

An increase in non-wage income (R) shifts the budget line outward, as shown in the figure below. This allows individuals to consume more goods and leisure. This results in a pure income effect: labor supply decreases and leisure increases. The budget line is defined by the following equations:

$$C + wL = R + wL_0 = R_0,$$

where R_0 represents potential income from both wages and non-wage sources. Rearranging, the budget line can be expressed as:

$$C = R + w(L_0 - L).$$



Key observations about the budget line:

- A change in non-wage income (R) shifts the budget line outward in parallel.

When the budget line shifts outward due to an increase in R, individuals can increase consumption (C) and leisure (L) simultaneously. As leisure is a normal good, this reduces the overall quantity of labor supplied. In neoclassical theory, a change in R leads to a pure income effect, which impacts labor supply as follows:

1. **Intensive Margin:** Hours worked by those already employed should decrease due to the income effect.

Hypotheses

From this theoretical framework, I hypothesize:

- **Intensive Margin:** The hours worked by employed individuals will decrease due to the income effect.

The optimal solutions derived from the labor-leisure model implicitly define labor supply. Let $L^* = \wedge(w, R_0)$ represent optimal leisure, and $h^* = L_0 - L^*$ the Marshallian or uncompensated labor supply. Here, w is the real wage, and R_0 is potential income. With this hypothesis formulated, I now turn to the first main part of my analysis by looking over empirical data and analysis.[1]

[1]In Appendix A1 I detail how the extensive margin would be affected through the reservation wage. While not part of my main analysis, see this section for the theoretical mechanisms affecting whether people choose to work or not.

Chapter 5

Data

For my empirical section, I use data from the Understanding Society's UK Household Longitudinal Study (UKHLS) Questionnaires. Specifically, I use the main survey which contains anonymous individual-level and household-level responses on work, education, income, family life, and more. The data is collected once a year by sending out a survey to households, tracking approximately 40,000 households (wave 1) during 2009 −2023.

The UKHLS includes several labor market outcomes, and in this context I examine labor market participation status, gross earnings per month, and average hours worked per week. I also collect sociodemographic factors such as age and marital status, along with information on benefits received and the economic situation of the respondent. In the data, variables are coded with positive values corresponding to the respondent's answers. They also have the option to select "inapplicable," "refusal," or "don't know," which I remove.

Employment

At each annual review, participants indicate their current economic status by selecting from a predefined list of options[1]. Specifically, I consider labor force outcomes such

[1]Options include: self-employed; employed; unemployed; retired; on maternity leave; looking after family or home; full-time student; on a government training scheme; unpaid worker in a family business; or doing something else.

as employment and unemployment in relation to receiving benefits. Since unemployment specifically refers to being in the labor force, available for work, but currently without employment (International Labour Organization, 1982), I exclude periods of non-employment that classify participants as being out of the labor force. This also aligns with the Swedish AKU, conducted by the Swedish Central Bureau of Statistics (Statistiska Centralbyrån, 2024).

Moreover, I define working-age individuals as those under 55 and either over 23 with a bachelor's degree or over 19 without a bachelor's degree and not currently a student (Jáñez, 2025; Kaplan and Schulhofer-Wohl, 2017). These are the individuals whose labor outcomes are most likely to be affected by receiving means-tested transfers, capturing variation across the relevant demographic spectrum.

Table 5.1: Employment Status Distribution

Employment Status	**Freq.**	**Percent**	**Cumulative**
Employed	171,560	71,52	71,52
Unemployed	19,594	8,17	79,69
Not in Labor Force	48,730	20,31	100.00
Total	**290,009**	**100.00**	**100.00**

Including individuals not in the labor force, I have 290,009 observations in total. After removing them, my dataset contains 241,279 observations.

The figures below provide an overview of the labor market in the UK over time. While there are fluctuations depending on the year, overall trends remain consistent throughout the study period.

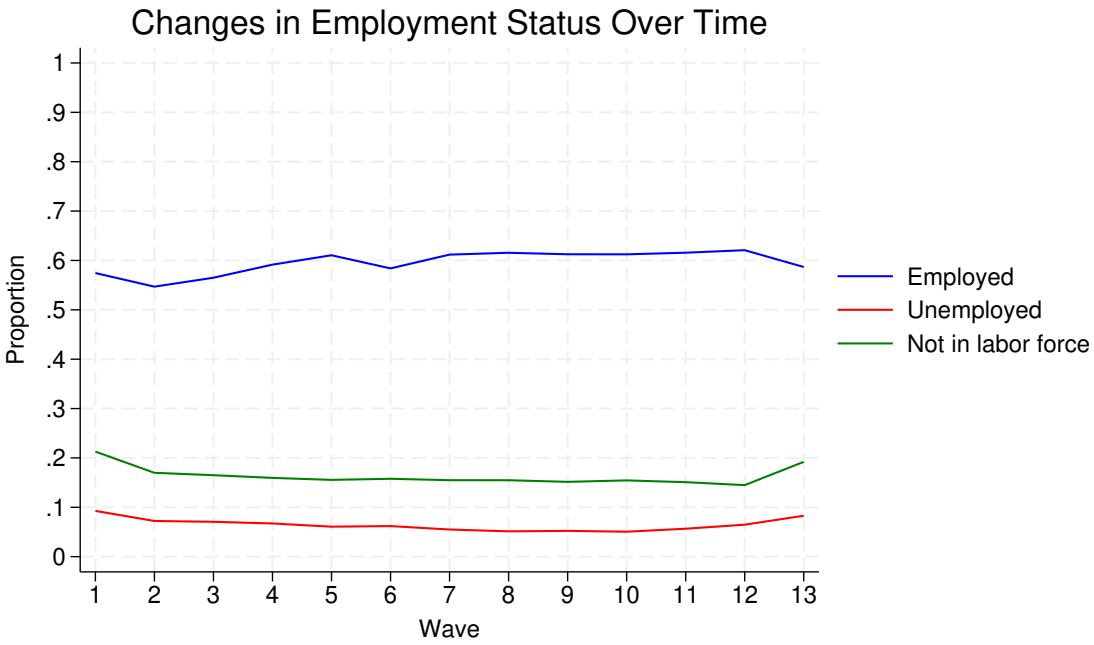


Figure 5.1: Changes in employment during the waves 1-13 expressed in percent.

Chapter 6

Empirical Method

For this analysis, I have to my disposal individual and household panel data between 2009-2023. An ideal empirical approach would be to randomize participants into two groups, one receiving benefits and the other not, and then compare the labor outcomes for the two different groups. This way, we avoid the self-selection bias in the real world data since individuals who receive different benefits are not random, and thus avoid a systematic difference. Since this is not possible due to practical reasons, I design an empirical approach that approximates the ideal using an individual fixed effects regression model.

Main Regression

When specifying the regression, I must ensure that all Ordinary Least Squares (OLS) assumptions are met, particularly the assumption that the expected error term is uncorrelated with the explanatory variables ($E(u|X) = 0$). If this assumption holds, my estimates with remain consistent and unbiased. However if this assumption is violated, my regression results can suffer from endogeneity or omitted variable bias, which could distort the results.

To get closer to satisfying the condition of $E(u|X) = 0$, I incorporate individual fixed effects into my OLS regression. Individual fixed effects control for time-invariant characteristics at the individual level. This essentially is an intercept included for each individual, meaning that I can control for all differences between individuals that

are constant over time. This is very relevant for analyzing intensive margin, since traits such as work ethic or ambition, which can influence labor outcomes but are not directly observable. Without this control, these unobserved characteristics could correlate with my explanatory variables, leading to biased estimates.

In addition to individual fixed effects, I include:

1. **Time-fixed effects:** These account for year-specific shocks, such as economic downturns or policy changes. These can affect labor outcomes across individuals. Since Universal Credit has been rolled out incrementally since 2013, I also have some natural variation in my data.

2. **Geographical fixed effects:** In my main regression, the geographical fixed effects essentially are to control for when people move between areas. These effects are important to control for, since different areas can have differences in job opportunities or local industries that affect labor supply.

3. **Time-varying individual controls:** Variables such as age or marital status, which can change over time and directly influence labor outcomes, are included to further control for observable heterogeneity.

The individual fixed effects model compares each individual to themselves over time, isolating the causal impact of receiving benefits. I believe this model is well-suited to my objective, as it is likely that individual traits, such as motivation or ambition, correlate with my explanatory variables. Moreover, I argue that the individual fixed effects model is preferable to a random effects model. A random effects model assumes that the individual-specific effect (α_i) is uncorrelated with the explanatory variables. If this assumption is violated, the random effects model produces biased and inconsistent estimates. This should not be the case since individual characteristics probably affects labor outcomes and means-tested transfer eligibility. In contrast,

the individual fixed effects model does not require this assumption, making it more robust in this case.

The main regression for the individual fixed effects model is specified as follows:

$$Y_{it} = \beta X_{it} + \delta D_{it} + \alpha_i + \text{timeFE} + \text{geoFE} + \epsilon_{it}$$

Where Y_{it} is a vector of labor market outcomes such as employment status, average hours worked per week, and the logarithm of the average hours worked per week. While employment status is defined as part of extensive margin (amount of employed people) and not part of my main scope of analysis, given the availability of data I'm find it relevant to run a regression on it, which complements the intensive margin. D_{it} is an indicator variable showing whether the individual received a benefit, and X_{it} represents sociodemographic controls[1]. timeFE represents time-fixed effects, and geoFE represents geographic area fixed effects. α_i is a vector containing individual fixed effects. Additionally to this, I run another individual fixed effects regression with an interaction term: log(social transfers) $\cdot$ D_{it}: this is essentially to control for the amount received from a benefit, to see if the amount received affects labor market outcomes.

$$Y_{it} = \beta X_{it} + \gamma D_{it} \cdot \log(\text{social transfers}) + \alpha_i + \text{timeFE} + \text{geoFE} + \epsilon_{it}$$

In addition to my main regression, I run two pooled OLS regressions to examine the general effects, assuming observations are not connected to any specific individual. Since I lose a lot of variation by using the individual-fixed effects model, this will help me verify the results of my main model. The first specification uses the indicator variable D_{it} (whether or not a participant received a benefit) as the variable of interest.

[1]Marital status, age, highest qualification

The second specification adds an interaction term to examine the combined effect of the indicator variable and the amount received. This allows me to address heterogeneous effects related to the benefit amount on labor outcomes and capture the baseline labor outcome effect of receiving a transfer. Additionally, I add time-invariant controls to my sociodemographic controls, since this model does not control for it.[2]

Unlike the individual fixed effects model, pooled OLS does not need to account for time-invariant individual characteristics, allowing me to include variables such as gender and ethnicity in the sociodemographic controls. Formally, the specifications are as follows:

$$Y_t = \beta X_{it} + \delta D_{it} + \text{timeFE} + \text{geoFE} + \epsilon_{it}$$

$$Y_t = \beta X_{it} + \gamma D_{it} \cdot \log(\text{social transfers}) + \text{timeFE} + \text{geoFE} + \epsilon_{it}$$

For all regressions I conduct, I cluster the standard errors at the individual level, as correlation on individual level can be correlated across time-periods. I cluster standard errors since, without clustering, the standard errors might be underestimated, leading to false significance in my results.

Endogeneity

To address potential sources of endogeneity which can bias my estimated relationship between means-tested transfers and my labor outcomes, I consider the following potential sources of endogeneity: omitted variable bias, multicollinearity, reverse causality.

[2]Age, gender, highest qualification, marital status, ethnicity

1. **Omitted Variable Bias:** I control for individual fixed effects, geographic fixed effects, time fixed effects, and a range of sociodemographic variables (e.g., age, marital status, qualifications) to minimize the risk of OVB. The reasons for each variable explained in the section above. Adding more variables raises risk of overfittning the model. Sensitivity tests with additional controls (e.g., household composition) show no significant differences in results, suggesting that omitted variable bias is unlikely to influence my findings.

2. **Multicollinearity:** I test for multicollinearity using the Variance Inflation Factor (VIF), to ensure that my coefficients are not inflated due to high correlation. All variables fall within the acceptable range (VIF < 10), confirming that multicollinearity is not a concern in this analysis.

3. **Reverse Causality and Endogeneity:** Reverse causality, that past labor market outcomes can influence the individuals' current eligibility for receiving means-tested transfers can be a concern. I perform lagged regressions to examine how past labor outcomes affect transfer receipt in order to investigate this effect. The results are shown in Appendix A2, and show that past employment status and hours worked are associated with current transfer receipt. This is not really surprising, as eligibility criteria for means-tested benefits often depend on prior income. However, I do not include these lagged variables in my main individual fixed-effects model to avoid introducing Nickell bias (Nickell, 1981). This bias occurs when lagged dependent variables are included in fixed-effects regressions, leading to inconsistent estimates.

Chapter 7

Descriptive statistics

During the 13-year period covered by my analysis, my sample consisted of 241,279 person-year observations. In total, £41,901,801 was given out in means-tested benefits during this 13-year period. This averages to an amount of £556, per recipients of means-tested transfers, during this period.[1] By looking at the differences between recipients and non-recipients of means-tested transfers, 75,384 individuals received some form of benefit, while 165,895 do not, corresponding to 31% percent of the sample. Tables 7.1 and 7.2 outline the average differences between these two groups.

From table 7.1 I can observe that recipients tend to be younger, work fewer hours per week, and have lower earnings. The mean monthly earnings for non-recipients is £2,357 compared to £1,234 for recipients, while the average weekly hours worked is 34.89 hours for non-recipients and 27.82 hours for recipients. This is not surprising, as fewer hours worked often result in lower earnings. Additionally, younger individuals tend to have higher unemployment rates, and thus it is not surprising that they tend to be recipients more often. Something to note is that non-recipients exhibit greater variability in earnings, suggesting a broader income range within this group. This is likely due to differences in occupation and some occupations earnings significantly more than others.

[1] Or, if looking at the whole population sample, this equals to an average of £174 per person.

Table 7.1: Descriptive Statistics for Continuous Variables

	No Transfers		Received Transfers		Total	
Variable	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Age	39.91	11.09	37.99	9.20	39.52	10.76
Earnings	2357.09	1544.52	1233.56	831.61	2179.74	1511.94
Hours Worked	34.89	9.55	27.82	10.88	33.78	10.11
N	165,895		75,384		241,279	

Examining table 7.2, I see that of unemployed participants, 61% received means-tested transfers, compared to 16% of employed participants. Recipients also tend to more commonly female, and education levels show a clear trend connected to the time spent in schooling, where 29% of individuals holding GCSE/O level qualifications receiving benefits, compared to only 8% of those with higher degree qualifications. Marital status is also interesting: single participants are more likely to receive transfers (22%) compared to married participants (17%), while divorced individuals show the highest rate of benefit receipt at 29%. This is also consistent with my expectations. Single or divorced households often have lower aggregate incomes, increasing their likelihood of seeking means-tested transfers.

Looking at Figure 7.3, there is a decline in all means-tested transfers from wave 0 to wave 12, followed by a sharp increase. Universal Credit, however, shows a gradual rise, reaching approximately 1,500 recipients per year by wave 13.

The observed decline in means-tested transfers between wave 0 and 12 coincide with the phased rollout of Universal Credit, which was designed to replace these legacy benefits. While the decline in other means-tested transfers may partly be explained by a transition to Universal Credit, the magnitude of the decrease suggests the transition

Table 7.2: Descriptive Statistics for Categorical Variables

	Total	Received Transfers (%)
Employment Status		
Employed	171,560	15,77
Unemployed	19,594	61,41
Sex		
Male	87,411	15.73
Female	103,746	24.43
Highest Qualification		
Higher Degree	26,490	8.43
1st Degree	36,737	10.92
Diploma in he	15,257	21.09
A Level	15,428	19.25
GCSE/O level	39,036	29.24
None of the alternatives	24,298	32.75
Marital Status		
Married	82.95	17.05
Single, never married	97,316	21.76
Divorced	15,462	29.12
N	7684	42095

has not managed to cover all recipients of legacy programs. It looks like a lot of recipients are without support, suggesting inefficiencies in the reform implementation. One explanation might be that recipients of legacy benefits no longer qualify under the new eligibility rules, and that there are inefficiencies in the transition to UC. This is in line with the implementation issues highlighted in the institutional framework - around 21% of recipients of legacy benefits have not made the switch. The steep decline in Jobseeker's Allowance and other means-tested transfers also might reflect stricter eligibility requirements implemented during this period.

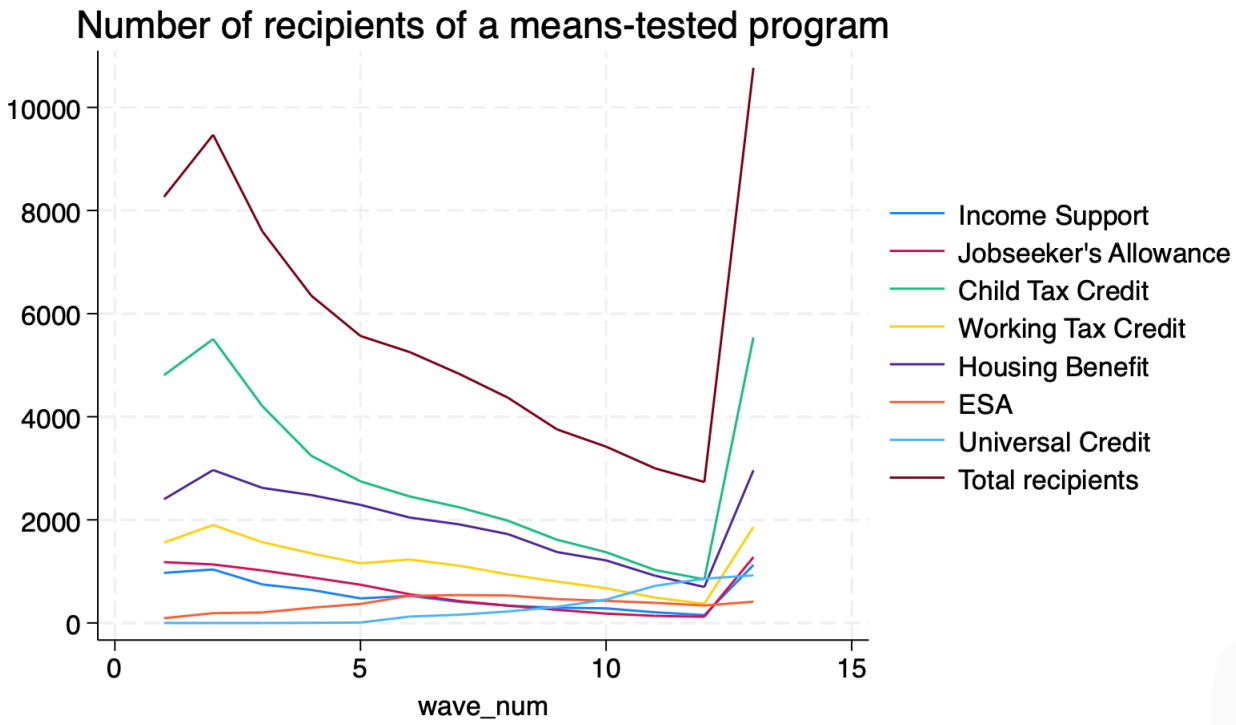


Figure 7.1: Changes in recipients of each means-tested program during the waves 1-13

Chapter 8

Results

My main regression results are presented in table 8.1. For total hours worked per week, I observe a negative correlation in both the absolute and logarithmic specifications. Specifically, total hours worked are associated with a decrease in 2.675 hours per week, while the logarithmic model suggests a 9.71% reduction. These results suggest an income effect may be at play: the additional income from transfers is associated with a reduced necessity to work longer hours. This finding aligns with my hypothesis that means-tested transfers (non-wage income) are correlated with decreases in labor supply at the intensive margin. This is aligned with Moffitt and Zahn (2024) who find that the intensive margin labor supply, while depending on program participation rates, overall is sensitive to non-labor income changes.

Employment status, while not specifically part of my research question, I believe still captures valuable insights by including it in this regression. I observe a negative correlation, suggesting that, all else being equal, receiving a means-tested transfer is correlated with a 2.91% decrease in employment probability. These results supports my hypothesis that receiving non-wage transfers raises the minimum reservation wage, making recipients less likely to seek employment. While this estimate only applied to my sample population, this suggests broad employment outcomes at the national level in the UK. Cook and East (2024) report no significant effect on SNAP transfers on employment in the U.S., which might suggest that program design and implementation have an important role in shaping labor supply responses.

Table 8.1: Individual Fixed Effects Model

VARIABLES	(1) Employment Status	(2) Hours Worked	(3) Ln Hours Worked
received_transfers	-0.126*** (0.00382)	-2.675*** (0.125)	-0.0971*** (0.00461)
Sociodemographic Factors	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes
Geographic Fixed Effects	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes
Constant	0.941*** (0.0407)	40.32*** (1.659)	3.701*** (0.0692)
Observations	171,677	154,002	153,999
R-squared	0.713	0.705	0.701

Notes: Clustered standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
The dependent variable in column (1) is employment status, a binary variable. In column (2), the dependent variable is total hours worked per week, and in column (3), it is the natural logarithm of hours worked per week. The variable *received_transfers* is a binary indicator for receiving means-tested transfers. The sociodemographic control X_{it} includes marital status, age, and highest qualification.

Table 8.2 presents the results for my main regression, that includes an interaction term between receiving a means-tested transfer and the logarithm of the transfer size. This interaction term allows me to examine how the size of the transfer affects labor supply outcomes. The correlation for on employment status is negative and significant in magnitude, at 2.91% reduction in employment.

For total hours worked, I find that a 1% increase in transfer size (log terms) is associated with a reduction in 0.648 hours worked per week. The elasticity which is calculated from the logarithmic specification (-0.0236) supports this results. Larger

transfer sizes are correlated with a reduction in hours worked, which is consistent with the income effect described in my theoretical framework.

Table 8.2: Individual Fixed Effects Model with Interaction Term

VARIABLES	(1) Employment Status	(2) Hours Worked	(3) Ln Hours Worked
Interaction term	-0.0291*** (0.000838)	-0.648*** (0.0278)	-0.0236*** (0.00104)
Sociodemographic Factors	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes
Geographic Fixed Effects	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes
Constant	0.936*** (0.0405)	40.31*** (1.655)	3.701*** (0.0691)
Observations	171,677	154,002	153,999
R-squared	0.715	0.706	0.702

Notes: Clustered standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
The dependent variable in column (1) is employment status, a binary variable. In column (2), it is total hours worked, and in column (3), it is the natural logarithm of hours worked. The *Interaction term* represents the product of two key variables, capturing the combined effect of the binary indicator variable D_{it} and log(social transfers), capturing how the amount of transfers is correlated with the dependent variable. The sociodemographic control X_{it} includes marital status, age, and highest qualification.

To contextualize my findings, I compare them with results from studies examining labor supply changes, following transfers or changes in marginal tax.

Benczúr et al. (2014) report that non-labor transfers have a consistently negative effect across subgroups, varying in magnitude depending on gender and marital status, aligning with my findings on reduced employment probability. Similarly, Bagain and Orsini (2014) report that means-tested transfers primarily affect the extensive margin, with limited effects on the intensive margin. My results show significant reductions on both employment and labor hours, which might reflect other preferences in labor

supply in the UK context, however, they discuss in their paper we cannot rule out differences in preferences across countries.

Moffitt and Zahn (2024) finds that marginal labor supply responses at the intensive margin vary with program conditions. They find the strongest reduction at low participation rates with high benefit guarantees. Since there has been an overall decrease in participation rates in means-tested transfers (as shown in my descriptive statistics part), this supports why my results are higher in magnitude. They also highlight the importance of policy design, as demographic and institutional differences can lead to varying labor supply responses depending on context.

These comparisons underline the robustness of my findings that transfers are correlated with a reduction in labor supply. However, magnitude and if the effect is on the intensive or extensive margin differ, suggesting that the effects of means-tested transfers are context-dependent, influenced by program design, population demographics and conditions of the labor market.

Mechanisms

To further evaluate the mechanisms underlying my hypothesis, I examine labor supply effects across income quartiles. This approach allows me to assess whether the impact of means-tested transfers varies by income level. Such an analysis is highly relevant because transfer recipients tend to have lower incomes and employment rates, and the correlations between transfers and labor outcomes may differ depending on an individuals position in the income distribution. From the previous section, studies highlight that effects can look differently depending on subgroups in the population, which makes this interesting to look at.

The sample is divided into four quartiles based on income, with Quartile 1 representing the lowest-income subgroup and Quartile 4 representing the highest. By

running my main regression on each subset, I aim to test whether lower-income individuals exhibit stronger labor supply responses, potentially due to higher effective marginal tax rates or greater reliance on benefits. Table 7.5 and 7.6 presents the results for the regressions.

I primarily focus on the lower three quartiles, as individuals in the top 25% of income distribution receiving means-tested transfers are atypical and might therefore not be a relevant subgroup for this analysis. Additionally, since individual fixed effects models remove much of the variation between individuals, I expect to lose significance in the output. As a result, my interpretations emphasize the direction and magnitude of coefficients rather than their statistical significance.

Table 8.3: Main Regression by Income Quartile

	(1) Employment Status	(2) Total Hours Worked	(3) Ln Total Hours Worked
Individual fixed effects			
Income quartile 1	-0.000845	-1.967***	-0.0868***
	(0.00125)	(0.180)	(0.00891)
Income quartile 2	0.00206*	-0.668***	-0.0165***
	(0.00115)	(0.167)	(0.00515)
Income quartile 3	-0.00104	-0.474**	-0.0136**
	(0.00133)	(0.214)	(0.00519)
Income quartile 4	-0.00206	-0.523	-0.0175*
	(0.00157)	(0.375)	(0.00817)

Notes: Clustered standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

For employment status, the effects are small across all quartiles. Quartile 1 shows a slight decrease in employment probability (0.0845%), while in Quartile 2 it shows an increase (0.206%), and in Quartile 3 showing a slight decrease (0.104%). These effects counterintuitively suggest a larger employment effect at higher income quartiles, even if the differences between groups are small to draw conclusions about any trend.

For total hours worked and its logarithmic specification, the effects are consistently negative across all quartiles. The reduction is most pronounced in Quartile 1. Total

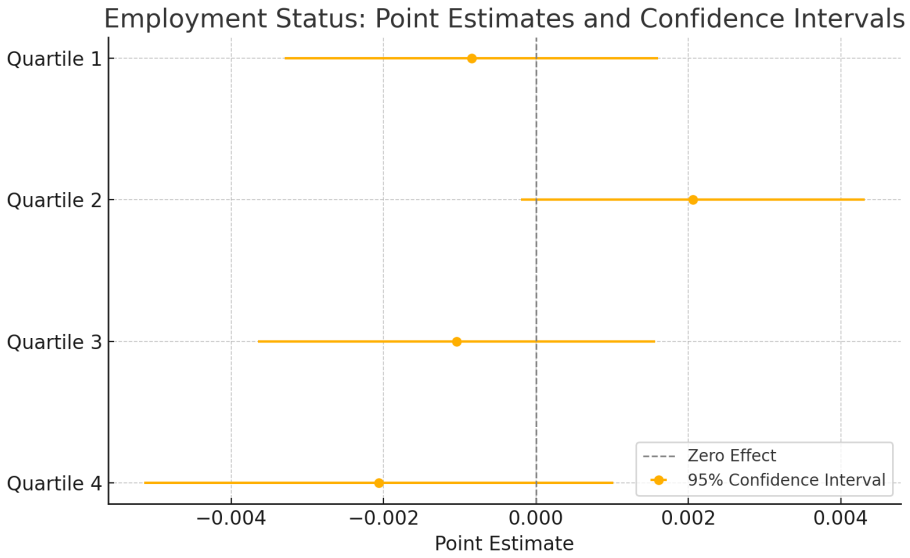


Figure 8.1: Employment status

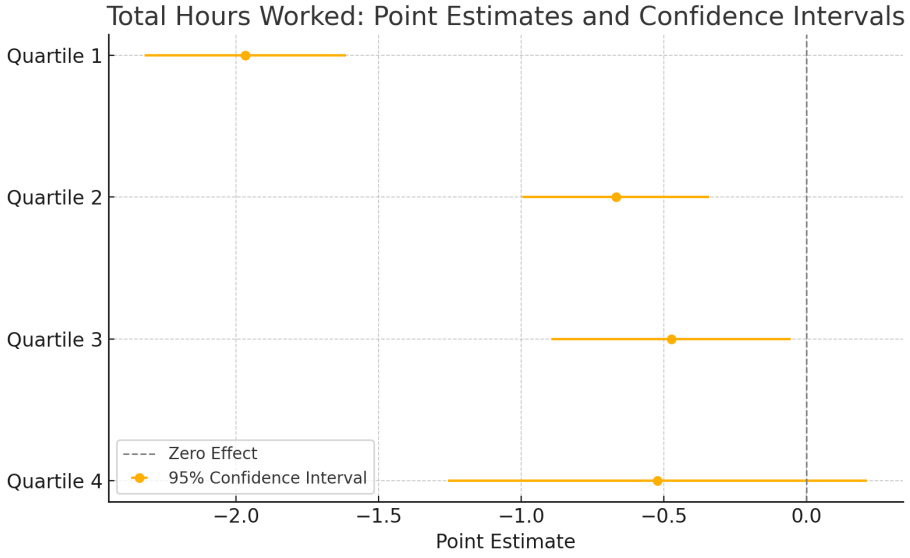


Figure 8.2: Hours worked

hours decrase 1.967 hours per week, compared to 0.668 hours in quartile 2 and 0.474 hours in quartile 3. The logarithmic model corroborates these results, with quartile 1 showing a 8.68% reducation in hours worked. These findings suggest that lower-income groups may be more sensitive to the income effect on the intensive margin, as additional income correlates with reduced necessity to work.

Table 8.4: Main regression with interaction term: income quartiles

VARIABLES	(1) Employment Status	(2) Total Hours Worked	(3) Ln Total Hours Worked
Income quartile 1: (interaction term)	-0.000235	-0.447***	-0.0199***
	(0.000246)	(0.0375)	(0.00186)
Income quartile 2: (interaction term)	0.000366	-0.154***	-0.00384***
	(0.000255)	(0.0363)	(0.00114)
Income quartile 3: (interaction term)	-4.08e-05	-0.139**	-0.00382***
	(0.000244)	(0.0476)	(0.00117)
Income quartile 4: (interaction term)	-0.000783	-0.101	-0.00394*
	(0.000491)	(0.0920)	(0.00204)

Notes: Clustered standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

When including an interaction term for transfer size, the results reinforce my earlier findings. For employment status, estimates vary for quartiles 1-3, but here quartile 1 has the greatest effect. However, the estimates are not significant in magnitude and no definite conclusion can be made. For quartile 1, a 1% increase in transfer size is associated with a 0.447-hour reduction in total hours worked and 1.99% in its logarithmic specification. These effects diminish in higher quartiles, with quartile 3 only showing a 0.101-hour reduction. These results also indicate that the income effect is the most pronounced for lower income quartiles regarding the intensive margin. A limitation is that the individual fixed effects model only tracks individuals with multiple observations, potentially excluding those who move between income quartiles over time. This limitation may bias my results by omitting individuals who move

between income quartiles, and the quartile-specific effects may not fully represent the entire population of transfer recipients.

Lastly, I briefly examine the how receiving a transfer impacts hours worked per week and employment rates. To note here is that these figures are not a proper event study, since an event study include much more rigorous considerations to its design (Miller, 2023). However, these figures can indicate interesting indicators which point towards interesting results if one would extend an analysis towards this direction. I first examine how receiving a transfer impacts mean hours worked per week and employment rates, as illustrated in Figures 7.1 and 7.2. For mean hours worked, the average starts at 35.82 hours per week and drops to 33.46 hours at the point when the recipient receives the transfer. Following this, hours worked gradually increase, reaching 35.71 hours per week six waves after receiving the transfer. Regarding employment rates, i observe that the initial level is at 92% employed. This steadily declines over time. When receiving the benefit, the employment rates reach their lowest level of 76%. Afterward, it begins to recover, increasing to 90% six waves after the transfer. This suggests that both mean hours worked and employment rates exhibit a temporary decline when receiving a transfer, followed by a gradual recovery. This pattern may reflect short-term patterns in regards to labor supply responses when it comes to receiving a benefit.

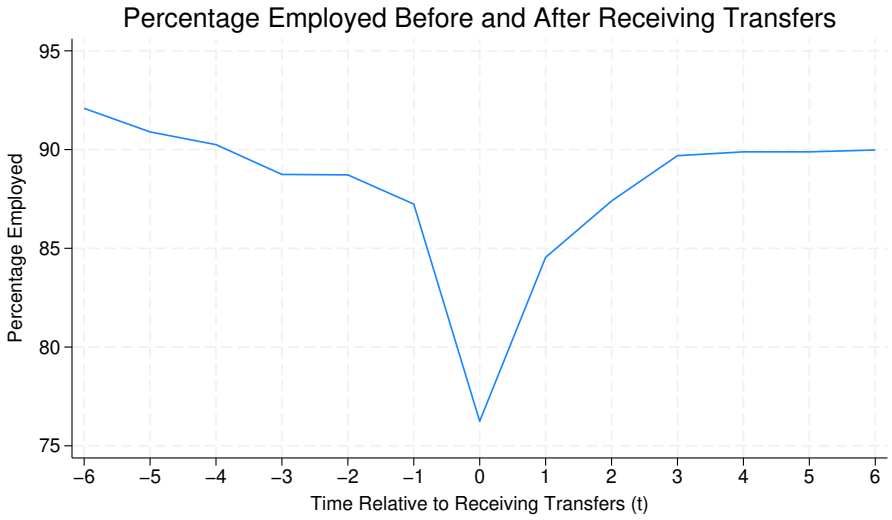


Figure 8.3: Employment status

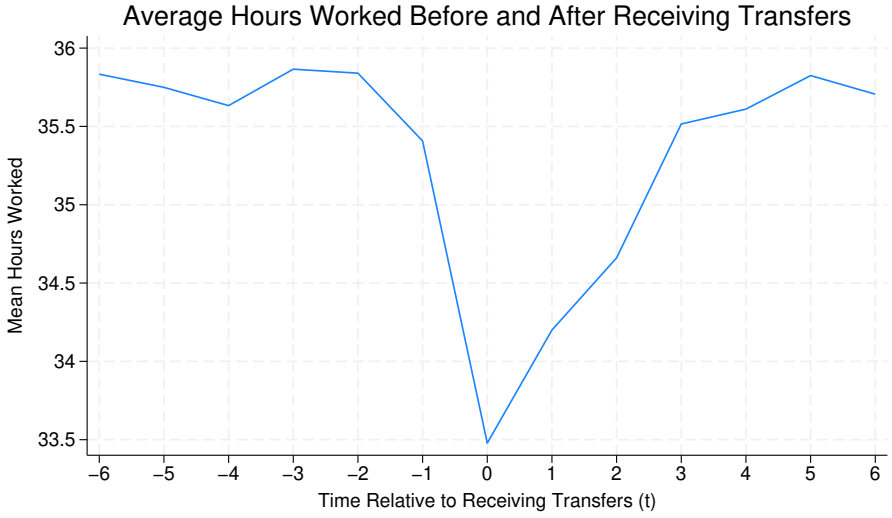


Figure 8.4: Hours worked

Chapter 9

Robustness

This section assesses the robustness of the empirical results to alternative model specifications and sensitivity analyses. I evaluate the reliability of my findings by comparing the main regression results to alternate specifications and testing the sensitivity of the results to incremental inclusion of controls. Outputs for all my results are provided in Appendix A2.

Model Comparisons

I tried alterantive specifications to try the robustness of my main regression. I conduct a pooled OLS and a pooled OLS with an interaction term. Both models produce results that are consistent with my main findings in terms of significance levels and the direction of the effects. The negative relationship between receiving means-tested transfers and hours worked is observed across all specifications.

The main model suits the data better compared to the Pooled OLS. Unlike Pooled OLS, the FE model accounts for unobservable characteristics such as work ethic, which I believe makes it better suited in this context. Furthermore, by removing time-invariant characteristics, the FE model ensures that the error term comprises only time-varying shocks, satisfying the assumption that $E(v) = 0$.

Sensitivity Analysis

I conduct a sensitivity analysis by incrementally adding controls to my main regression. I start with sociodemographic factors and then I add time fixed effects and geographic fixed effects. I find no significant changes in the direction or significance of the estimated coefficients. There are only minor differences in magnitude. These consistent results reinforce the robustness of my main findings.

Implications

My robustness checks confirm that the main results are not sensitive to the model specification or exclusion of some controls. While the alternative specifications yield similar results as my main model, as argued here and in the empirical section, my main model better suited than Pooled OLS.

After investigating the robustness of my regressions, which ground my empirical results for the thesis, I move towards the lifecycle model in upcoming sections. The lifecycle model will provide a foundation for me to investigate the impacts of a UBI scheme but also the trade-offs between means-tested transfers and UBI.

Chapter 10

Lifecycle Model

After conducting my empirical analysis on existing means-tested transfers in the UK, with the purpose providing a grounded empirical analysis which complements my lifecycle model, I now turn to the second part of my thesis. This section introduces the lifecycle labor supply model, in which I examine individual-level responses to transfers. I will first establish a baseline model where means-tested transfers are present, and then I build up towards the case where individuals have universal basic income.

Like previous papers on individual level labor market decisions (Lander, 2024; Laun and Wallenius, 2015), I do not solve for the general equilibrium outcomes or decisions of firms in the economy. Rather I focus on partial equilibrium to see individual level responses to receiving transfers. Given this, wages are not determined endogenously in the model, but rather they are exogenous parameters calibrated to match real-world data.

Households

Time is discrete and individuals in the model enter the economy at age 23 (the age by which education decisions are completed and entry into labor force happens), and live until the age of 82.[1] Each individual is thus active for 60 model periods, corresponding to 60 years, and retire at the age of 65.

[1] Average lifespan age in the UK

In each period, every individual makes consumption, saving and labor supply decisions to maximize their utility for the remaining lifetime periods. The individual i maximizes their lifetime utility:

$$\max \sum_{t=0}^{T} \beta^t \left(\frac{C_t^{\sigma-1}}{\sigma-1} - \varphi \frac{(H_t)^{\gamma+1}}{\gamma+1} \right),$$

where C_t is consumption, H_t is the fraction of time allocated to labor (hours worked), and $1 - H_t$ is leisure.

Income and employment transitions

Whether or not an individual receives income depends on if they are employed or not. If U (unemployed), the individual can get a job next period with probability λ. If E (employed), then the individual risks losing their job with probability δ the next period. Furthermore, an individuals total income depends on wage w_t and hours worked H_t. The number of hours spent working is chosen by the individual as to maximize their utility.

Regarding wages, consistently with tradition in Economics literature analyzing earnings profiles (Hall and Mishkin, 1982), I make the assumption that individual salaries are hump-shaped: starting at a lower than average level when they enter the economy and reach the earnings peak in their fifties. After that the labor income slowly starts decreasing. In my model, wages are stochastic and wages w_t depend on two factors, a deterministic age-wage profile $f[s]$ and a stochastic shock factor φ_{it}

$$w_t = f[t] \cdot \varphi_{it},$$

where $f[t]$ is the deterministic age-wage profile (hump-shaped, as described) and φ_{it} is a stochastic productivity shock that evolves according to a Markov process $P(\varphi_{i,t+1}|\varphi_{i,t})$.

This ensures that wage shocks are persistent but stochastic, capturing heterogeneity in individual productivity and wages. Individuals are, in this sense, assumed to be heterogeneous in terms of how likely they are to suffer a shock in terms of productivity, thus affecting wages and labor market participation.

Employment Transition

In this model, the state of employment evolves according to transition probabilities, where δ is the probability to lose a job between time periods. λ is the probability of finding a job between time periods. The probabilities can be expressed as follows, where $e_t = 1$ if someone is employed.

$$\mathbb{P}(e_{t+1} = 1 \mid e_t = 1) = 1 - \delta, \quad \mathbb{P}(e_{t+1} = 0 \mid e_t = 1) = \delta,$$

$$\mathbb{P}(e_{t+1} = 1 \mid e_t = 0) = \lambda, \quad \mathbb{P}(e_{t+1} = 0 \mid e_t = 0) = 1 - \lambda.$$

The expected future value is:

$$\mathbb{E}\left[V_{t+1}(S_{t+1}) \mid S_t\right] = \begin{cases} (1-\delta)V_{t+1}(A_{t+1}, 1, T_{t+1}, t+1) + \delta V_{t+1}(A_{t+1}, 0, T_{t+1}, t+1), & \text{if } e_t = 1, \\ \lambda V_{t+1}(A_{t+1}, 1, T_{t+1}, t+1) + (1-\lambda)V_{t+1}(A_{t+1}, 0, T_{t+1}, t+1), & \text{if } e_t = 0. \end{cases}$$

Budget Constraint

The budget constraint is:

$$A_{t+1} = (1+r)A_t + Y_t - C_t + T_t, \quad A_{t+1} \geq 0, \quad C_t \geq 0,$$

where Y_t depends on the individual's employment status e_t and wage w_t, given by:

$$Y_t = \begin{cases} w_t H_t, & \text{if } e_t = 1, \\ b, & \text{if } e_t = 0. \end{cases}$$

Here, $w_t H_t$ is the wage multiplied by hours worked by the individual, and b is a fixed unemployment benefit value.

Means-Tested Transfers

In each period, there is a possibility that individuals receive means-tested transfers T_t. The means-tested transfers are stochastic, and eligibility is determined by the income threshold $\bar{Y}$. The probability of receiving a means-tested transfer is therefore given by:

$$T_t = \begin{cases} R_0, & \text{with probability } p_m \text{ if } Y_t \leq \bar{Y}, \\ 0, & \text{otherwise.} \end{cases}$$

If the individual is a recipient such that $(T_t = R_0)$, there is a probability δ^p that they will lose the benefit in the next period even if they remain eligible. If their income exceeds $\bar{Y}$, they automatically lose the transfer. If the individual is eligible for the transfer (but a non-recipient), they can receive the transfer with probability p_m. The transfer amount is R_0, and the state transition probabilities for are as follows:

$$\mathbb{P}(T_{t+1} = R_0 \mid T_t = R_0, Y_t \leq \bar{Y}) = 1 - \delta^p,$$

$$\mathbb{P}(T_{t+1} = 0 \mid T_t = R_0, Y_t \leq \bar{Y}) = \delta^p,$$

$$\mathbb{P}(T_{t+1} = R_0 \mid T_t = 0, Y_t \leq \bar{Y}) = p_m,$$

$$\mathbb{P}(T_{t+1} = 0 \mid T_t = 0, Y_t \leq \bar{Y}) = 1 - p_m.$$

If $Y_t > \bar{Y}$, the transition is deterministic so that the individual automatically loses the transfer.

$$\mathbb{P}(T_{t+1} = 0 \mid Y_t > \bar{Y}) = 1.$$

The expected future value incorporates the transfer dynamics:

$$\mathbb{E}\left[V_{t+1}(S_{t+1}) \mid S_t\right] = \begin{cases} (1-\delta^p)V_{t+1}(A_{t+1}, e_{t+1}, R_0, t+1) + \delta^p V_{t+1}(A_{t+1}, e_{t+1}, 0, t+1), & \text{if } T_t = R_0, \\ p_m V_{t+1}(A_{t+1}, e_{t+1}, R_0, t+1) + (1-p_m)V_{t+1}(A_{t+1}, e_{t+1}, 0, t+1), & \text{if } T_t = 0. \end{cases}$$

Solving the model

The individual's value function depends on the state vector S_t, which includes:

$$S_t = (A_t, e_t, T_t, t),$$

where:

- A_t: Assets at the beginning of period t,
- $e_t \in \{0, 1\}$: Employment status ($e_t = 1$ if employed, $e_t = 0$ if unemployed),
- T_t: Means-tested transfer status, $T_t \in \{0, R_0\}$ if you are a recipient or not
- t: Current age (or time period).

From this, the value function becomes:

$$V_t(S_t) = \max_{C_t, H_t} \left\{ \frac{C_t^{\sigma-1}}{\sigma-1} - \varphi \frac{(H_t)^{\gamma+1}}{\gamma+1} + \beta \mathbb{E}\left[V_{t+1}(S_{t+1}) \mid S_t\right] \right\},$$

subject to:

$$A_{t+1} = \begin{cases} (1+r)A_t + w_t H_t + T_t - C_t, & \text{if } e_t = 1, \\ (1+r)A_t + b + T_t - C_t, & \text{if } e_t = 0, \end{cases}$$

$$H_t \geq 0, \quad C_t \geq 0, \quad A_{t+1} \geq 0.$$

Terminal Condition

In the final period ($t = T$), there are no further decisions:

$$V_T(A_T, 1, R_0, T) = \max_{C_T, H_T} \left\{ \frac{C_T^{\sigma-1}}{\sigma - 1} - \varphi \frac{(H_T)^{\gamma+1}}{\gamma + 1} \right\},$$

$$\text{subject to } C_T \leq (1 + r)A_T + w_T H_T + R_0,$$

$$V_T(A_T, 1, 0, T) = \max_{C_T, H_T} \left\{ \frac{C_T^{\sigma-1}}{\sigma - 1} - \varphi \frac{(H_T)^{\gamma+1}}{\gamma + 1} \right\},$$

$$\text{subject to } C_T \leq (1 + r)A_T + w_T H_T,$$

$$V_T(A_T, 0, T_T, T) = \max_{C_T} \left\{ \frac{C_T^{\sigma-1}}{\sigma - 1} \right\},$$

$$\text{subject to } C_T \leq (1 + r)A_T + b + T_T.$$

Chapter 11

Calibration

The section describes the calibration of the parameters I use in my lifecycle model. In total, there are 17 parameters related to utility function preferences, evolution of wages, employment, and transfer transition rates, among other things. I calibrate the model to match the relevant characteristics of the British labor market. For variables I calibrate myself, I use the data from Understanding Society's UKHLS Main Survey.

Labor elasticity

Following the methods often used in estimation exercises using microdata, for my estimation of labor elasticity γ, the Frisch elasticity, I use the method extensively employed by MaCurdy (1982), Browning et al. (1985), Altonji (1986), Keane and Rogerson (2012), by regressing changes in hours on changes in wages. From the utility function of the model specified in the previous section, the first-order condition for optimal labor hours is:[1]

$$\lambda_t w_t = \varphi H_t^{\gamma}$$

Taking the logs of this equation gives a similar version of the model used by MaCurdy (1982) and others in their estimation exercises using microdata:

[1] See Appendix A3 for derivations of optimal first-order optimal conditions

$$log(\varphi) + \gamma log(H_t) = log(\lambda_t) + log(w_t)$$

$$log(H_t) = \tfrac{1}{\gamma} log(\lambda_t) + \tfrac{1}{\gamma} log(w_t) - \tfrac{1}{\gamma} log(\varphi)$$

$$log(H_t) = \tfrac{1}{\gamma} log(w_t) + F_i + u_{it}$$

where $F_i = \frac{1}{\gamma}\left(\log(\lambda_t) - \log(\varphi)\right)$ and u_{it} is an error term. I then obtain γ by taking the estimate, which I call b for simplicity in this case, and calculate γ:

$$\gamma = \tfrac{1}{b}$$

I obtain the following estimates: $\gamma = 2.941$ and Frisch elasticity $= 0.340$.

Weight of labor disutility

Next, I need to estimate the weight of labor disutility φ for the utility of the individual. The problem that arises here is that this typically requires data on consumption (MaCurdy, 1981). I therefore approximate this weight by assuming that consumption is a fixed proportion κ of ones labor income. Beginning with the first-order conditions[2], φ is solved as:

$\lambda_t w_t = \varphi H_t^{\gamma}$

Since the first-order condition specifies the following:

$\lambda_t = C_t^{\sigma-2}$

I get:

$\varphi = \frac{C_t^{\sigma-2} w_t}{H_t^{\gamma}}$

[2]See Appendix A3 for derivations

As mentioned earlier, since I do not have consumption data in my dataset, to solve for the weight of labor disutility, I assume consumption is proportional to income such that: $C_t = k \cdot w_t \cdot H_t$. Here I assume $k = 0.708$, based on estimates for the UK by Clementi et al. (2007). Then, consumption can be expressed as: $\log(C_t) = \log(k) + \log(w_t) + \log(H_t)$. Substituting into the first-order condition, I get:

$log(w_t) = \frac{log(\varphi)}{1-(\sigma-2)} + \frac{\gamma}{1-(\sigma-2)} log(H_t) + \frac{(\sigma-2)}{1-(\sigma-2)} log(H_t) + u_{it}$

From this, I obtain a value for $\varphi = 0.101$. While slightly on the lower side of expectations, a relatively high labor elasticity $\gamma = 2.941$ from earlier calibrations should balance this out.

Income

Consistent with tradition in economic literature analyzing earnings profiles (Hall and Mishkin, 1982), I assume that agents' salaries are hump-shaped: starting at a lower-than-average level when they enter the economy, peaking in their fifties, and then gradually decreasing.

However, the difficulty with this variable is that I do not have observations on wage offers received by individuals outside the labor force. I only have observations in my sample for those satisfying a reservation wage condition, which is not a random or representative selection. This problem is called sample selectivity bias. As a consequence, I cannot straightforwardly regress observed wages on the personal characteristics of those who work when inferring the distribution of wage rates. Thus, the variables that determine whether someone participates in the labor force exert an indirect influence on the mean of the observed wage distributions (Deaton and Muellbauer, 1980). To control for this, I estimate a wage process based on the methodology by Daruich and Fernández (2024), utilizing the Heckman selection estimator approach (Heckman, 1980).

Using this approach, the age profile for wages is estimated as: $w_{it} = \beta_0 + \beta_1 Age_{it} + \beta_2 Age_{it}^2 + \beta_3 X_{it} + \gamma_i + \psi_{it}$ where X_{it} controls for selection into work based on a Heckman selection estimator[3]. My age-wage profile is:

$$1.412 + 0.0567 * Age - 0.000557 * Age^2 - 0.117 * Mills + \gamma_t + \varphi_{it}$$

where γ_{it} is time fixed effects, averaged out over my period = 0.13106, and φ_{it} is the residual. The Mills estimator is -0.117.

I then solve for the idiosyncratic shock, which affects wages and is interpreted here as a productivity factor. I solve for idiosyncratic shock ψ by recovering the residual in the UKHLS data, using this equation:

$$log(\psi_{ij}^e) = \lambda^e log(\theta_{ic}) + \eta_{ij}^e$$

From this, I recover $\rho_e = 0.8113$ and $\sigma^2 = 0.1329$, which shows the persistence of shocks along with the variance.

Unemployment and employment

I estimate the transition probabilities for the chance of finding a job (λ) and the chance of losing a job (δ) as follows. I calculate the number of people employed in the current period who were unemployed previously, and the proportion gives $\lambda = 0.310$. For δ, I take the number of unemployed people and the number of people employed in the previous period. Taking the proportion gives $\delta = 0.0270$.

[3]See Appendix A3 for detailed results

Means-tested transfers

For the amount people receive in means-tested transfers, I set the value to $R_0 = £395$, based on the base value provided by the Department of Work and Pensions. Regarding the threshold rate, there is no fixed threshold; rather, Universal Credit is phased out depending on how much you earn and your living situation. Since there is no exact cutoff, but instead transfers are proportional to earnings, I derive this threshold number by calculating the maximum wage you can earn before your transfers become zero. For someone working, the base income (without additional benefits) is calculated as the difference between your wage and a monthly fixed allowance times 0.55 (£404). Using this, the income threshold is: £1138.55[4].

While this approach may overestimate the amounts people receive in means-tested transfers, since I assume a fixed amount cut off at the threshold rather than phased out, I believe it improves comparability to the UBI case later, where individuals all receive a fixed amount in transfers.

I also calculate the probability of receiving a means-tested transfer among eligible individuals as $\delta_p = 0.346$. For the risk of losing a means-tested transfer, p_m, I calculate the value as $p_m = 0.234$.

Other parameters

For other variables in the model, as in Laun and Wallenius (2015), I set the interest rate to $r = 3\%$, and the discount parameter β to $1/(1 + r) = 0.97$, ensuring that the discount rate and the interest rate offset each other to smooth consumption. For consumption risk aversion, I set $\sigma = 2$ to ensure consumers are moderately risk-averse. Unemployment benefits are taken as the Jobseeker's Allowance, the UK's equivalent

[4]This income is derived from $(x - 404) * 0.55 - 404 = 0$. Solve for x gives 1138.55

to unemployment benefits, and set to 392 based on the base level of benefits eligible individuals can receive.

Summary of all estimates

Here is a summary of the variables I use in my lifecycle model. For earnings and benefits, I use annual values.

Table 11.1: Lifecycle Model Parameter Estimates

Parameter	**Definition**	**Value**
β	Discount factor	0.97
r	Interest rate	3%
σ	Risk aversion consumption	2.0
φ	Weight of labor disutility	0.101
γ	Leisure elasticity	2.941
fs	$1.412 + 0.0567 \cdot \text{Age} - 0.000557 \cdot \text{Age}^2 + \text{Mills} + Y_t$	N/A
Mills	Mills estimate	-0.117
Y_t	Average time effect	0.13106
ρ	Persistence of idiosyncratic shock	0.8
σ_n	Std. dev. of idiosyncratic shock	$\sqrt{0.2}$
λ	Probability of finding a job	0.310
δ	Probability of losing a job	0.0270
b	Unemployment benefit	$392 \cdot 12$
$y_{\text{threshold}}$	Income eligibility	$1138 \cdot 12$
R_0	Means-tested transfer	$395 \cdot 12$
p_m	Probability of receiving transfer	0.347
δ_p	Probability of losing transfer	0.234

Chapter 12

Simulation results

This section presents the baseline lifecycle model, which captures lifecycle dynamics while serving as a baseline for examining the effects of a universal basic income later on. The model incorporates minimal assumptions and focuses on the role of wages, transfers, and employment status on labor outcomes. Comparisons to empirical data also provide context for evaluating its performance.

Welfare dynamics

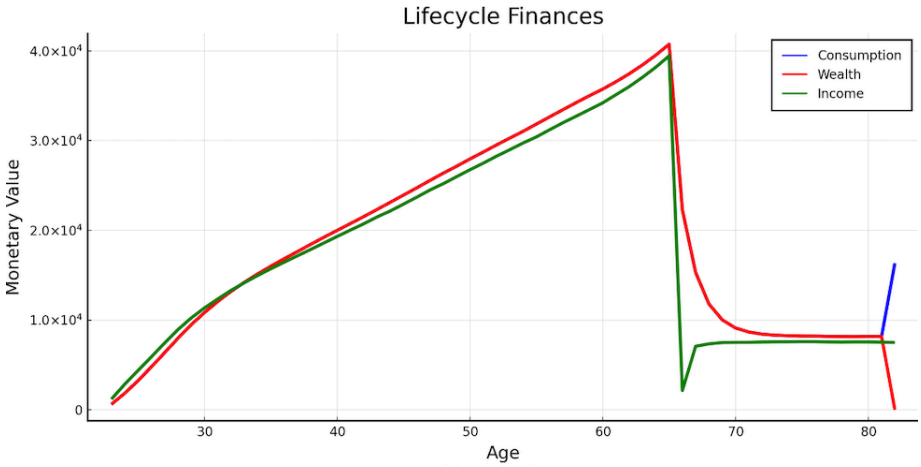


Figure 12.1: Outcomes of consumption, income, and wealth in the lifecycle model.

Starting with the standard lifecycle trajectories for income, consumption, and wealth, the model shows the expected patterns that are typically observed in lifecycle models. Figure 12.1 illustrates this. Individuals dissave during early years, accumulate

more savings as they become older, and then dissave when they go into retirement, indicating consumption smoothing.

Income peaks at age 65, which diverges from real-life dynamics where it typically peaks around the 50s. This is reasonably caused by the sharp cutoff in working hours.

Employment and transfer rates

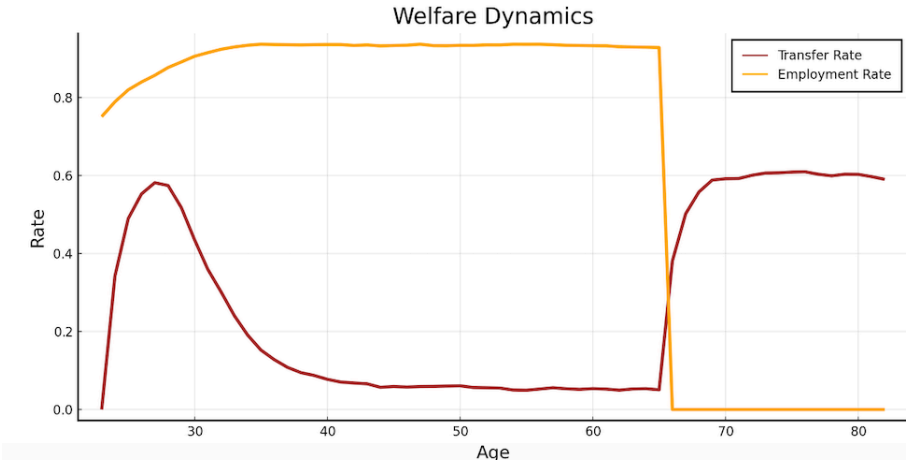


Figure 12.2: Outcomes of consumption, income, and wealth in the lifecycle model.

Employment and transfer rates follow plausible lifecycle dynamics. Regarding employment, it starts lower for young individuals (Figure 12.2), reflecting the fact that young people are new to the labor market and have limited experience. However, this rate also grows quickly and stabilizes around the 90% mark before dropping after retirement. Transfer rates are also the highest for young people and retired people, which is realistic given that this benefit is given out during periods of unemployment.

Working hours

Figure 12.3 shows the lifecycle trajectory for working hours during an individual's lifetime. Similarly to the trajectories of income, consumption, and wealth, working hours follow a similar trend that peaks right before retirement. Typically, it would be

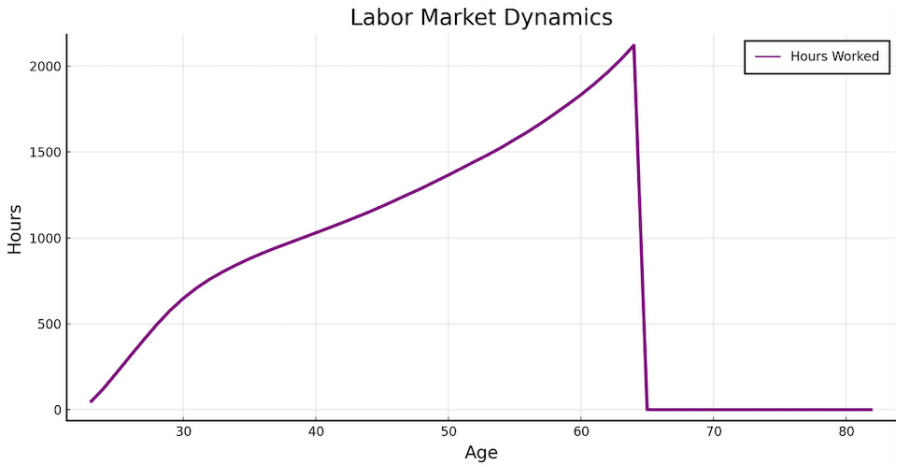


Figure 12.3: Outcomes of working hours in the lifecycle model.

more expected that young people work more compared to older people. This difference may be linked to the wage profile in the model, and exploring alternative profiles could refine this. However, the overall pattern remains consistent with expected behavior.

Differences between recipients and non-recipients

This section evaluates the income dynamics of recipients and non-recipients of means-tested transfers across the lifecycle, to evaluate how means-tested transfers affect certain subgroups. The population is divided into recipients and non-recipients, and their lifecycle trajectories are shown below. I also conduct a comparison of real-world data taken from UKHLS data to evaluate how my model matches real-world patterns.

Employment dynamics

Recipients of means-tested transfers consistently exhibit lower employment rates than non-recipients across the lifecycle, as shown in Figure 12.4. Employment levels for

recipients peak early, between ages 25 to 30, before declining steadily as individuals exit the labor force. For non-recipients, employment rates instead follow a stable pattern and stabilize at just above 90%. The employment rates of non-recipients remain higher throughout their working years until retirement, where everyone in the model goes into retirement. Comparison with real data shown in Figure 12.5 shows that the simulated data aligns with real-world data in several aspects. Recipients of means-tested transfers seem to consistently have lower employment rates than non-recipients. I also observe that while non-recipients tend to follow a very stable trajectory, the employment rates for recipients vary and reach their peak at just under 80% around age 40. While the simulated data also has a peak, which is around 85%, its peak is much earlier compared to real-world data. This might be a result of exogenously calibrated transition rates for employment, which push the rates for recipients up early.

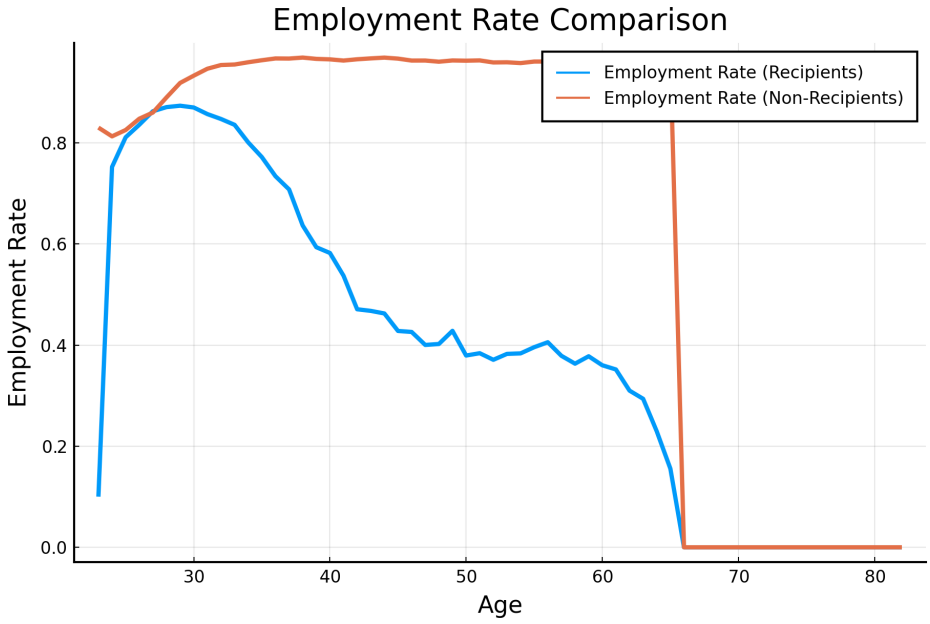


Figure 12.4: Simulated data



Figure 12.5: Real data

Income dynamics

Figure 12.6 illustrates income trajectories for recipients and non-recipients over the lifecycle. Recipients consistently earn lower incomes throughout their lives, reflecting reduced labor force participation and reliance on means-tested transfers. There is one exceptionbefore the age of 30. This suggests that the transfer rates are higher relative to the age-wage profile during this period. The income trajectory of recipients peaks early, around ages 2530, before declining gradually. In contrast, non-recipients experience higher incomes, which increase steadily until midlife around ages 4050, before stabilizing and then declining as they approach retirement.

Figure 12.7 displays a comparison to real-world data from UKHLS. My model broadly captures the trajectories of the real-world datarecipients have an overall very flat trajectory in terms of their income. The income of non-recipients also increases

a lot. The data shows a more curved trend than the model does, but overall it has a similar trend. The data also shows a peak around age 55 to 60, possibly due to outliers in the data, such as entrepreneurs.

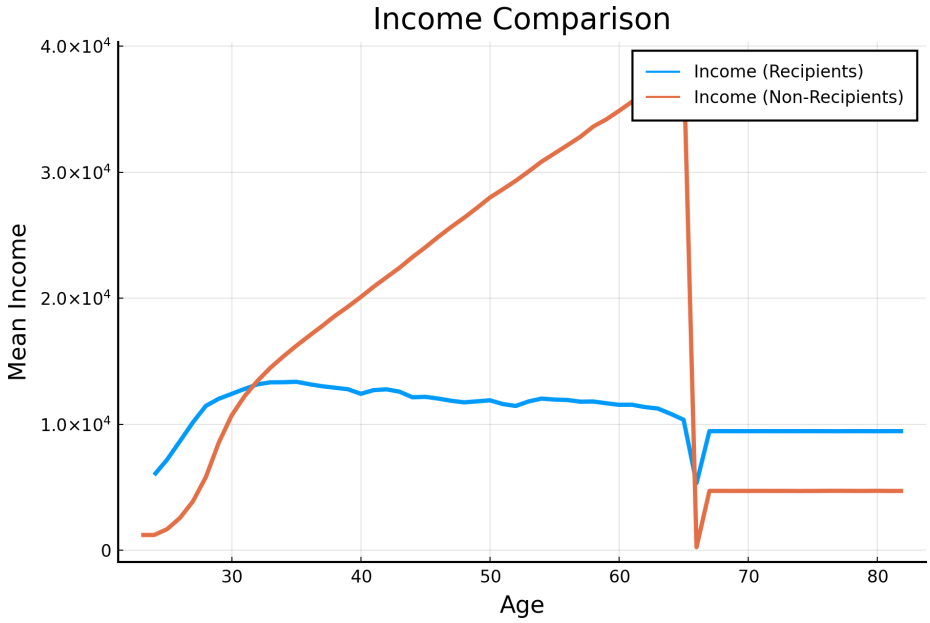


Figure 12.6: Simulated

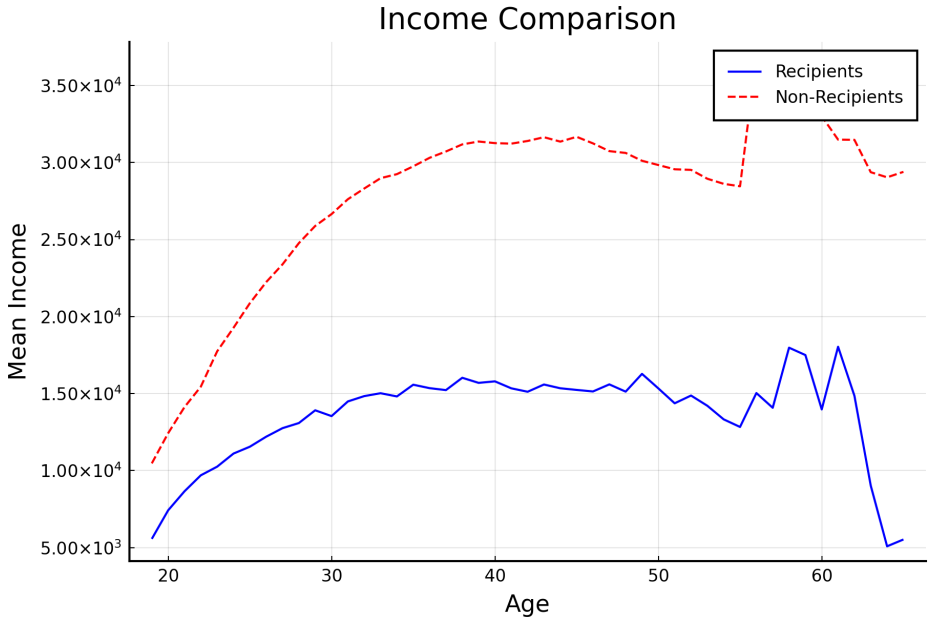


Figure 12.7: Real data

Labor hours

Figure 12.8 displays the differences between recipients and non-recipients in labor hours worked. This follows a similar trajectory to incomenon-recipients work significantly more hours than recipients throughout the lifecycle, which is also reflected in the real-world data in Figure 12.9. This suggests that the model may capture the income effectpeople receiving a non-wage transfer are not as incentivized to work, and thus work fewer hours. The model seems to overstate the volatility in labor hours, and the peak at age 65 is higher than observed in the data. However, the general pattern seems to capture the differences between recipients and non-recipients.

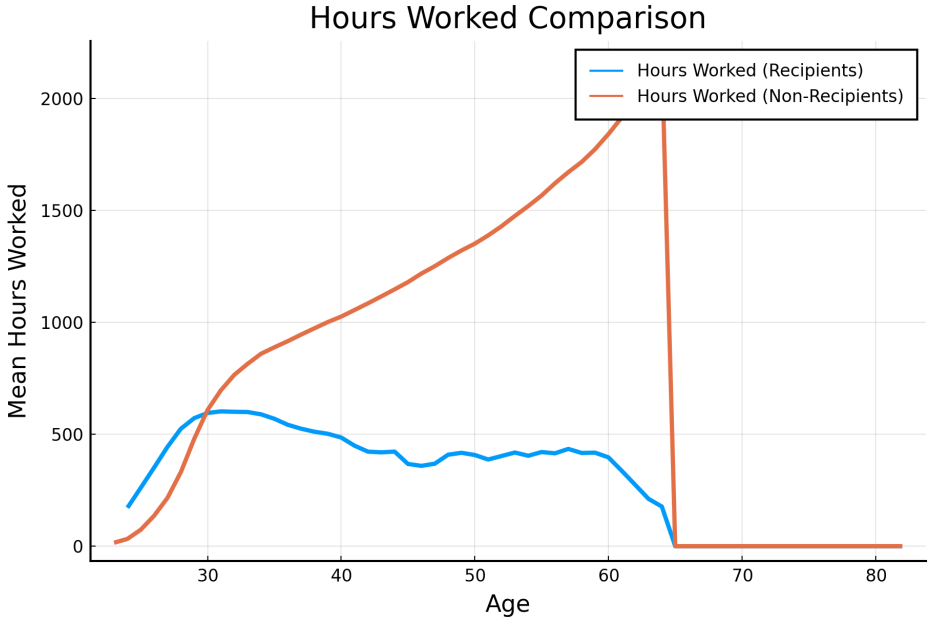


Figure 12.8: Simulated

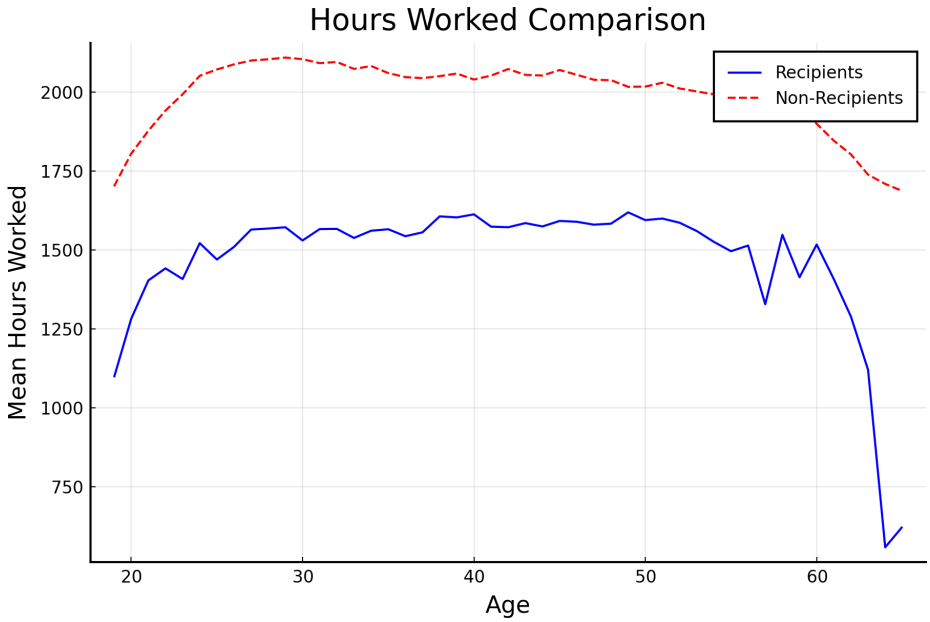


Figure 12.9: Real data

Summary and implications

These results from my baseline model highlight the strengths and limitations of capturing lifecycle income and labor dynamics. The model successfully replicates major patterns, including the lower employment rates, incomes, and labor hours for individuals in the simulation, and shows a significant difference between recipients and non-recipients regarding lifecycle trajectories. While the model does not perfectly align with all empirical patterns, such as the timing of income peaks or labor hours volatility, given that the model is relatively simple, it still manages to capture the main effects as expected. Thus, this model provides a grounded framework for further analyzing lifecycle dynamics under a UBI. These deviations might highlight areas for future extensions, such as phased-out retirement or age-dependent preferences in working and leisure.

Overall, the baseline model replicates key patterns observed in real-world data, including differences in employment rates, income trajectories, and labor hours. Despite some overstated trends, the model achieves its purpose in providing a foundational framework for examining the impact of a UBI, with its focus on key assumptions.

Chapter 13

Introducing a Universal Basic Income Policy

In this section, I introduce the UBI policy as a lump-sum transfer made every period to all individuals once they become adults.

The benchmark analysis considers a level of UBI that has been suggested by policymakers and is currently tested in the short-run, small-scale environment of the YC Research group in Oakland, California. I assume that all adults (ages 23-65) receive the equivalent of an annual transfer of £6,317[1]. This number is equivalent to $1,000 per month in 2020 dollars, and the number proposed by Andrew Yang in his 2020 presidential campaign. It is also used by Daruich and Fernández (2024), Golosov et al. (2016), Hoynes and Rothstein (2019), and Luduvice (2021). I assume the policy is introduced at the start of the lifecycle model. I examine the consequences of such a policy, analyzing how it affects labor supply outcomes.

Lifecycle profiles

Figure 13.1 shows the lifecycle trajectories of consumption, income, and wealth under the UBI scheme. As expected, individuals follow a standard lifecycle pattern with dissaving during youth and saving at prime working ages. Individuals seem to smooth consumption more compared to the baseline, indicating that people are able to save more during this scheme. Similarly to the baseline, the UBI model also peaks in consumption, wealth, and income at age 65, before dropping after retirement.

[1] Converted from $8,000

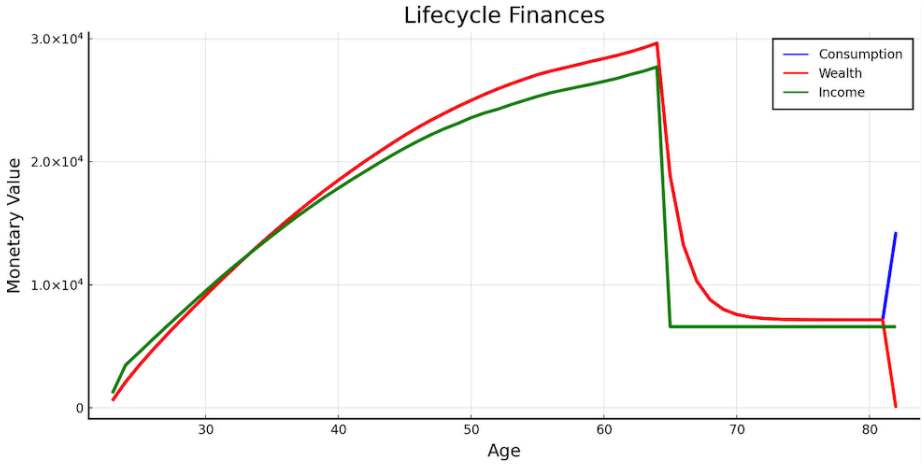


Figure 13.1: Outcomes of consumption, income, and wealth in the lifecycle model.

Employment dynamics

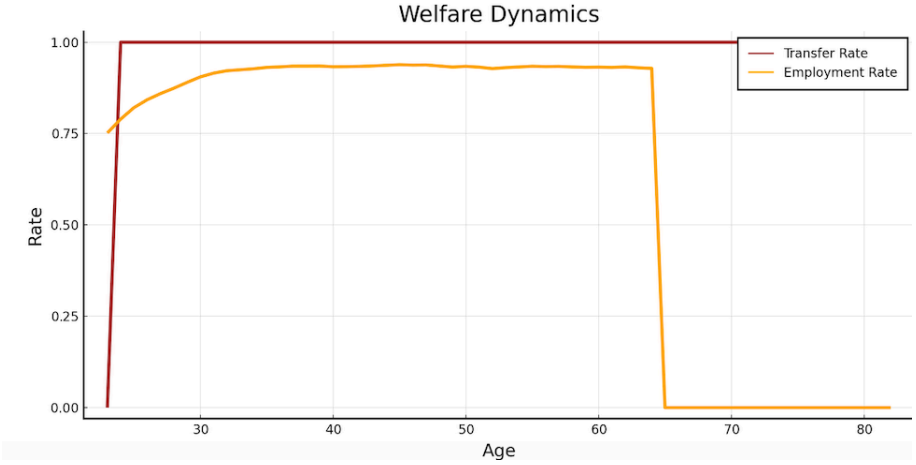


Figure 13.2: Employment rates and transfer receipt under the UBI scheme.

Employment dynamics under the UBI scheme remain largely unchanged from the baseline model, as shown in Figure 13.2. Employment rates increase during early adulthood, stabilizing at approximately 90% for most of the working life, before declining sharply at retirement age. This closely reflects real-life dynamics. As

expected under a universal UBI policy, transfer rates remain at 100% throughout the individuals' lifetimes, since all adults are eligible for the lump-sum transfer regardless of employment status.

Behavioral responses

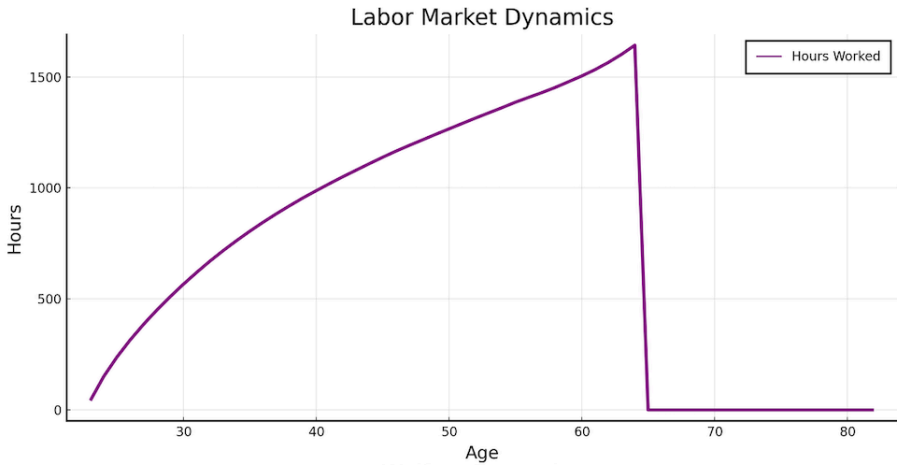


Figure 13.3: Labor supply outcomes under the UBI scheme.

Figure 13.3 illustrates the effects of UBI on labor hours. The plot shows a reduction in labor supply under UBI, driven primarily by the intensive margin adjustments. While employment rates remain stable, workers reduce hours worked, which indicates an income effect making people content with working less.

Contextualizing these findings, they are mainly in line with research on UBI in lifecycle dynamic models. Guner et al. (2023), find that decreases in labor hours and productivity under a UBI scheme with 0.9 percentage points. Luduvice (2021) find a 7 percentage point decrease in labor hours worked, and that UBI can both increase or decrease consumption, depending on how high the UBI and the following tax rates are, and that lower UBI levels decrease consumption. Furthermore, Daruich and Fernández (2024) report a significant decrease in hours worked, regardless of educational background. They find a decrease between 15.3 to 45.6 percentage points

in a general equilibrium framework, depending on model design. They also find a decrease in overall consumption for individuals as well. Interestingly, they find that agents in high-income percentiles tend to be more affected than those in low-income percentiles when it comes to wealth.

The table below displays some comparisons between the respective models and their effects on consumption, wealth, income, employment, transfer rate, and hours worked. It shows that overall welfare decreases on all fronts, with decreases in consumption, labor hours, and overall wealth.

Table 13.1: Summary statistics for the Means-Tested Transfers and UBI models, including percentage differences relative to means-tested transfers

Variable	**Means-Tested Transfers (Mean)**	**UBI (Mean)**	**% Difference**
Consumption	19,216.96	15,913.81	-17.20%
Wealth	18,944.65	15,675.57	-17.28%
Income	17,749.99	14,699.59	-17.19%
Hours Worked	760.10	646.58	-14.93%
Employment Rate	0.656	0.640	-2.44%

This exercise allows me to show that the implementation of a Universal Basic Income results in labor supply losses in terms of the intensive margin, with reduced working hours, consistent with Luduvice (2021), and Daruich and Fernández (2024). As income increases due to a universal transfer, the marginal rate of consumption decreases, thus making it more worthwhile to take leisure time instead of working. Even if a means-tested transfer program indicates an income effect that reduces recipients' labor supply, these effects seem to hold also when applied to the greater population, thus increasing the labor supply reduction in magnitude. While the magnitude of decrease in labor supply differs between papers (Daruich and Fernández (2024) find a decrease between 15.3-45.6% in labor hours worked, while Guner et al. (2023) find a decrease of 0.9%,) there seems to be a consensus that labor hours decrease following

a Universal Basic Income scheme. Exactly how much labor hours decrease (or any of the other welfare measures such as consumption or wealth) depend on the policy design in place for the implementation of Universal Basic Income.

Chapter 14

Conclusion

This thesis evaluates the labor market effects of means-tested transfers and explores the potential implications of introducing a universal basic income as an alternative. I combine a grounded empirical analysis with a lifecycle model, with the intention of shedding light on the trade-offs between these two welfare approaches.

The empirical analysis indicates significant negative effects of means-tested transfers on the intensive margins of labor supply. Specifically, receiving a means-tested transfer correlates with a a 2.7-hour weekly reduction in labor hours. These findings suggest that, despite their intent to incentivize work, means-tested transfers are correlated with a negative effect on labor supply, likely due to income effects. Extrapolated to the UK population, the implications on the national level of labor hours and productivity are substantial.

To investigate whether a UBI scheme could mitigate these effects, I developed a lifecycle model calibrated on the UK economy. I construct a UBI policy as a counterfactual economy and my simulations indicate that introducing a UBI would further decrease labor supply, with hours worked declining by 14.9%. This is in line with theoretical expectations and the findings by Guner et al. (2023), Daruich and Fernández (2024), and Luduvice (2021). The results highlight the trade-offs between equity and efficiency in welfare design.

These findings contribute to the current debate on welfare reform, particularly in a UK context - but is also relevant for neighboring countries - where means-tested

transfers constitute a significant share of welfare expenditures. From an inefficiency standpoint, while UBI offers simplicity and inclusivity, it can exacerbate labor disincentives compared to the current means-tested systems. On a larger societal level, a UBI program would have large implications on a country's workforce, and a declined labor force is generally associated with several potential questions and challenges regarding such as economic growth or fiscal sustainability.

Regarding inefficiencies, take-up rates of means-tested programs in the UK today range from 50%-96%, with lower rates associated with job-related benefits (Ko and Moffitt, 2022). From a welfare standpoint, this is certainly a consideration for challenges with means-tested programs. Furthermore, Isaacs (2008) estimates that the cost of running means-tested welfare programs such as food stamps or the TANF programs in the US can be as high as 15% each dollar issued. While my analysis abstracts from these costs, transitioning to a simpler system might address such inefficiencies, though the broader implications for labor markets require further exploration.

By combining robust empirical methods with lifecycle simulations, this thesis bridges the current divide between case-based quantitative analysis and simulation-based explorations, offering insights into the labor market effects of welfare design. It contributes to the literature by extending the study of UBI to a UK context, offering insights into the labor market effects of welfare design in a country with one of Europes highest shares of means-tested transfers.

I end this thesis with three comments. First, as labor market choices interconnect with several aspects of a consumers life, exploring a framework which incorporates extensive margin choices, taxation, and more, on both a partial equilibrium framework as well as a general equilibrium approach could further shed light on the labor effects of a Universal Basic Income program. Secondly, the design and implementation of welfare policies, including eligibility criteria and transfer sizes, are critical in shaping

labor market responses. Future research could explore how modifications in means-tested programs or UBI systems can balance redistribution goals with maintaining labor incentives. Finally, further investigation into the long-term implications of UBI and means-tested programs on administrative costs and productivity, is essential for these policy debates.

Bibliography

Altonji, J. (1986). Intertemporal substitution in labor supply: Evidence from micro data. *Journal of Political Economy*, 94(3):S176–S215.

Bagain, O. and Orsini, K. (2014). Comparing labor supply elasticities in europe and the united states: New results. *Journal of Human Resources*, 49(3):723–838.

Banerjee, A., Niehaus, P., and Suri, T. (2019). Universal basic income in the developing world. *Annual Review of Economics*, 11:959–983.

Benczúr, P., Kátay, G., Kiss, A., and Rácz, O. (2014). Income taxation, transfers, and labour supply at the extensive margin. *Banque de France*. JRC89930.

Blundell, R. and MaCurdy, T. (1999). Handbook of labor economics. *Handbook of Labor Economics*, 3:1559–1695.

Browning, M., Deaton, A., and Irish, M. (1985). A profitable approach to labor supply and commodity demands over the life-cycle. *Econometrica*, 53(3):503–544.

Cahuc, P., Carcillo, S., and Zylberberg, A. (2004). *Labor Economics*. MIT Press, 2nd edition.

Clementi, F., Gallegati, M., and Kaniadakis, G. (2007). Kappa-generalized statistics in personal income distribution. *The European Physical Journal B*, 57(2):187–193.

Coady, D., Jahan, S., Matsumoto, R., and Shang, B. (2021). Guaranteed minimum income schemes in europe: Landscape and design. *International Monetary Fund, IMF Working Paper*.

Conesa, J., Li, B., and Li, Q. (2023). A quantitative evaluation of universal basic income. *Journal of Public Economics*, 223:104881.

Cook, J. and East, C. (2024). The effect of means-tested transfers on work: Evidence from quasi-randomly assigned snap caseworkers. *National Bureau of Economic Research, NBER Working Paper*.

Daruich, D. and Fernández, R. (2024). Universal basic income: A dynamic assessment. *American Economic Review*, 114(1).

Deaton, A. and Muellbauer, J. (1980). An almost ideal demand system. *The American Economic Review*, 70(3):312–326.

Department of Work and Pensions (2022). Jobseekers have four weeks to find work before widening their search. Press release. Available at: https://www.gov.uk/government/news/ jobseekers-have-four-weeks-to-find- work-before-widening-their-search. Accessed: 2024-12-04.

Diamond, P. (1998). Optimal income taxation: An example with a u-shaped pattern of optimal marginal tax rates. *American Economic Review*, 88(1):83–95.

Gentilini, U., Grosh, M., Rigolini, J., and Yemtsov, R. (2020). Exploring universal basic income: A guide to navigating concepts, evidence, and practices. *World Bank*.

Golosov, M., Troshkin, M., and Tsyvinski, A. (2016). Redistribution and social insurance. *American Economic Review*, 106(2):359–386.

Guner, N., Kaygusuz, R., and Ventura, G. (2023). Rethinking the welfare state. *Econometrica*, 91(6):2261–2294.

Hall, R. and Mishkin, F. (1982). The sensitivity of consumption to transitory income: Estimates from panel data on households. *Econometrica*, 50(2):461–481.

Hanna, R. and Olken, B. A. (2018). Universal basic incomes versus targeted transfers: Anti-poverty programs in developing countries. *Journal of Economic Perspectives*, 32(4):201–226.

Heckman, J. (1980). A life cycle model of female labour supply. *The Review of Economic Studies*, 47(1):47–74.

Heim, B. (2015). Labor supply. *International Encyclopedia of the Social & Behavioral Sciences*, 2:190–198.

Hoynes, H. and Rothstein, J. (2019). Universal basic income in the united states and advanced countries. *Annual Review of Economics*, 11:929–958.

Institute for Fiscal Studies (2024). Universal credit: Incomes, incentives, and the remaining roll-out. IFS Report R322.

International Labour Organization (1982). C158 - termination of employment convention, 1982 (no. 158). Available at: https://normlex.ilo.org/dyn/normlex/fr/f?p=NORMLEXPUB:55:0::NO::P55$_T YPE, P55_L ANG, P55_D OCUMENT$, $P55_N ODE : CON, en, C158, /Document$. Accessed: 04.12.2024.

Isaacs, J. (2008). The costs of benefit delivery in the food stamp program. *Contractor and Cooperator Report*, 39:1–67.

Jaimovich, N., Saporta-Eksten, I., Setty, O., and Yedid-Levi, Y. (2024). Universal basic income: Inspecting the mechanisms. *IZA Discussion Paper*.

Jones, D. and Marinescu, I. (2022). The labor market impacts of universal and permanent cash transfers: Evidence from the alaska permanent fund. *American Economic Journal: Economic Policy*, 14(2):315–340.

Jáñez, Á. (2025). Means-tested programs and interstate migration in the united states. *Review of Economic Dynamics*, 55:101256.

Kaplan, G. and Schulhofer-Wohl, S. (2017). Inflation at the household level. *Journal of Monetary Economics*, 91:19–38.

Keane, M. and Rogerson, R. (2012). Micro and macro labor supply elasticities: A reassessment of conventional wisdom. *Journal of Economic Literature*, 50(2):464–476.

Kearney, M. and Mogstad, M. (2019). Universal basic income (ubi) as a policy response to current challenges. *Brookings*. Available at: https://www.brookings.edu/articles/ universal-basic-income-as-a-policy-response-to-current-challenges/.

Ko, W. and Moffitt, R. (2022). Take-up of social benefits. *IZA discussion paper series*, 15351.

Lander, D. (2024). Estimating life-cycle income processes including means-tested transfers. *Economics Letters*, 242.

Laun, T. and Wallenius, J. (2015). A life cycle model of health and retirement: The case of swedish pension reform. *Journal of Public Economics*, 127:127–136.

Lopez-Daneri, M. (2016). Nit picking: The macroeconomic effects of a negative income tax. *Journal of Economic Dynamics and Control*, 68:1–16.

Luduvice, A. (2021). The macroeconomic effects of universal basic income programs. *FRB of Cleveland Working Paper*, (21-21).

MaCurdy, T. (1981). An empirical model of labor supply in a life-cycle setting. *Journal of Political Economy*, 89(6):1059–1085.

MaCurdy, T. (1982). The use of time series processes to model the error structure of earnings in a longitudinal data analysis. *Journal of Econometrics*, 18(1):83–114.

Miller, D. (2023). An introductory guide to event study models. *Journal of Economic Perspectives*, 37(2):203–230.

Mirrlees, J. (1971). An exploration in the theory of optimum income taxation. *The Review of Economic Studies*, 38(2):175–208.

Moffitt, R. (2015). Economics of means-tested transfer programs: Introduction. *NBER Working Paper Series*, (21715):959–983.

Moffitt, R. and Zahn, M. (2024). The marginal labor supply disincentives of welfare: Evidence from administrative barriers to participation. *National Bureau of Economic Research Working Paper*, 26028.

National Audit Office (2024). One in five legacy benefit claimants not switching to universal credit. *NAO Report*. Available at: https://www.nao.org.uk/press-releases/
one-in-five-legacy-benefit-claimants-not-switching-to-universal-credit/. Accessed: 17.10.2024.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, 49(6):1417–1426.

Parijs, P. V. and Vanderborght, Y. (2017). *Basic Income: A Radical Proposal for a Free Society and a Sane Economy*. Harvard University Press.

Ramsey, F. (1927). A contribution to the theory of taxation. *The Economic Journal*, 37(145):47–61.

Ravaillon, M. (2019). Guaranteed employment or guaranteed income? *World Development*, 115:209–221.

Revenue Benefits (2024a). Universal credit: Benefit cap. Available at: https://revenuebenefits.org.uk/universal-credit/guidance/entitlement-to-uc/benefit-cap/. Accessed: 17.10.2024.

Revenue Benefits (2024b). Universal credit: Capital rules. Available at: https://revenuebenefits.org.uk/universal-credit/guidance/entitlement-to-uc/capital-rules/. Accessed: 17.10.2024.

Saez, E. (2001). Using elasticities to derive optimal income tax rates. *The Review of Economic Studies*, 68(1):205–229.

Santos, M. and Rauh, C. (2022). How do transfers and universal basic income impact the labor market and inequality? *CEPR Discussion Paper*, (DP16993).

Screen Slate (2020). Go brrr. Available at: https://www.screenslate.com /sites/default/files /inline-images/brrr1.png. Accessed: 24.11.2024.

Stantcheva, S. (2017). Optimal taxation and human capital policies over the life cycle. *Journal of Political Economy*, 125(6).

Statistiska Centralbyrån (2024). Arbetskraftsundersökningarna (aku). Available at: https://www.scb.se/hitta-statistik/ statistik-efter-amne/

arbetsmarknad/arbetskraftsundersokningar/ arbetskraftsundersokningarna-aku/. Accessed: 04.12.2024.

Stern, A. (2016). *Raising the Floor: How a Universal Basic Income Can Renew Our Economy and Rebuild the American Dream*. PublicAffairs.

Yang, A. (2018). *The War on Normal People: The Truth About America's Disappearing Jobs and Why Universal Basic Income Is Our Future*. Hachette Books.

Appendix A1

Derivations in the theoretical framework

The choice problem of the individual

Looking at the theoretical aspects of the labor-leisure models, we have a consumer whose utility is defined as the choice between consumption and leisure, given by the following:

Utility function: $U = U(C, L)$, where:
C = consumption of goods
L = consumption of leisure
L_0 = total amount of time
$h = L_0 - L$ = working time

Assume an individual with a convex indifference curve (meaning diminishing returns of the marginal rate of substitution). The individual's choice problem is an optimization problem of their utility curve, let the budget constraint be defined as:

Budget constraint: $C \leq wh + R$,[1] where:
w = real hourly wage
wh = real wage income

[1] The budget constraint can also be written as: $C \leq w(L_0 - L) + R$ or $C + wL \leq wL_0 + R \equiv R_0$

R = other income

The interpretation of the budget constraint can be done as following:

1. The individual disposes of their potential income R_0, obtained by devoting all of their time to working and using other resources R. Leisure or consumer goods can be bought with this income.

2. The wage is the price as well as the opportunity cost of leisure.

The individual's decision problem thus becomes:

$$\begin{aligned} \text{Max}_{\{C,L\}} \quad & U(C,L) \\ \text{s.t.} \quad & C + wL \leq R_0 \end{aligned}$$

Assuming an interior solution such that $0 < L < L_0$ and $C > 0$ and that $\mu > 0$ is the Lagrange multiplier. The Lagrangian is then:

$$\mathcal{L}(C, L, \mu) = U(C, L) + \mu(R_0 - C - wL)$$

First order conditions:

$U_c(C, L) + \mu = 0$

$U_L(C, L) - \mu w = 0$

Complementary slackness gives that $\mu(R_0 - C - wL) = 0$ with $\mu \geq 0$. Since $\mu = U_c(C, L) > 0$ with an interior solution, it follows that the budget constraint is binding. The optimal solution is then:

$$\frac{U_l(C^*, L^*)}{U_c(C^*, L^*)} = w^* \tag{A1.1}$$

$$C^* + wL^* = R_0 \tag{A1.2}$$

To work or not work

This section examines the relationship between wage rate w and labor force participation. Here I focus on what factors drive individuals to enter the labor market in the first place.

The decision to work depends on the **Reservation wage** $\bar{w}$ - the minimum wage an individual is willing to work. Formally:

$$\bar{w} = \frac{U_L(R, L_0)}{U_C(R, L_0)}$$

Where U_L and U_C represent the marginal utility of leisure and consumption, respectively. R is the potential income from non-wage sources. This solution is derived by, in the consumer's utility maximization problem, assuming a reservation wage $\bar{w}$ instead of assuming an interior solution. For detailed derivations of the reservation wage, see next section.

An increase in non-wage income R affects the extensive margin of labor supply as follows:

1. Higher non-wage income decreases the utility value of leisure U_L: individuals can afford to consume more without working. This reduces the need for work and increases the value of leisure: $U_L(R_0, L_) \uparrow$.

2. Higher non-wage income reduces the marginal utility of consumption U_C: as consumption increases with non-wage income, the utility of additional consumption decreases due to diminshing marginal utility of consumption. Therefore $U_C(R_0, L_0) \downarrow$

As non-wage income increases, the utility of leisure rises, while the marginal utility of consumption decreases. These effects combine to increase the reservation wage, reducing labor force participation.

The combined effect of a higher U_L and lower U_C is thus the following: whether or not someone works still depends on if the labor wage exceeds the reservation wage. But as R rises, it should be more common for the reservation wage not to be met, therefore also decreasing the extensive margin.

Implication: Whether an individual enters the labor market depends on whether the offered wage exceeds the reservation wage. As non wage income R increases, it becomes more common for reservation wage to exceed labor wage, reducing labor force participation in the extensive margin.

Reservation wage

I assume there is a reservation wage $\bar{w}$.

Utility for someone not working at all is:

$$U(R, L_0) = U_{notworking},$$

For someone not working $L = L_0$

$$U(R + \bar{w} \cdot h, L_0 - h) = U_{working},$$

Here, the reservation wage $\bar{w}$ is when the individual is indifferent between working and not working:

$$U(R, L_0) = U(R + \bar{w} \cdot h, L_0 - h),$$

Now, I consider an infinite small amount of work $h \to 0$ and use a Taylor expansion around $h = 0$

Then I get:

$$U(R + \bar{w} \cdot h, L_0 - h) \approx U(R_0, L_0) + h[\bar{w} \cdot U_C(R_0, L_0) - U_L(R_0, L_0)],$$

At the reservation wage $\bar{w}$, the individual is indifferent, meaning the change in utility from working $h \to 0$ is zero:

$$h[\bar{w} \cdot U_C(R_0, L_0) - U_L(R_0, L_0)] = 0,$$

Since $h > 0$ it follows that:

$$\bar{w} \cdot U_C(R_0, L_0) = U_L(R_0, L_0),$$

Appendix A2

Sensitivity analysis and robustness

Pooled OLS regressions output

Table A2.1: Regression Results: Impact of Transfers on Employment and Labor Outcomes

VARIABLES	(1) Employment Status	(2) Total Hours Worked	(3) Ln Total Hours Worked
Received Transfers	-0.246*** (0.00412)	-7.305*** (0.135)	-0.252*** (0.00533)
Sociodemographic Factors	Yes	Yes	Yes
Time Fixed Effects (wave)	Yes	Yes	Yes
Geographic Fixed Effects (GOR)	Yes	Yes	Yes
Constant	0.812*** (0.00832)	51.86*** (0.398)	4.037*** (0.0132)
Observations	178,453	159,837	159,834
R-squared	0.156	0.156	0.144

Notes: Clustered standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2.2: Regression Results: Interaction Term on Employment and Labor Outcomes

VARIABLES	(1) Employment Status	(2) Total Hours Worked	(3) Ln Total Hours Worked
Interaction Term (Received Transfers × Log Total Transfers)	-0.0521*** (0.000857)	-1.571*** (0.0270)	-0.0545*** (0.00108)
Sociodemographic Factors	Yes	Yes	Yes
Time Fixed Effects (Wave)	Yes	Yes	Yes
Geographic Fixed Effects (GOR)	Yes	Yes	Yes
Constant	0.808*** (0.00825)	-51.69*** (0.397)	4.031*** (0.0132)
Observations	178,453	159,837	159,834
R-squared	0.169	0.161	0.150

Notes: Clustered standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

These two tables shows the regression results for my Pooled OLS models. They show similar results in direction and significance compared to my main regressions. Regression 1 shows significant results for total hours worked per week and the logarithm of total hours worked per week. We find that for both of these, we have a positive effect. Employment status we see a negative effect on employment status. Similar results can be observed for the specification with interaction terms added.

Income quartiles for pooled OLS analysis

Table A2.3: Pooled OLS with dummy: income quartiles

	(1) Employment Status	**(2) Wage**	**(3) Ln(Wage)**
Received Transfers			
Income quartile 1	-0.000228	-3.425***	-0.129***
	(0.000893)	(0.162)	(0.00798)
Income quartile 2	0.00106*	-1.425***	-0.0386***
	(0.000644)	(0.167)	(0.00532)
Income quartile 3	-4.21e-05	-0.560*	-0.0115
	(0.000769)	(0.211)	(0.00500)
Income quartile 4	-0.00296*	-1.998***	-0.0448***
	(0.00179)	(0.367)	(0.00839)

Notes: Clustered standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2.4: Pooled OLS with interaction term: income quartiles

	(1) Employment Status	(2) Wage	(3) Ln(Wage)
Interaction term			
Income quartile 1	-4.91e-05	-0.707***	-0.0267***
	(0.000170)	(0.0305)	(0.00152)
Income quartile 2	0.000153	-0.318***	-0.00873***
	(0.000142)	(0.0349)	(0.00112)
Income quartile 3	-0.000123	-0.165***	-0.00367**
	(0.000105)	(0.0472)	(0.00114)
Income quartile 4	-0.000951*	-0.481***	-0.0114***
	(0.000536)	(0.0896)	(0.00212)

Notes: Clustered standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Checking for multicollinearity

Table A2.5: Variance Inflation Factor (VIF) Results

Variable	**VIF**	**1/VIF**
dvage	1.19	0.840843
sex	1.17	0.853847
qfhigh_dv	1.08	0.926190
marstat	1.16	0.864462
racel_dv	1.16	0.864523
health	1.04	0.962642
received_transfers	1.05	0.953632
Mean VIF	**1.76**	

I run VIF tests for multicollinearity. For the time-fixed and geographic fixed effects, all variables are within the acceptable range for correlation (at or below 3).

Sensitivity analysis individual fixed effects regression

I run the model several times with and without several control variables to see how the model changes for my individual fixed effects model. First, I run a regression including only the fixed effects term, excluding time-fixed effects, geographic-fixed effects and sociodemographic fixed effects. Then I incrementally add these variables to the regression to see if there is a loss in significance or change in direction or magnitude of my variable of interest. As shown in the output, there is no significant loss in significance, magnitude or direction with the inclusion of time-fixed effects or geographic fixed effects. When adding sociodemographic effects I do so incrementally with adding and removing certain variables.

Table A2.6: Sensitivity Analysis for Employment Status Regression

Variable	(1)	(2)	(3)	(4)	(5)	(6)
dvage	0.000249	0.000249	8.11e-05	-0.000229	-0.000496	-0.000409
	(0.000235)	(0.000238)	(0.000240)	(0.000277)	(0.000497)	(0.000497)
qfhigh_dv	–	-0.000359**	-0.000358**	-0.000360**	-0.000677**	-0.00605**
	–	(0.000169)	(0.000169)	(0.000169)	(0.000274)	(0.000256)
marstat	–	–	0.00190	0.00197	0.00234	0.00349
	–	–	(0.00131)	(0.00131)	(0.00194)	(0.00233)
received_transfer	-0.126***	-0.126***	-0.126***	-0.126***	-0.126***	-0.126***
	(0.00369)	(0.00373)	(0.00380)	(0.00380)	(0.00382)	(0.00382)
Time Fixed Effects	-	-	-	Yes	Yes	Yes
Geographic Fixed Effects	-	-	-	-	Yes	Yes
Observations	184,514	184,514	171,677	171,677	171,677	171,677
R-squared	0.705	0.705	0.712	0.712	0.713	0.713

Notes: Clustered standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2.7: Sensitivity Analysis for Total Hours Worked Regression

Variable	(1)	(2)	(3)	(4)	(5)	(6)
dvage	0.0505***	0.0505***	0.0438***	0.0424***	0.0142	0.0168
	(0.0124)	(0.0126)	(0.0127)	(0.0149)	(0.0149)	(0.0149)
qfhigh_dv	–	-0.0179**	-0.0180**	-0.0174**	-0.0175**	-0.00605**
	–	(0.00774)	(0.00774)	(0.00774)	(0.00775)	(0.00256)
marstat	–	–	0.0532	0.0508	0.0537	0.00349
	–	–	(0.0593)	(0.0592)	(0.0592)	(0.00233)
received_transfer	-2.597***	-2.597***	-2.626***	-2.630***	-2.676***	-2.675***
	(0.121)	(0.121)	(0.125)	(0.125)	(0.125)	(0.125)
Time Fixed Effects	-	-	Yes	Yes	Yes	Yes
Geographic Fixed Effects	-	-	-	Yes	Yes	Yes
Observations	165,831	165,831	154,002	154,002	154,002	154,002
R-squared	0.699	0.699	0.704	0.704	0.705	0.705

Notes: Clustered standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Lagged results

Table A2.8: Regression Results: Impact of Lagged Employment Status on Transfer Receipt

	Transfer Receipt Model
Lagged Variables	
Lagged Employment Status	-0.0321***
	(0.0105)
Current Employment Status	-0.273***
	(0.0132)
Sociodemographic Effects	Yes
Time Fixed Effects	Yes
Constant	1.151***
	(0.0544)
Observations	70,241
R-squared	0.680

Notes: Clustered standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2.9: Regression Results: Impact of Lagged Total Hours Worked on Transfer Receipt

	Transfer Receipt Model (Lagged Hours)
Lagged Variables	
Lagged Total Hours Worked	-0.00175***
	(0.000152)
Current Total Hours Worked	-0.00148***
	(0.000153)
Sociodemographic Effects	Yes
Time Fixed Effects	Yes
Constant	0.955***
	(0.0594)
Observations	65,971
R-squared	0.664

Notes: Clustered standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The positive and significant coefficient for lagged labor income across all labor supply measures (employment status, total hours worked, and log hours worked) indicates path dependency: individuals who earned more in the past are more likely to remain employed and work more hours in the present. This reflects continuity in labor market attachment.

Appendix A3

Derivations in the lifecycle model

First order conditions

The First Order Conditions (FOCs) for the individual's optimization problem can be derived from the value function:

$$V_t(S_t) = \max_{C_t, H_t} \left\{ \frac{C_t^{\sigma-1}}{\sigma-1} - \varphi \frac{(H_t)^{\gamma+1}}{\gamma+1} + \beta \mathbb{E}\left[V_{t+1}(S_{t+1}) \mid S_t\right] \right\},$$

subject to the budget constraint:

$$A_{t+1} = \begin{cases} (1+r)A_t + w_t H_t + T_t - C_t, & \text{if } e_t = 1, \\ (1+r)A_t + U_t + T_t - C_t, & \text{if } e_t = 0, \end{cases}$$

and non-negativity constraints on C_t, H_t, and A_{t+1}.

The Lagrangian for the problem is:

$$\mathcal{L} = \frac{C_t^{\sigma-1}}{\sigma-1} - \varphi \frac{H_t^{\gamma+1}}{\gamma+1} + \beta \mathbb{E}\left[V_{t+1}(S_{t+1}) \mid S_t\right] + \lambda_t \left((1+r)A_t + Y_t + T_t - C_t - A_{t+1}\right),$$

where λ_t is the Lagrange multiplier associated with the budget constraint.

FOCs Taking the derivatives with respect to C_t, H_t, and A_{t+1}, we get:

1. FOC for C_t:

$$C_t^{-\sigma} = \lambda_t.$$

2. FOC for H_t:

$$\varphi H_t^{\gamma} = \lambda_t w_t.$$

3. FOC for A_{t+1}:

$$\lambda_t = \beta(1+r)\mathbb{E}\left[\frac{\partial V_{t+1}}{\partial A_{t+1}} \mid S_t\right].$$

Heckman estimator for the age-wage profile calibration

Table A3.1: Heckman Estimation

VARIABLES	**Log Hourly Wage**
Age and Experience	
Age (`dvage`)	0.0567***
	(0.00123)
Age^2 (`dvage2`)	-0.000557***
	(1.56e-05)
Education and Demographics	
Education (`qfhigh_dv`)	-0.00405***
	(4.73e-05)
Gender (`sex`)	-0.182***
	(0.00278)
Selection Correction	
Mills Ratio (`mills`)	-0.117***
	(0.0136)
Constant	1.412***
	(0.0288)
Observations	150,535
R-squared	0.147

Notes: Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: UKHLS dataset. The regression results include a year fixed effects. To control for selection into work I use a Heckman-selection estimator. The inverse Mills ratios is constructed by estimating the labor force participation equation, using the number of children as well as year-region fixed effects.