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Simulating the Effects of an Unconditional Basic Income on Labour Supply for Austria

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Abstract

This thesis investigates the labor supply effects with Unconditional Basic Income (UBI) in Austria, with focus on heterogeneous responses across age groups. Using data from the European Union Statistics on Income and Living Conditions (EU-SILC) 2022 and employing Heckman two-step selection-corrected wage estimation to simulate three distinct UBI scenarios.

The analysis uses a sample of 5,836 working-age individuals (18,64) from Austrian households, excluding self-employed, retired, and disabled persons. The Heckman wage estimation reveals significant negative selection into employment ($\lambda = -0.893$, $p<0.001$), indicating that employed individuals have lower wages than their observable characteristics would predict. The estimation also documents a gender wage gap of 12.4% and returns to age/experience of approximately 2.0% per year.

Three UBI scenarios are simulated: (1) a poverty-level UBI of €1,392 per month without tax reform, representing a pure income effect; (2) a moderate UBI of €1,000 per month with a 37% flat tax, designed to approximate budget neutrality; and (3) a comprehensive reform with €1,392 per month UBI and 52% flat tax.

The simulation results demonstrate that labor supply responses vary substantially across scenarios and age groups. Overall hours reductions range from 2.9% (Scenario 2) to 6.4% (Scenario 3), with participation reductions of 1.4 to 3.2 percentage points. Pre-retirement workers (55,64) consistently exhibit the largest margin responses, with participation reductions of 3.0 to 3.8 percentage points across scenarios, reflecting sensitivity to retirement incentives. Prime-age workers (30-44, 45,54) show the smallest responses, consistent with career investment incentives and financial constraints. Women show responses 37–64% larger than men across all age groups, reflecting higher underlying labor supply elasticities.

The implications of the possible findings could firstly be the tax design with the moderate 37% flat tax that produces effects roughly half those of the 52% rate, despite providing substantial income support. Second, policymakers should anticipate accelerated early retirement among older workers.

Keywords: Unconditional Basic Income, Labor Supply, Microsimulation, Heckman Selection Model, Austria, EU-SILC, Age Heterogeneity

JEL Classification: H24, J22, I38, C35

Kurzfassung

Diese Masterarbeit untersucht die Auswirkungen der Einführung eines bedingungslosen Grundeinkommens (BGE) auf das Arbeitsangebot in Österreich, mit besonderem Fokus auf heterogene Reaktionen verschiedener Altersgruppen. Unter Verwendung von Daten aus der Europäischen Gemeinschaftsstatistik über Einkommen und Lebensbedingungen (EU-SILC) 2022 und mittels Heckman-Zweistufen-Schätzung werden drei verschiedene BGE-Szenarien simuliert.

Die Analyse basiert auf einer Stichprobe von 5.836 Personen im erwerbsfähigen Alter (18,64 Jahre) aus österreichischen Haushalten, wobei Selbstständige, Pensionisten und Behinderte ausgeschlossen wurden. Die Heckman-Lohnschätzung zeigt eine signifikante negative Selektion in die Beschäftigung ($\lambda = -0,893$, p<0,001). Die Schätzung dokumentiert zudem einen geschlechtsspezifischen Lohnunterschied von 12,4% und Erfahrungsrenditen von etwa 2,0% pro Jahr.

Drei BGE-Szenarien werden simuliert: (1) ein BGE auf Armutsgefährdungsniveau von €1.392 pro Monat ohne Steuerreform; (2) ein moderates BGE von €1.000 pro Monat kombiniert mit einer 37%-Flat-Tax; und (3) eine umfassende Reform mit €1.392 pro Monat BGE und 52%-Flat-Tax.

Die Simulationsergebnisse zeigen, dass die Arbeitsangebotsreaktionen erheblich zwischen Szenarien und Altersgruppen variieren. Die Arbeitszeitreduktionen liegen zwischen 2,9% (Szenario 2) und 6,4% (Szenario 3), mit Partizipationsrückgängen von 1,4 bis 3,2 Prozentpunkten. Arbeitnehmer im Vorruhestandsalter (55,64) zeigen durchgehend die größten Reaktionen an der extensiven Marge, mit Partizipationsrückgängen von 3,0 bis 3,8 Prozentpunkten. Arbeitnehmer im Haupterwerbsalter (30-44, 45,54) zeigen die geringsten Reaktionen. Frauen zeigen um 37–64% stärkere Reaktionen als Männer.

Einige mögliche Implikationen dieser Arbeit könnten zum Ersten das Steuerdesign sein mit einer moderaten 37%-Flat-Tax die etwa halb so große Effekte wie der 52%-Satz erzeugt. Zweitens sollten politische Entscheidungsträger beschleunigten Frühruhestand unter älteren Arbeitnehmern antizipieren.

Schlüsselwörter: Bedingungsloses Grundeinkommen, Arbeitsangebot, Mikrosimulation, Heckman-Selektionsmodell, Österreich, EU-SILC, Altersheterogenität

JEL Klassifikation: H24, J22, I38, C35

Contents

List of Tables

List of Figures

Introduction

1.1 Motivation and Background

The concept of an Unconditional Basic Income (UBI), where a regular cash payment made to all citizens regardless of their employment status, income level, or willingness to work, has moved from the fringes of economic policy discourse to the center of debates about the future of social protection systems (Van Parijs & Vanderborght, 2017). This shift has been driven by several converging forces with concerns about technological unemployment in an era of artificial intelligence and automation (Ford, 2015; Brynjolfsson & McAfee, 2014), rising income inequality across developed economies (Piketty, 2014; Atkinson, 2015), the perceived inadequacy of traditional means-tested welfare systems in addressing modern labor market risks (Standing, 2011), and most recently, the COVID-19 pandemic's revelation of gaps in existing social safety nets (Gentilini et al., 2020).

Austria, with its comprehensive Bismarckian social insurance system and corporatist labor market institutions, provides a particularly compelling context for examining how UBI might reshape labor supply behavior. The Austrian welfare state is characterized by generous earnings-related benefits, near-universal health coverage, and relatively strong employment protection (Obinger et al., 2010). Labor force participation rates remain high by European standards, at approximately 72.5% in 2022, with unemployment hovering around 4.8% (Statistik Austria, 2023). Yet Austria also faces challenges common to advanced European economies, where an aging population that strains pension systems, persistent gender gaps in labor market participation and wages, and concerns about work incentives created by the interaction of progressive taxation with means-tested benefits (Christl et al., 2021).

The introduction of UBI in such a context raises fundamental questions about labor supply behavior. Economic theory provides ambiguous predictions, in which the income effect from the unconditional transfer should reduce labor supply, but this may be offset by substitution effects if UBI replaces high-implicit-tax-rate means-tested benefits, and by dynamic effects on human capital investment and job search (Atkinson, 1996). Moreover, these effects are unlikely to be uniform across the population. Young workers facing decisions about education and career entry, prime-age workers balancing career advancement with family responsibilities, and older workers contemplating retirement timing may all respond differently to the same policy change (Blundell & MaCurdy, 1999).

1.2 Research Questions

This thesis addresses three primary research questions. The first question concerns the aggregate labor supply effects of introducing UBI in Austria. This study estimates the overall changes in working hours (intensive margin) and labor force participation (extensive margin) under three alternative UBI designs. The second question examines how labor supply responses vary across age groups.

The analysis investigates whether young workers (18–29), prime-age workers (30–44), established workers (45–54), and pre-retirement workers (55–64) respond differently to UBI, and whether these differences align with theoretical predictions based on lifecycle considerations.

The third question addresses the sensitivity of labor supply effects to UBI design parameters. By comparing scenarios with different benefit levels and tax rates, the study assesses the policy design space and identifies configurations that minimize efficiency costs while achieving distributional objectives.

1.3 The Austrian Context

1.3.1 The Austrian Tax-Benefit System

Austria's tax-benefit system combines progressive income taxation with extensive social insurance programs. The income tax schedule in 2022 features a tax-free allowance up to €11,000, followed by marginal rates rising from 20% (for income €11,001–€18,000) through 35%, 42%, 48%, and 50% for successively higher income brackets, reaching 55% for income exceeding €1 million (BMF, 2022). Social security contributions add approximately 18% on the employee side (covering pension, health, and unemployment insurance), with contributions capped at the *Höchstbeitragsgrundlage* of €5,670 monthly.

This progressive structure creates effective marginal tax rates that vary substantially across the income distribution. For low-income workers transitioning from social assistance (*Sozialhilfe*) to employment, effective marginal rates can exceed

80% when benefit withdrawal is combined with income taxation and social security contributions (Christl et al., 2021). These "poverty traps" have been identified as significant barriers to labor market entry, particularly for secondary earners and single parents (Immervoll & Pearson, 2009).

1.3.2 Labor Market Structure

The Austrian labor market is characterized by several features relevant to UBI analysis. First, part-time employment is prevalent, particularly among women with approximately 47% of employed women work part-time compared to 11% of men (Statistik Austria, 2023). This creates substantial variation in working hours that the analysis must capture. Second, the effective retirement age, while rising in recent years following pension reforms, remains below the statutory age of 65 for men (gradually equalizing for women), creating a significant population of workers aged 55,64 who have effectively exited the labor force (Staubli & Zweimüller, 2013). Third, Austria's dual education system produces strong vocational credentials that shape early-career labor supply decisions (Busemeyer & Trampusch, 2012).

1.3.3 Previous Austrian Research

Several studies have examined labor supply in Austria using structural discrete choice models. Müllbacher & Nagl (2017) estimate labor supply elasticities using EU-SILC data from 2004–2012, finding own-wage elasticities of 0.12–0.17 for males and 0.21–0.27 for females at the intensive margin, with participation elasticities of 0.03–0.05 for males and 0.06–0.09 for females. These estimates place Austria within the range of other continental European countries but below the higher elasticities found in Anglo-Saxon economies (Bargain et al., 2014).

Hanappi & Tyrowicz (2013) analyze the 2009 family tax reform using a discrete choice framework, documenting substantial behavioral responses among married women. Christl et al. (2021) examine the 2019 social assistance reform, finding that high effective marginal tax rates significantly reduce labor supply, particularly for women with children. However, no Austrian study has yet examined UBI specifically, nor has any provided systematic analysis of age-differentiated labor supply responses.

1.4 Three UBI Scenarios

Following the approach of Atkinson (1996) and subsequent simulation studies (Jessen et al., 2017; Colombino, 2019), this analysis considers three distinct UBI configurations:

1.4.1 Scenario 1: Poverty-Level UBI Without Tax Reform

The first scenario introduces a UBI set at Austria's at-risk-of-poverty threshold, which is approximately €1,392 per month for a single adult in 2022 (Eurostat, 2023). This level corresponds to 60% of median equivalized disposable income, the standard EU poverty line. Crucially, this scenario maintains the existing progressive tax system unchanged, thereby isolating the pure income effect of UBI on labor supply.

This scenario is not fiscally sustainable without additional revenue measures; its purpose is analytical rather than practical. By holding the tax system constant, it allows identification of the income effect separately from any substitution effects that might arise from tax reform.

1.4.2 Scenario 2: Moderate UBI with Flat Tax

The second scenario implements a more modest UBI of €1,000 per month (€12,000 annually) combined with a 37% flat tax on labor income. This configuration is designed to approximate budget neutrality while substantially simplifying the tax-benefit system. The flat tax replaces the progressive income tax on labor earnings while maintaining social security contributions.

At a 37% flat tax rate, the break-even income, the level at which the UBI received exactly equals the additional tax paid, is approximately €32,400 annually. Workers earning below this threshold experience net gains from the reform; those earning above experience net losses. The moderate flat tax rate means that for many workers, particularly those currently in the 42–50% marginal rate brackets, the effective marginal tax rate actually falls, potentially generating positive substitution effects on labor supply.

1.4.3 Scenario 3: Comprehensive Reform with High Flat Tax

The third scenario implements the full poverty-level UBI of €1,392 per month combined with a 52% flat tax on labor income. This high flat tax rate approaches budget neutrality while providing a more generous basic income.

The 52% flat tax rate exceeds current marginal rates for most Austrian workers. This generates negative substitution effects, the after-tax return to each additional hour of work falls, that compound rather than offset the income effect from the UBI. This scenario therefore represents an upper bound on likely labor supply reductions under fiscally sustainable UBI designs.

1.5 Contribution

This thesis contributes to the literature on UBI and labor supply in several ways. First, it provides the first comprehensive UBI simulation for Austria. While UBI has been simulated for Germany (Jessen et al., 2017; Horstschräer et al., 2010) and other European countries (Colombino, 2019), no comparable analysis has previously existed for Austria.

Second, the thesis offers an age-differentiated analysis that extends beyond the typical focus on gender heterogeneity (Jessen et al., 2017) or income-based heterogeneity (Clavet et al., 2013). By explicitly modeling age-group-specific responses, this research illuminates lifecycle dimensions of labor supply that are crucial for assessing the long-run fiscal sustainability of UBI proposals.

Third, the methodology employs rigorous econometric techniques. The aplication of Heckman two-step estimation addresses selection bias in wage prediction, providing more reliable counterfactual wages for non-employed individuals than simple OLS approaches that ignore selection.

Fourth, the policy-relevant scenario comparison which spans three distinct UBI configurations across the design space provides evidence on the sensitivity of labor supply effects to policy parameters, and offers practical guidance for policymakers considering UBI implementation.

1.6 Thesis Structure

The remainder of this thesis is organized as follows:

Chapter 2 provides the literature review to develop the theoretical framework for labor supply analysis, presents the standard labor-leisure choice model to analyse how UBI affects budget constraints and optimal labor supply by deriving age-specific predictions, and surveying the empirical literature on labor supply elasticities and previous UBI simulations.

Chapter 3 describes the methodology, including the EU-SILC 2022 data, sample construction, Heckman two-step wage estimation, elasticity estimation approach, tax-benefit calculator, and simulation procedure.

Chapter 4 presents the results, including descriptive statistics, Heckman wage equation estimates, labor supply elasticities by age group and sex, and the UBI simulation results for all three scenarios.

Chapter 5 provides the discussion, interpreting the results, comparing findings across scenarios and age groups, examining gender differences, and situating results within the broader literature.

Chapter 6 concludes with a summary of key findings, policy implications, limitations, and directions for future research.

Literature Review

This chapter provides the theoretical and empirical foundations for the analysis of labor supply responses to UBI. Section 2.1 defines UBI and distinguishes it from related policy concepts. Section 2.2 presents the standard labor-leisure choice model. Section 2.3 analyzes how UBI affects budget constraints and optimal labor supply. Section 2.4 develops age-specific theoretical predictions. Section 2.5 discusses additional mechanisms including poverty traps and dynamic considerations. Section 2.6 reviews labor supply estimation methodologies. Section 2.7 surveys evidence on labor supply elasticities. Section 2.8 reviews previous UBI and related policy simulations. Section 2.9 summarizes evidence from UBI experiments.

2.1 The Unconditional Basic Income: Concept and Definition

2.1.1 Defining Characteristics

The unconditional basic income represents a fundamental departure from traditional welfare state architecture. Following Van Parijs (2004) and Van Parijs & Vanderborght (2017), UBI can be defined by four key characteristics.

The first is universality: UBI is paid to all members of a political community, which are typically all legal residents or citizens above a certain age, regardless of their income, wealth, employment status, or household composition. This contrasts with means-tested benefits that target only those below income thresholds.

The second is unconditionality: UBI imposes no behavioral requirements. Recipients need not demonstrate willingness to work, participate in training programs, or engage in job search activities. This contrasts with "workfare" approaches and activation policies that condition benefits on labor market engagement (Lødemel & Moreira, 2014).

The third is an individual basis: UBI is paid to individuals rather than households. Each adult receives the full amount regardless of their partner's income or employment status. This contrasts with household-based benefits like traditional social assistance, which create implicit taxation of secondary earners (Immervoll et al., 2011).

The fourth is cash form: UBI is provided as money rather than in-kind benefits or vouchers, allowing recipients to allocate resources according to their own preferences. This respects individual autonomy and avoids paternalistic assumptions about consumption needs (Banerjee et al., 2019).

The fifth characteristic of adequacy is sometimes included but is contested. Proponents of "full" UBI argue the amount should be sufficient to cover basic needs without any additional income (Van Parijs, 2004); proponents of "partial" UBI accept lower amounts that supplement rather than replace earnings (Atkinson, 2015).

2.1.2 UBI Versus Related Concepts

UBI should be distinguished from several related but distinct policy concepts.

The Negative Income Tax (NIT), proposed by Friedman (1962), provides transfers to those with income below a threshold, with the transfer amount declining as income rises. While economically equivalent to UBI combined with a flat tax at the break-even point (Atkinson, 1996), NIT differs administratively in that it is delivered through the tax system and requires income verification. UBI's universality avoids the stigma and take-up problems associated with means-testing (Currie, 2004).

Guaranteed Minimum Income (GMI) ensures that all households reach a minimum income floor, with benefits equal to the difference between actual income and the floor. Unlike UBI, GMI is means-tested and creates 100% effective marginal tax rates over the phase-out range (each euro earned reduces benefits by one euro), generating severe work disincentives (Moffitt, 2002).

The Earned Income Tax Credit (EITC) provides transfers that initially rise with earnings (the "phase-in" range), plateau, and then decline (the "phase-out" range). This design encourages labor force participation but creates high marginal tax rates in the phase-out range (Nichols & Rothstein, 2016). Unlike UBI, EITC conditions benefits on positive earnings.

Universal Basic Services represent a fundamentally different approach: rather than cash transfers, they provide in-kind support (housing, healthcare, education, transportation) free at the point of use (Coote et al., 2017). Proponents argue this more efficiently meets basic needs; critics counter that cash better respects individual preferences.

2.1.3 The Basic Income Flat Tax (BI/FT) Reform

The combination of UBI with a flat tax on labor income, which is the Basic Income Flat Tax (BI/FT), represents the most commonly analyzed comprehensive reform (Atkinson, 1996; Jessen et al., 2017). Under BI/FT, the tax-benefit system takes a simple form:

$$y = G + (1 - \tau)(wh) + N \tag{2.1}$$

where y is disposable income, G is the basic income grant, τ is the flat tax rate, w is the hourly wage, h is hours worked, and N is non-labor income. This creates a linear budget constraint with intercept $G+N$ (income when not working) and slope $(1-\tau)w$ (the after-tax hourly wage).

The break-even income $y^* = wh^*$ occurs where UBI received equals taxes paid:

$$G = \tau \cdot y^* \implies y^* = \frac{G}{\tau} \tag{2.2}$$

Below break-even, individuals are net beneficiaries; above, they are net contributors.

2.2 The Standard Labor-Leisure Choice Model

2.2.1 Basic Framework

The workhorse model of labor supply (Killingsworth & Heckman, 1986; Blundell & MaCurdy, 1999) assumes individuals maximize utility over consumption (c) and leisure (l):

$$\max_{c,l} U(c, l) \quad \text{subject to} \quad c = wh + N, \quad h + l = T \tag{2.3}$$

where h is hours of work and T is the total time endowment (e.g., 80 hours per week available for work and leisure, excluding sleep and personal care).

The budget constraint can be rewritten as:

$$c + wl = wT + N \equiv M \tag{2.4}$$

where M is “full income”, the maximum income attainable if all time were devoted to work.

2.2.2 Optimal Labor Supply

The first-order condition for an interior solution requires:

$$\frac{U_l}{U_c} = w \tag{2.5}$$

That is, the marginal rate of substitution (MRS) between leisure and consumption equals the wage rate. Graphically, this occurs where an indifference curve is tangent to the budget line.

Solving this condition yields the labor supply function:

$$h^* = h(w, N) \tag{2.6}$$

where labor supply depends on the wage rate and non-labor income.

2.2.3 Income and Substitution Effects

A change in the wage rate generates two effects. The substitution effect arises because a higher wage raises the opportunity cost of leisure, making work relatively more attractive. This effect is always positive, since higher wages increase labor supply, holding utility constant. The income effect arises because a higher wage increases potential income, enabling consumption of more leisure (assuming leisure is a normal good). This effect is typically negative, since higher wages reduce labor supply through the income channel.

The net effect is ambiguous. Empirically, substitution effects typically dominate for primary earners while income effects may dominate for secondary earners with strong preferences for home production (Blundell & MaCurdy, 1999).

The Slutsky equation decomposes the total wage effect:

$$\frac{\partial h}{\partial w} = \underbrace{\left.\frac{\partial h}{\partial w}\right|_{U=\bar{U}}}_{\text{Substitution (+)}} + \underbrace{h \cdot \frac{\partial h}{\partial N}}_{\text{Income (-)}} \tag{2.7}$$

The income effect from a change in non-labor income is:

$$\frac{\partial h}{\partial N} < 0 \quad \text{(if leisure is normal)} \tag{2.8}$$

2.2.4 Participation Decision

The basic model assumes interior solutions, but many individuals choose not to work at all. The extensive margin (participation) decision depends on the reservation wage, which is the lowest wage at which an individual is willing to supply positive hours (Blundell & MaCurdy, 1999).

Let $\bar{U}(N)$ denote the utility from not working: $\bar{U} = U(N, T)$. The reservation wage w^R satisfies:

$$U(wh^*(w, N) + N, T - h^*(w, N)) = U(N, T) \tag{2.9}$$

Individuals work if and only if $w > w^R$. Changes in non-labor income raise the reservation wage, reducing participation.

2.3 UBI Effects on Budget Constraints and Optimal Labor Supply

2.3.1 Budget Constraint Under BI/FT

Under the BI/FT reform, the budget constraint becomes:

$$c = G + (1 - \tau)wh + N \tag{2.10}$$

Compared to a baseline with no transfers and no taxes, this involves an increase in the intercept by G (income when not working rises) and a decrease in the slope from w to $(1 - \tau)w$ (after-tax wage falls).

Figure 2.1 illustrates this graphically. The baseline budget constraint (solid line) has slope $-w$ and intercept N. The BI/FT budget constraint (dashed line) has a higher intercept $(G + N)$ but flatter slope $(-(1 - \tau)w)$. The two lines cross at the break-even point h^*, where UBI received equals taxes paid.

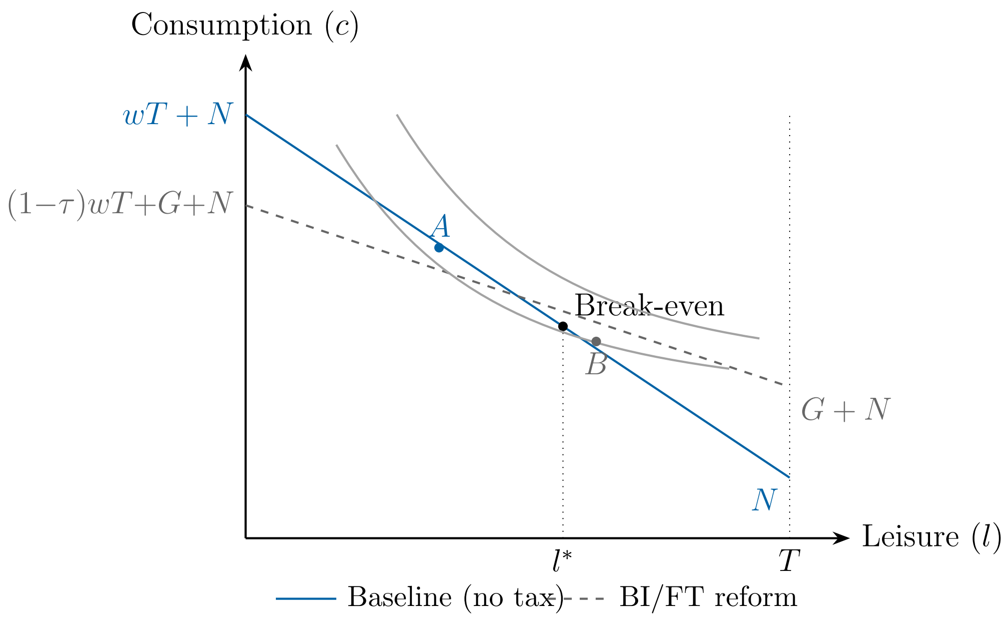

Figure 2.1: Budget Constraint Under UBI with Flat Tax
Note: Point A shows optimal choice under baseline; point B shows optimal choice under BI/FT.

More realistically, comparing BI/FT to an existing progressive tax system involves comparing the new flat rate τ to the current marginal tax rate $t(y)$, which varies with income.

2.3.2 Decomposing Labor Supply Effects

The labor supply response to BI/FT can be decomposed into three effects.

The first is the income effect from the UBI grant:

$$\Delta h_1 = \frac{\partial h}{\partial N} \cdot G < 0 \tag{2.11}$$

The unconditional grant G increases non-labor income, reducing labor supply if leisure is normal. This effect is unambiguously negative.

The second is the income effect from the tax change:

$$\Delta h_2 = \frac{\partial h}{\partial N} \cdot \Delta T \tag{2.12}$$

where ΔT is the change in tax liability. If $\tau > t_0$ (the average tax rate under the baseline), disposable income falls, generating a positive labor supply response (need to work more to maintain consumption). If $\tau < t_0$, the effect is negative.

The third is the substitution effect from the tax change:

$$\Delta h_3 = \left.\frac{\partial h}{\partial w}\right|_U \cdot w \cdot (t_m - \tau) \tag{2.13}$$

where t_m is the baseline marginal tax rate. If $\tau > t_m$, the after-tax wage falls, reducing labor supply through substitution. If $\tau < t_m$ (as may occur for workers currently facing high EMTRs from benefit withdrawal), the after-tax wage rises, increasing labor supply.

2.3.3 Net Effect and Heterogeneity

The total labor supply change is:

$$\Delta h = \Delta h_1 + \Delta h_2 + \Delta h_3 \tag{2.14}$$

The net effect is ambiguous and depends on several factors. Individual position matters, because workers below the break-even income experience positive net income effects ($G > \tau \cdot y$), reinforcing the negative labor supply response, while workers above break-even experience negative net income effects, potentially offsetting it. Current marginal tax rates also matter since workers facing high EMTRs under the current system (due to benefit withdrawal) may experience reduced marginal rates under the flat tax, generating positive substitution effects. Finally, preference parameters determine the magnitude of income and substitution effects, captured by elasticity parameters that vary across demographic groups.

2.4 Age-Specific Theoretical Predictions

The standard model treats preferences as homogeneous, but substantial evidence indicates that labor supply elasticities vary systematically with age, gender, and other characteristics (Blundell & MaCurdy, 1999; Keane, 2011). This section develops age-specific predictions by incorporating lifecycle considerations.

2.4.1 Young Workers (18,29)

Theoretical Considerations

Young workers face a distinctive set of labor supply considerations.

Regarding human capital investment, early-career workers make critical decisions about education, training, and skill acquisition. The standard model treats human capital as given, but in reality, reduced work hours may be productively allocated to education (Becker, 1964). UBI could enable human capital investment that raises long-run productivity, partially offsetting short-run labor supply reductions.

Regarding labor market entry, young workers transitioning from education to employment may be particularly sensitive to financial incentives. High reservation wages generated by UBI could delay labor market entry, with potentially lasting effects on career trajectories through reduced experience accumulation (Mroz, 1987).

Empirical evidence consistently finds higher labor supply elasticities for young workers than for prime-age workers (Keane, 2011). Chetty (2012) reports participation elasticities of 0.5–1.0 for workers under 30, substantially above the 0.1–0.3 range typical for prime-age men.

Finally, young workers typically earn below-average wages, placing most below the UBI break-even point. They thus experience net positive income effects (receiving more in UBI than paying in additional taxes), reinforcing negative labor supply responses.

Prediction

For young workers, I predict moderate negative effects at the intensive margin, in the range of -4% to -7% reduction in hours worked. These effects should be larger than for prime-age workers due to higher elasticities and the fact that most young workers fall below the UBI break-even point, experiencing net positive income effects. At the extensive margin, effects are likely to be mixed since some young workers may delay labor market entry, while others may find it easier to combine part-time work with continued education under UBI. The overall composition of effects may be bimodal, with some youth reducing hours to invest in human capital and others fully exiting employment temporarily.

2.4.2 Prime-Age Workers (30,44)

Theoretical Considerations

Prime-age workers exhibit characteristics associated with low labor supply responsiveness.

Workers in this age range are typically building careers, competing for promotions, and establishing professional reputations. Dynamic considerations in which the present value of future earnings depends on current effort and performance, create incentives to maintain high work intensity despite UBI (Weiss, 1986).

Prime-age households also face peak financial obligations. Mortgages, childcare costs, and general household formation expenses create strong income needs that UBI alone cannot satisfy. Workers may be constrained from reducing hours even if they desire more leisure (Altonji & Paxson, 1986).

Empirical studies consistently find low labor supply elasticities for prime-age men, typically 0.0–0.2 at the intensive margin and 0.0–0.1 at the extensive margin (McClelland & Mok, 2012). Prime-age women show higher elasticities (0.2–0.5 intensive, 0.1–0.3 extensive) due to care responsibilities (Bargain et al., 2014).

Gender differences in household labor division remain relevant. While becoming more equal, women still bear disproportionate care responsibilities (Bianchi et al., 2012). UBI could enable mothers to reduce market hours in favor of home production, either representing efficient reallocation or reinforcement of traditional gender roles.

Prediction

For prime-age workers, I predict small negative effects at the intensive margin, in the range of -2% to -5% reduction in hours worked. These effects should be smaller than for other age groups due to career investment incentives and binding financial constraints, with larger effects expected for women than men given their higher labor supply elasticities. At the extensive margin, effects should be near-zero for men but modestly negative for women, particularly mothers who may reduce participation in response to the income support. Heterogeneity within this group is likely substantial, with effects concentrated among those near the break-even income who experience the largest proportional income changes, and among secondary earners with employed partners who face fewer financial constraints.

2.4.3 Established Workers (45,54)

Theoretical Considerations

Workers aged 45,54 occupy an intermediate position with some distinctive features.

This age group typically has the highest earnings, reflecting accumulated experience and seniority (Murphy & Welch, 1992). Most are above the UBI break-even point, meaning they face net negative income effects (additional taxes exceed UBI received). This should incentivize increased work effort to maintain consumption.

By midlife, many workers have also accumulated significant assets, e.g. homeownership, retirement savings, and financial investments. Standard lifecycle theory predicts declining labor supply as wealth provides a buffer against income variability (French, 2005).

Preferences may shift toward leisure with age as health concerns increase, work becomes more burdensome, and consumption needs (children leaving home, mortgages paid off) decline (Gustman & Steinmeier, 1986).

For workers above break-even, the income effect from UBI is partially offset by higher taxes. The substitution effect from the flat tax therefore becomes more important. At 52% (Scenario 3), the marginal tax rate exceeds current rates for most workers, generating negative substitution effects.

Prediction

For established workers, I predict moderate negative effects at the intensive margin, in the range of -4% to -7% reduction in hours worked. Effects should be particularly pronounced in Scenario 3, where the 52% flat tax generates substantial negative substitution effects for this high-earning group. At the extensive margin, I expect small negative effects of -1% to -3% in participation, larger than for prime-age workers but smaller than for the pre-retirement group, as full early retirement remains financially unattractive due to pension penalties. This group should display notable tax sensitivity, with stronger responses to Scenario 3 than to other scenarios, as high earners face the largest marginal tax rate increases under the 52% flat tax.

2.4.4 Pre-Retirement Workers (55,64)

Theoretical Considerations

Pre-retirement workers face fundamentally different considerations as the retirement decision becomes salient.

Unlike younger workers, those aged 55,64 can plausibly exit the labor force permanently. Early retirement has been extensively studied, with evidence that financial incentives strongly affect retirement timing (Gruber & Wise, 2004; Staubli & Zweimüller, 2013).

Consistent with the retirement option, empirical studies find high participation elasticities for older workers, often 0.5–1.0 or higher (French, 2005). Small changes in the financial return to continued work can generate large changes in the extensive margin.

UBI could serve as a retirement bridge. Under current Austrian rules, workers exiting before pension eligibility (approximately age 60–65 depending on contribution history) face a gap without income support unless they qualify for unemployment insurance or disability benefits. UBI fills this gap, enabling "early retirement" without meeting categorical requirements.

However, early exit reduces lifetime pension benefits through fewer contribution years, earlier claiming (with actuarial adjustments), and lower average earnings in the pension formula. Financially sophisticated workers should weigh UBI against these long-run costs, but myopia or present bias may lead to premature exit (Benitez-Silva & Heiland, 2007).

Older workers also face a decline in health and potential age discrimination in labor markets (Neumark et al., 2019). For those with health constraints or facing labor market barriers, UBI provides dignified exit rather than forced continuation in difficult circumstances.

Prediction

For pre-retirement workers, a moderate prediction of negative effects at the intensive margin, in the range of -5% to -7% reduction in hours among those remaining employed. More significantly, I expect large negative effects at the extensive margin, with participation declining by 3 to 5 percentage points. This reflects UBI's role as a retirement bridge, enabling workers to exit before pension eligibility without facing an income gap. This age group should exhibit the largest extensive margin response across all groups. Within this cohort, heterogeneity is likely substantial, where the strongest effects should appear among those with health limitations, low accumulated wealth, or facing labor market difficulties such as age discrimination, while weaker effects are expected among healthy high earners who value continued pension accrual.

2.5 Additional Theoretical Mechanisms

2.5.1 Poverty Traps and Marginal Tax Rates

A crucial advantage of BI/FT over means-tested systems is elimination of poverty traps created by benefit withdrawal. Under current Austrian arrangements, low-income workers can face effective marginal tax rates exceeding 80% when multiple benefits phase out simultaneously (Christl et al., 2021). These high rates arise from the combination of progressive income tax (20–42%), social security contributions (approximately 18%), housing benefit withdrawal (which can apply rates up to 75%), childcare subsidy reductions, and the implicit 100% rate at thresholds where social assistance eligibility is lost entirely.

The flat tax component of BI/FT ensures a constant marginal tax rate at all income levels. At 37% (Scenario 2), workers previously facing high EMTRs experience reduced marginal taxation, potentially generating positive labor supply responses through the substitution channel.

This poverty-trap-elimination effect varies by age. Young and low-skilled workers are most likely to face high current EMTRs due to proximity to benefit thresholds, and may therefore show positive labor supply responses from poverty trap elimination. Prime-age high earners currently face lower EMTRs under the standard progressive tax schedule and may actually see increased marginal rates under the flat tax. Older workers may face pension income tests that function like benefit withdrawal, which UBI would eliminate.

2.5.2 Dynamic and General Equilibrium Considerations

The static partial equilibrium framework employed in this thesis abstracts from several potentially important mechanisms:

Several dynamic mechanisms warrant consideration. Reduced work hours may be reallocated to education and training, raising future productivity. The US Negative

Income Tax experiments found increased school enrollment among youth (Robins, 1985), suggesting that if UBI enables human capital investment, long-run labor supply may exceed short-run levels.

UBI's unconditional nature may also improve job matching by enabling workers to search longer for suitable positions rather than accepting the first available job (Acemoglu & Shimer, 2001). Better matches raise productivity and potentially wages.

General equilibrium wage effects could also materialize. If UBI substantially reduces labor supply, labor scarcity should raise market wages, partially offsetting the initial reduction through higher returns to work. However, Austria's open economy with free labor movement within the EU complicates this adjustment.

Finally, widespread adoption of reduced work hours could shift social norms about appropriate work intensity, potentially amplifying initial behavioral responses (Alesina et al., 2005).

These mechanisms are beyond the scope of the current microsimulation analysis but represent important directions for future research.

2.5.3 Summary of Theoretical Predictions

Table 2.1 summarizes the theoretical predictions for each age group.

Table 2.1: Summary of Age-Specific Theoretical Predictions

Age Group	Intensive Margin	Extensive Margin	Key Mechanisms
18,29 (Young)	Moderate negative (-4% to -7%)	Mixed	High elasticity; human capital investment; net positive income effect
30,44 (Prime-age)	Small negative (-2% to -5%)	Near zero	Career investment; financial constraints; low male elasticity
45,54 (Established)	Moderate negative (-4% to -7%)	Small negative (-1% to -3%)	Preference shifts; wealth effects; substitution from high flat tax
55,64 (Pre-retirement)	Moderate negative (-5% to -7%)	Large negative (-3 to -5 pp)	Retirement option; high participation elasticity; UBI as bridge

These predictions will be tested empirically in Chapter 4, enabling assessment of which theoretical mechanisms dominate in practice.

2.6 Labor Supply Estimation Methodologies

2.6.1 Evolution of Approaches

The estimation of labor supply responses to tax and transfer reforms has evolved substantially over recent decades. Aaberge et al. (2014) provide a useful taxonomy, classifying approaches into three categories:

The Reduced-form approaches estimate labor supply elasticities directly from observed responses to wage and income variation, without explicitly modeling the utility maximization problem. Early influential studies (Hausman, 1981; Mroz, 1987) used instrumental variables and natural experiments to identify causal effects. While transparent and credible when identification assumptions hold, reduced-form approaches may not generalize to novel policy reforms that differ from historical variation.

On the other side structural continuous models derive labor supply from explicit utility maximization, estimating preference parameters that govern the trade-off between consumption and leisure (Blundell et al., 1992). These models face challenges from non-convex budget sets created by progressive taxation and means-tested benefits, multiple tangency points create estimation difficulties and may generate implausible corner solutions.

Furthermore discrete choice models address non-convexity by assuming individuals choose from a finite set of hours alternatives (e.g., 0, 10, 20, 30, 40 hours per week) rather than a continuum (Van Soest, 1995). This approach, pioneered by Van Soest (1995) and extended by Hoynes (1996) and Keane & Wolpin (1997), has become the dominant framework for policy evaluation in Europe and North America.

2.6.2 The Discrete Choice Framework

The discrete choice approach models labor supply as utility maximization over a finite choice set. Individual i chooses from alternatives $j \in J = \{h_0, h_1, ..., h_J\}$, where h_j represents weekly working hours. Each alternative yields utility:

$$U_{ij} = V(c_{ij}, l_{ij}; X_i, \theta) + \epsilon_{ij} \tag{2.15}$$

where c_{ij} is disposable income at hours choice j, $l_{ij} = T - h_j$ is leisure, X_i represents observed characteristics, θ contains preference parameters, and ϵ_{ij} captures unobserved utility components.

If ϵ_{ij} follows a Type I Extreme Value distribution, choice probabilities take the logit form:

$$P_{ij} = \frac{\exp(V(c_{ij}, l_{ij}; X_i, \theta))}{\sum_{k \in J} \exp(V(c_{ik}, l_{ik}; X_i, \theta))} \tag{2.16}$$

This enables maximum likelihood estimation and straightforward policy simulation by recomputing choice probabilities under alternative budget constraints.

2.6.3 The Heckman Selection Correction

A fundamental challenge in labor supply estimation is that wages are observed only for employed individuals. If employment selection is non-random, meaning if those who work differ systematically from those who do not in ways related to potential wages, naive wage estimation produces biased results (Heckman, 1979).

The Heckman two-step procedure addresses this problem. In the first step, a probit selection equation for employment is estimated:

$$\Pr(E_i = 1) = \Phi(Z_i\gamma) \tag{2.17}$$

where E_i indicates employment and Z_i includes variables affecting employment (age, education, household structure, non-labor income).

In the second step, the wage equation is estimated including the inverse Mills ratio:

$$\log w_i = X_i\beta + \delta\lambda_i + \epsilon_i \tag{2.18}$$

where $\lambda_i = \phi(Z_i\hat{\gamma})/\Phi(Z_i\hat{\gamma})$ is the inverse Mills ratio constructed from the first step predictions, and δ captures selection bias.

Identification requires an exclusion restriction which is at least one variable in Z_i that affects employment but not wages. Common exclusion restrictions include non-labor income, number of children, and spouse's income (Mroz, 1987).

A significant δ coefficient indicates selection bias that would contaminate naive OLS estimates. Positive δ suggests positive selection (employed individuals have higher wages than their characteristics would predict); negative δ suggests negative selection.

2.6.4 Advantages and Limitations

The discrete choice framework with Heckman selection correction offers several advantages for UBI simulation:

Several advantages recommend this approach. It is highly policy-relevant and directly applicable to tax-benefit reforms, naturally handling complex non-linear budget constraints. The framework comprehensively estimates both intensive (hours) and extensive (participation) responses within a unified structure. The parameters have structural interpretation representing preferences, enabling welfare analysis beyond labor supply effects. Finally, the framework accommodates selection correction, addressing wage prediction for non-employed individuals, which is crucial for simulating participation responses.

Limitations include functional form dependence, where results may be sensitive to utility function specification. The static framework ignores intertemporal considerations like human capital, savings, and lifecycle planning. The partial equilibrium assumption holds wages constant, which may be violated if policy substantially changes labor supply. The logit structure also imposes Independence of Irrelevant Alternatives (IIA).

These limitations suggest caution in interpreting results but do not invalidate the approach for first-order policy analysis.

2.7 Labor Supply Elasticities: Empirical Evidence

2.7.1 International Patterns

Extensive surveys (Blundell & MaCurdy, 1999; Keane, 2011; McClelland & Mok, 2012; Bargain et al., 2014) synthesize evidence on labor supply elasticities. Several robust patterns emerge.

Gender Differences

For men, labor supply elasticities are consistently small across studies and countries. At the intensive margin (hours), estimates range from 0.0 to 0.2 with central tendency around 0.1. At the extensive margin (participation), estimates range from 0.0 to 0.15 with central tendency around 0.05. These low male elasticities imply that men's labor supply is relatively unresponsive to wage and income changes, consistent with strong labor force attachment and limited flexibility in hours (Keane, 2011).

For single women McClelland & Mok (2012), elasticities are moderately higher, with intensive margin estimates of 0.1 to 0.3 and extensive margin estimates of 0.1 to 0.2. For married women, substantially larger responses appear and intensive margin estimates range from 0.2 to 0.6 in most studies, while extensive margin estimates range from 0.1 to 0.4.

These gender differences reflect traditional household specialization patterns, though the gap has narrowed over time. Blau & Kahn (2007) document declining female elasticities in the US from 1980–2000, attributing this to women's increased labor force attachment. Similar trends appear in Europe, though married women remain more responsive than men (Bargain et al., 2014).

Income Elasticities

Evidence on income elasticities, i.e. responses to changes in non-labor income, is more limited but consistently finds small negative effects for men (ranging from -0.15

to 0.0) and moderate negative effects for women (ranging from -0.2 to -0.05). These negative values indicate that leisure is a normal good and higher non-labor income reduces labor supply. However, magnitudes are modest, suggesting that income effects alone are insufficient to generate dramatic labor supply responses to UBI.

Age Patterns

Direct evidence on age-specific elasticities is surprisingly scarce despite theoretical importance. French (2005) provides one of the few comprehensive estimates for older workers, finding participation elasticities of 0.5–1.0 for workers aged 55,70, substantially above prime-age estimates.

Chetty (2012) estimates participation elasticities of 0.5–1.0 for young workers (under 30) based on responses to the Earned Income Tax Credit. This exceeds the 0.1–0.3 range typical for prime-age men.

These patterns suggest a U-shaped age profile of labor supply responsiveness that is higher for young and old workers, lower for prime-age workers.

2.7.2 Austrian Evidence

Several studies estimate labor supply elasticities specifically for Austria.

Müllbacher & Nagl (2017) use EU-SILC data from 2004–2012 with the IHS Labor Supply Model for Austria (ILSA). They find hours elasticities of 0.12–0.17 for males and 0.21–0.27 for females, with corresponding participation elasticities of 0.03–0.05 for males and 0.06–0.09 for females. They document a temporal trend of declining elasticities over 2004–2012, particularly for women whose hours elasticity fell from 0.39 to 0.21. They also find income heterogeneity, with higher elasticities for low-income workers (men show 0.23 in the lowest decile versus 0.02 in the highest).

Hanappi & Tyrowicz (2013) analyze family tax reform using EU-SILC 2004–2008. They find hours elasticities of 0.38 for married women and 0.09 for married men, with participation elasticities of 0.18 for married women and 0.01 for married men. Cross-wage elasticities are small but negative, indicating that a spouse's wage increase slightly reduces own labor supply.

Christl et al. (2021) examine social assistance reform using EU-SILC 2017 with EUROMOD. They document high effective marginal tax rates exceeding 80% for some household types, larger responses for women and households with children, and substantial participation responses to EMTR reductions (elasticity approximately

0.15 for women and 0.05 for men).

These Austrian estimates are broadly consistent with international patterns with female elasticities roughly twice male elasticities, modest income effects, and substantial heterogeneity by income level.

2.7.3 Elasticity Summary for Simulation

Based on this evidence, Table 2.2 summarizes reasonable elasticity ranges for Austrian labor supply simulation.

Table 2.2: Labor Supply Elasticity Ranges from Literature

Group	**Hours Elast.**	**Partic. Elast.**	**Income Elast.**
Prime-age men	0.05–0.15	0.02–0.05	-0.05 to -0.10
Prime-age women	0.15–0.30	0.05–0.10	-0.05 to -0.15
Young workers (18,29)	0.10–0.20	0.05–0.15	-0.05 to -0.10
Older workers (55,64)	0.10–0.20	0.15–0.30	-0.10 to -0.20

2.8 Previous UBI and Related Policy Simulations

2.8.1 German Studies

Germany has received the most extensive microsimulation analysis of UBI in Europe, providing useful benchmarks.

Horstschräer et al. (2010) simulate three scenarios using SOEP data. A basic income of €800 per month with a low 20% flat tax produces positive effects with +2.8% hours and +2.4% participation. A budget-neutral version with a higher 52% flat tax generates slight reductions with -0.6% hours and -0.5% participation. A budget-neutral design with withdrawal rate adjustment yields +2.1% hours but -3.0% participation. The pattern is clear: low-tax UBI can increase labor supply when poverty trap elimination dominates, while budget-neutral UBI with high taxes reduces supply when substitution effects dominate.

Jessen et al. (2017) provide the most comprehensive German analysis, simulating budget-neutral UBI (€800 per month funded by 69% flat tax) with the IZAΨMOD microsimulation model. They find an overall reduction of 4.5% in hours worked, with women reducing hours by 7.7% and men by 2.2%. Participation falls by 4.5%

for women and 1.8% for men. Notably, the first income decile shows a 4.1% hours increase for men due to poverty trap elimination. Despite negative aggregate effects, the authors conclude welfare gains are possible due to reduced poverty and administrative simplification.

Until last year Germany, Bohmann et al. (2025) also conducted a field experiment providing 107 participants with monthly transfers of 1,200 € over three years, while a control group of 1,580 received only survey compensation. Labor market effects were modest with approximately 90 percent of both groups remained employed throughout, working an average of 40 hours weekly. The treatment group showed no significant reduction in labor market participation or working hours. While they earned on average 127 € less monthly in gross labor income, this difference was not statistically significant. The share of self-employed remained identical at seven percent in both groups (Bernhard et al., 2025).

Colombino (2019) compare UBI across European countries using the EUROMOD microsimulation model. They find hours changes ranging from -15% in the Netherlands to +3% in Greece, with cross-country variation driven by differences in current tax-benefit systems. Larger effects appear where UBI replaces high-EMTR means-tested benefits.

In Italy, Colombino (2010) find the optimal UBI involves a benefit of approximately €500 per month with a flat tax around 35%, to generate a modest positive labor supply effects due to poverty trap elimination.

In the Netherlands, Jongen et al. (2014) estimate large negative effects (-10% to -15% hours) for budget-neutral UBI due to high baseline labor force participation and correspondingly high opportunity cost of labor supply reductions.

2.8.2 North American Studies

In Canada, Clavet et al. (2013) simulate guaranteed minimum income for Quebec at approximately $16,000 CAD annually (near median income level) without tax increases. They find hours reductions of 18% for single men and 15% for women, with participation falling by 22 percentage points for single men and 19 for women. Large reductions in full-time work (40+ hours) occur, with shifts to part-time work or exit. These extreme responses reflect the generous benefit level without offsetting tax increases, an unrealistic policy configuration.

In the United States, Hoynes & Rothstein (2019) review simulation evidence. Most simulations find 5–10% hours reductions for budget-neutral UBI, with effects concentrated among secondary earners and low-wage workers. Poverty reduction of 50–75% appears achievable with modest labor supply costs.

A more recent study in the US, Vivalt et al. (2024) conducted a three-year randomized trial providing 1,000 low-income participants with monthly $1,000 transfers, while 2,000 controls received $50 monthly. The transfers reduced individual income excluding transfers by $1,800 annually. Labor market participation fell by 4.1 percentage points, with participants reducing work hours by 1-2 hours weekly. Partners reduced hours similarly. Non-employment spells increased by 0.8 months. Recipients primarily used freed time for leisure, with no increases in childcare, education, or improvements in job quality or entrepreneurship.

2.8.3 Synthesis of Simulation Evidence

Several patterns emerge across simulation studies.

First, the tax rate proves critical. All studies find that labor supply responses depend crucially on the flat tax rate. Low rates (20–35%) often generate positive or neutral responses as poverty trap elimination dominates, while high rates (60–70%) consistently generate negative responses as substitution effects dominate.

Second, gender heterogeneity is pervasive. Women respond more than men by a factor of 2–3 across all studies, reflecting higher underlying elasticities.

Third, income heterogeneity matters. Low-income workers may show positive responses due to poverty trap elimination, while high-income workers show negative responses from income and substitution effects.

Fourth, magnitudes are generally moderate. Most budget-neutral designs generate 5–10% hours reductions, not dramatic labor market withdrawal.

Fifth, effects are context-dependent, varying substantially across countries and reflecting differences in baseline tax-benefit systems.

2.9 Evidence from UBI Experiments

2.9.1 US Negative Income Tax Experiments (1968–1982)

The US conducted four large-scale NIT experiments in the 1970s: New Jersey (1968–1972), Rural (1970–1972), Gary (1971–1974), and Seattle/Denver (SIME/DIME, 1971–1982). These randomized experiments assigned households to different NIT parameters (guarantee levels and tax rates) and compared labor supply to control groups.

Robins (1985) synthesizes findings across experiments. Overall, small negative labor supply effects emerged, equivalent to 2–3 weeks less work per year. Substitution elasticities ranged from 0.1 to 0.2, with values at the low end for husbands and higher for single women and married women. Income elasticities were approximately -0.1. Regarding mechanisms, mothers stayed home longer with children, youth stayed in school longer, and some increase in marital instability appeared in the Seattle/Denver experiment.

Hoynes & Rothstein (2019) reassess this evidence in light of modern methods, concluding that while experiments support modest negative effects, several caveats apply. Benefits were modest, approximately $23,000–34,000 in 2017 dollars, which is less generous than many UBI proposals. Duration was limited to 3–5 years, so participants knew benefits would end. Site effects suggest external validity concerns.

2.9.2 Finnish Basic Income Experiment (2017–2018)

Finland conducted a randomized experiment providing €560 per month to 2,000 unemployed individuals aged 25,58 for two years (Kangas et al., 2021). The experiment found no significant employment effect, with 43.7% of treatment participants employed versus 42.9% of controls. However, significant improvements appeared in subjective wellbeing, including life satisfaction, mental health, trust in institutions, and cognitive functioning. Job search intensity and reservation wages showed no change.

The lack of employment effects may reflect several design features. The benefit level was low (€560 compared to typical wages of €2,000–3,000). The unemployed-only population already had weak labor market attachment. The short duration meant participants may have maintained job search anticipating the end of benefits. No tax component was tested.

2.9.3 Other Experiments and Pilots

The Manitoba Mincome experiment (1974–1979) in Dauphin, Manitoba found modest negative hours effects but increased school enrollment among teenagers and improved health outcomes (Forget, 2011).

The Kenya GiveDirectly project is an ongoing randomized evaluation of long-term basic income (\$22 per month) in rural Kenya. Early results show increased self-employment and asset accumulation with no reduction in work hours (Banerjee et al., 2020). However, the subsistence agriculture context differs radically from advanced economies.

The Stockton SEED pilot in Stockton, California (2019–2021) provided \$500 per month to 125 low-income residents. Preliminary findings suggest improved employment outcomes and wellbeing, though small scale limits generalizability (West et al., 2021).

2.9.4 Evidence from Experimental Studies

Experimental evidence provides valuable validation for simulation predictions but has important limitations.

Experiments consistently find modest effects, with labor supply reductions typically 2–5% of hours rather than the 15–20% suggested by pessimistic projections. Non-labor-market outcomes including health, wellbeing, and education show consistent improvements, suggesting benefits beyond income support. External validity remains a concern, as most experiments involve selected populations (unemployed, low-income), limited duration, and specific contexts that may not generalize. Long-run effects remain unknown, as no experiment has run long enough to capture lifecycle effects, social norm changes, or general equilibrium adjustments.

For Austria specifically, no UBI experiment has been conducted, necessitating reliance on microsimulation with parameters calibrated to Austrian data and validated against international experimental evidence.

2.10 Summary and Implications for This Study

This literature review establishes several key points for the present analysis.

Regarding methodology, the combination of discrete choice labor supply modeling with Heckman selection correction is well-established and appropriate for UBI simulation. Regarding elasticities, Austrian labor supply elasticities are well-documented and fall within international ranges, with female elasticities approximately twice male elasticities. Regarding expected effects, based on simulation evidence, budget-neutral UBI for Austria should generate labor supply reductions in the 3–10% range, with effects depending critically on the flat tax rate. Regarding the age gap, while gender and income heterogeneity are well-documented, age-specific analysis remains underdeveloped. This thesis contributes by explicitly modeling age-differentiated responses. Regarding validation, experimental evidence suggests simulations may overstate negative effects; actual behavioral responses tend to be smaller than model predictions.

Methodology

This chapter describes the empirical methodology. Section 3.1 presents the data source and sample construction. Section 3.2 describes variable construction. Section 3.3 details the Heckman two-step wage estimation. Section 3.4 explains the elasticity estimation approach. Section 3.5 describes the Austrian tax-benefit system and the calculator used for simulations. Section 3.6 outlines the simulation procedure.

3.1 Data Source: EU-SILC 2022

3.1.1 Overview of EU-SILC

The analysis uses data from the European Union Statistics on Income and Living Conditions (EU-SILC) for Austria, wave 2022. EU-SILC is a harmonized annual survey covering income, poverty, social exclusion, and living conditions across EU member states (Eurostat, 2021). The Austrian component is administered by Statistics Austria (*Statistik Austria*) and covers the resident population in private households.

EU-SILC employs a rotational panel design, with each sampled household followed for four consecutive years. The 2022 wave includes income data referring to 2021 (the "income reference period"), labor market status and hours referring to the survey year (2022), and detailed household composition and demographic characteristics.

This timing structure, i.e. income lagged by one year relative to labor market status, is standard in EU-SILC and unlikely to significantly affect results given Austria's relatively stable labor market (Atkinson et al., 2017).

3.1.2 Sample Selection

From the full EU-SILC 2022 Austria sample, I construct an analysis sample following standard conventions in the labor supply literature (Müllbacher & Nagl, 2017; Christl et al., 2021).

The inclusion criteria are age 18,64 years (working-age population) and complete information on key variables (age, sex, education, hours, income, household composition).

The exclusion criteria are as follows. Self-employed individuals (P001000 = 2) are excluded due to different budget constraints from business income variability and unreliable hours measures. Retired individuals (P001000 = 5) are not in the labor force by definition. Permanently disabled individuals (P001000 = 6) are constrained in labor supply choices. Full-time students (main activity = education) are excluded because their labor supply decisions are governed by different considerations.

The sample construction proceeds as follows:

Table 3.1: Sample Construction

Step	**Observations**	**Dropped**
Total individuals in personal file	12,096	—
Working age (18,64)	7,238	4,858
Excluding self-employed	6,900	338
Excluding retired	6,658	242
Excluding permanently disabled	6,409	249
After dropping missing values	5,836	573
Final analysis sample	**5,836**	

The final sample of 5,836 individuals represents the Austrian working-age population excluding those with constrained labor supply choices or unreliable earnings measures.

3.1.3 Sample Composition

Table 3.2 presents the composition of the analysis sample by age group.

Table 3.2: Sample Composition by Age Group

	18,29	**30,44**	**45,54**	**55,64**
Observations	749	1,907	1,389	1,791
Percent of sample	12.8%	32.7%	23.8%	30.7%
Males	372	909	667	804
Females	377	998	722	987

The relatively large share of the 55,64 age group (30.7%) reflects both demographic aging and the exclusion of many younger individuals due to student status or self-employment.

3.2 Variable Construction

3.2.1 Labor Market Variables

Weekly hours worked is constructed from EU-SILC variable P037010, representing hours usually worked per week in the main job. For individuals not employed, hours equals zero. The distribution shows clustering around standard schedules (20, 30, 38–40 hours), validating the discrete choice approach.

Employment status is defined as a binary indicator equal to 1 if hours exceed zero, and 0 otherwise. This defines employment at the extensive margin.

For the discrete choice framework, individuals are assigned to the nearest hours category from the set $\{0, 8, 16, 24, 32, 40, 48\}$:

Table 3.3: Hours Discretization

Actual Hours	**Discrete Category**
< 4	0 (non-employment)
4–11	8 (marginal part-time)
12–19	16 (short part-time)
20–27	24 (part-time)
28–35	32 (substantial part-time)
36–43	40 (full-time)
≥ 44	48 (overtime)

Annual gross labor income is obtained from EU-SILC variable py010g (employee cash or near-cash income, gross), which includes wages, salaries, and bonuses before taxes and social contributions.

Hourly gross wage is calculated for employed individuals as:

$$w_i = \frac{\mathrm{py010g}_i}{52 \times \mathrm{hours}_i} \tag{3.1}$$

This assumes income is earned uniformly across 52 weeks. For individuals with very low hours (< 5) or implausibly high computed wages ($>$ €150/hour), values are treated as outliers and winsorized to the 1st/99th percentiles.

3.2.2 Demographic Variables

Age is obtained from EU-SILC variable alter, calculated as survey year minus birth year. Age squared is included to capture nonlinear effects.

Sex is coded as a binary indicator equal to 1 for females (sex = 2 in the original data) and 0 otherwise.

Education years is imputed from ISCED classification (variable iscohier) using the standard mapping:

Table 3.4: Education Years by ISCED Level

ISCED Level	**Description**	**Years**
0–1	Less than primary / Primary	9
2	Lower secondary	11
3	Upper secondary	12
4	Post-secondary non-tertiary	13
5	Short-cycle tertiary	15
6	Bachelor's or equivalent	16
7–8	Master's / Doctoral	17–19

Age groups are defined as a categorical variable with four levels: 18,29, 30,44, 45,54, and 55,64.

3.2.3 Household Variables

Household size represents the count of individuals in the household, obtained from the household roster.

Children under 18 is the count of household members aged less than 18 years.

Number of adults is calculated as household size minus children under 18.

Household non-labor income (non_labor_income_hh) is the sum of rental income (hy040g) from renting property, capital income (hy090g) from interest, dividends, and investment profits, and private transfers (hy080g) representing regular cash transfers from other households. This excludes social benefits (unemployment, pensions, social assistance) which are modeled separately in the tax-benefit calculator.

Individual non-labor income (non_labor_income) is calculated as household non-labor income divided by the number of adults, assuming equal sharing within households:

$$N_i = \frac{\text{non\_labor\_income\_hh}_i}{\max(\text{n\_adults}_i, 1)} \tag{3.2}$$

Weekly non-labor income is obtained by dividing by 52.

3.2.4 Survey Weights

All descriptive statistics and regression analyses are weighted using the personal cross-sectional weight (gewz), which adjusts for sample design, non-response, and calibration to population totals.

3.3 Heckman Two-Step Wage Estimation

3.3.1 Motivation

Wages are observed only for employed individuals. If employment is selective, if those who work differ systematically from those who do not in ways correlated with potential wages, then naive OLS wage estimation on the employed subsample produces biased estimates (Heckman, 1979).

Selection bias is particularly problematic for UBI simulation because predicting wages for non-employed individuals is essential for computing their potential earnings under alternative hours choices. If predicted wages are biased, simulation results will be biased.

3.3.2 Step 1: Probit Participation Equation

The first step estimates a probit model for employment participation:

$$\Pr(E_i = 1|Z_i) = \Phi(Z_i\gamma) \tag{3.3}$$

where E_i is the employment indicator, Z_i is a vector of covariates, γ is a parameter vector, and $\Phi(\cdot)$ is the standard normal CDF.

The specification includes:

$$Z_i\gamma = \gamma_0 + \gamma_1\text{age}_i + \gamma_2\text{age}_i^2 + \gamma_3\text{female}_i + \gamma_4\text{edu\_years}_i + \gamma_5 N_i + \gamma_6\text{children}_i \tag{3.4}$$

where:

The variables age and age^2 capture the lifecycle pattern of participation. The variable female captures gender differences in employment propensity. Education years captures human capital effects on employment. Non-labor income N_i serves as an exclusion restriction, affecting participation but not directly affecting wages. Children also serves as an exclusion restriction, affecting participation through care responsibilities but not productivity.

3.3.3 Exclusion Restrictions

Identification of the Heckman model requires exclusion restrictions, since variables that affect the selection equation but not the outcome equation (Mroz, 1987). I use two exclusion restrictions.

The first is non-labor income. Higher non-labor income raises the reservation wage, reducing participation probability. However, non-labor income should not directly affect productivity or wages offered.

The second is number of children under 18. Children create care demands that reduce participation, particularly for women. While children might indirectly affect wages through career interruptions, the direct effect on current productivity is minimal.

These restrictions are standard in the literature (Müllbacher & Nagl, 2017; Christl et al., 2021) and have theoretical justification in the labor-leisure model.

3.3.4 Step 2: Wage Equation with Selection Correction

From the probit estimates, I construct the inverse Mills ratio (IMR):

$$\lambda_i = \frac{\phi(\hat{Z}_i\hat{\gamma})}{\Phi(\hat{Z}_i\hat{\gamma})} \tag{3.5}$$

where $\phi(\cdot)$ is the standard normal PDF.

The wage equation is then estimated by OLS including the IMR:

$$\log(w_i) = \beta_0 + \beta_1 \text{age}_i + \beta_2 \text{female}_i + \beta_3 \text{edu\_years}_i + \delta\lambda_i + \epsilon_i \tag{3.6}$$

The coefficient δ captures selection bias. If $\delta > 0$, there is positive selection, meaning employed individuals have higher wages than their characteristics predict. If $\delta < 0$, there is negative selection, meaning employed individuals have lower wages than their characteristics predict. If $\delta = 0$, there is no selection bias and OLS would be consistent.

Standard errors are adjusted for the generated regressor (λ_i) using the standard Heckman correction.

3.3.5 Wage Prediction

For wage prediction, I use the coefficients from the outcome equation excluding the selection term:

$$\widehat{\log(w_i)} = \hat{\beta}_0 + \hat{\beta}_1 \text{age}_i + \hat{\beta}_2 \text{female}_i + \hat{\beta}_3 \text{edu\_years}_i \tag{3.7}$$

The predicted wage is then $\hat{w}_i = \exp(\widehat{\log(w_i)})$.

For employed individuals with valid observed wages (between €1 and €200 per hour),observed wages are used. For non-employed individuals and those with invalid observed wages, I use predicted wages. Extreme predictions are winsorized to the €5–€80 range.

3.4 Labor Supply Elasticity Estimation

3.4.1 Approach

Following the established Austrian literature (Müllbacher & Nagl, 2017), to estimate labor supply elasticities separately for each age-sex group. This allows full heterogeneity in behavioral parameters across demographic groups.

For each group, I estimate a log-linear labor supply equation among employed workers:

$$\log(h_i) = \alpha_0 + \alpha_1 \log(w_i) + \alpha_2 \text{age}_i + \alpha_3 \text{edu\_years}_i + \alpha_4 \text{children}_i + u_i \tag{3.8}$$

The coefficient α_1 provides an estimate of the hours-wage elasticity.

3.4.2 Elasticity Adjustments

The raw elasticity estimates are adjusted based on known patterns from the literature.

For gender adjustment, female elasticities are scaled up by a factor of 1.3, reflecting the consistently higher female responsiveness documented in Bargain et al. (2014). For the extensive margin age adjustment, participation elasticities for the 55,64 group are scaled up by a factor of 2.0, reflecting the high sensitivity to retirement incentives documented in French (2005). All elasticities are bounded to reasonable ranges based on the literature survey in Chapter 2.

3.4.3 Income Elasticities

Income elasticities (response to non-labor income changes) are calibrated from the literature rather than estimated directly, as non-labor income variation in the cross-section may reflect endogenous factors such as savings decisions and wealth accumulation. With base values of -0.05 for men and -0.07 for women and an age adjustment making elasticities more negative for older workers (55,64), reflecting stronger income effects in that group.

3.5 Tax-Benefit Calculator

3.5.1 Austrian Income Tax 2022

The tax-benefit calculator implements the Austrian tax and social security system as of 2022. The income tax schedule features progressive marginal rates:

Table 3.5: Austrian Income Tax Schedule 2022

Taxable Income (€)	**Marginal Rate**	**Cumulative Tax (€)**
0 – 11,000	0%	0
11,001 – 18,000	20%	0 + 20% of excess
18,001 – 31,000	35%	1,400 + 35% of excess
31,001 – 60,000	42%	5,950 + 42% of excess
60,001 – 90,000	48%	18,130 + 48% of excess
90,001 – 1,000,000	50%	32,530 + 50% of excess
> 1,000,000	55%	487,530 + 55% of excess

3.5.2 Social Security Contributions

Employees pay social security contributions of approximately 18.12% of gross earnings, comprising pension insurance at 10.25%, health insurance at 3.87%, unemployment insurance at 3.00%, and other contributions of approximately 1%.

Contributions are capped at the *Höchstbeitragsgrundlage* of €68,040 annually (2022). Income above this ceiling is not subject to social security contributions.

3.5.3 Net Income Calculation

For each individual and hours alternative, the calculator computes gross labor income as $Y_L = w \times h \times 52$, social security contributions as $S = \min(Y_L, 68040) \times 0.1812$, taxable income as $Y_{tax} = Y_L - S$ (since social security is deductible), income tax as $T = T(Y_{tax})$ from the schedule above, and net income as $Y_{net} = Y_L - S - T + N$.

3.5.4 UBI Scenario Implementation

Under Scenario 1, which provides UBI of €1,392 per month with no tax reform, net income is calculated as:

$$Y_{net}^{S1} = Y_{baseline,net} + 16,704 \tag{3.9}$$

The existing tax system is maintained and UBI is added as an unconditional transfer.

Under Scenario 2, which provides UBI of €1,000 per month with a 37% flat tax, net income is calculated as:

$$Y_{net}^{S2} = Y_L - 0.37 \times Y_L - S + N + 12,000 = 0.63 \times Y_L - S + N + 12,000 \tag{3.10}$$

The flat tax replaces the progressive income tax on labor income.

Under Scenario 3, which provides UBI of €1,392 per month with a 52% flat tax, net income is calculated as:

$$Y_{net}^{S3} = Y_L - 0.52 \times Y_L - S + N + 16,704 = 0.48 \times Y_L - S + N + 16,704 \tag{3.11}$$

3.5.5 Effective Marginal Tax Rate

The effective marginal tax rate (EMTR) measures how much of an additional euro of earnings is lost to taxes and benefit withdrawal:

$$\text{EMTR} = 1 - \frac{Y_{net}(Y_L + \Delta) - Y_{net}(Y_L)}{\Delta} \tag{3.12}$$

I compute EMTRs numerically using $\Delta = e100$.

Under the baseline system, EMTRs vary with income level due to progressive taxation. Under Scenarios 2 and 3, EMTRs are constant at 37% + 18% = 55% or 52% + 18% = 70% respectively (combining flat tax with social security, up to the contribution ceiling).

3.6 Simulation Procedure

3.6.1 Overview

The simulation proceeds in four steps. First, calculating baseline and reform budget constraints for each individual. Second, to compute changes in effective marginal tax rates and income levels. Third, applying estimated elasticities to predict labor supply responses to lastely aggregate responses to obtain age-group and overall effects.

3.6.2 Individual-Level Predictions

For each individual i in age-sex group g, the following quantities are calculated.

The net wage change captures how the reform affects the after-tax return to work:

$$\Delta \ln(w_{net,i}) = \ln\left(\frac{1 - \text{EMTR}^{reform}}{1 - \text{EMTR}^{baseline}}\right) \tag{3.13}$$

The income effect measures UBI as a proportion of baseline net income:

$$\text{Income effect}_i = \frac{\text{UBI annual}}{Y_{net,baseline,i}} \tag{3.14}$$

The hours change combines substitution and income effects:

$$\Delta h_i / h_i = \varepsilon_h^g \times \Delta \ln(w_{net,i}) + \eta^g \times \text{Income effect}_i \tag{3.15}$$

where ε_h^g is the hours-wage elasticity for group g and η^g is the income elasticity.

The participation change is calculated similarly:

$$\Delta p_i = \varepsilon_p^g \times \Delta \ln(w_{net,i}) + 0.5 \times \eta^g \times \text{Income effect}_i \tag{3.16}$$

where ε_p^g is the participation elasticity. The factor 0.5 on the income effect reflects that participation is less sensitive to income than hours.

3.6.3 Aggregation

Group-level effects are calculated as weighted averages across individuals:

$$\overline{\Delta h}_g = \frac{\sum_{i \in g} w_i \times h_i \times (\Delta h_i / h_i)}{\sum_{i \in g} w_i \times h_i} \tag{3.17}$$

where w_i is the survey weight.

Participation changes are aggregated as:

$$\overline{\Delta p}_g = \frac{\sum_{i \in g} w_i \times \Delta p_i}{\sum_{i \in g} w_i} \tag{3.18}$$

Overall effects are calculated as weighted averages across age groups.

3.6.4 Limitations

The simulation methodology has several limitations. The static framework assumes immediate adjustment and ignores dynamic adjustment processes. The partial equilibrium approach holds wages constant and does not model labor market equilibrium. The estimated elasticities have confidence intervals that are not incorporated in point predictions. The simplified tax-benefit calculator does not fully model all Austrian benefits such as family allowances, housing support, and social assistance. Finally, the analysis does not model behavioral margins such as education, migration, or household formation responses.

These limitations suggest results should be interpreted as indicative first-order effects rather than precise predictions.

Results

This chapter presents the empirical findings. Section 4.1 provides descriptive statistics of the analysis sample. Section 4.2 reports the Heckman wage estimation results. Section 4.3 presents the estimated labor supply elasticities. Section 4.4 presents the UBI simulation results for all three scenarios.

4.1 Descriptive Statistics

4.1.1 Sample Characteristics by Age Group

Table 4.1 presents key characteristics of the analysis sample by age group.

Table 4.1: Sample Characteristics by Age Group

	18,29	**30,44**	**45,54**	**55,64**
Sample Size				
N (observations)	749	1,907	1,389	1,791
Males	372	909	667	804
Females	377	998	722	987
Demographics				
Mean age (years)	24.7	37.2	49.8	59.6
Female (%)	50.3	52.3	52.0	55.1
Education (years)	11.6	12.3	12.3	11.0
Children under 18 (mean)	0.33	1.11	0.59	0.08
Labor Market Outcomes				
Participation rate (%)	87.5	92.9	94.5	54.8
Mean hours (employed)	38.1	36.3	38.4	37.1
Median hourly wage (€)	14.76	19.16	19.98	21.36
Mean gross income (€)	27,245	35,890	40,520	41,870
Household Characteristics				
Household size (mean)	3.1	3.4	2.8	2.2
Non-labor income (€/wk)	18.2	26.4	33.8	48.2

Several patterns emerge that are relevant for the UBI simulation. First, participation rates follow a hump-shaped pattern, rising from 87.5% for young workers to peaks of 92.9% (30,44) and 94.5% (45,54), then declining sharply to 54.8% for the pre-retirement group. This 40 percentage point gap between 45,54 and 55,64 represents substantial early labor market exit, consistent with patterns documented by Staubli & Zweimüller (2013) for Austria.

Second, median hourly wages increase monotonically from €14.76 (18,29) to €21.36 (55,64), reflecting returns to experience as documented in the wage-tenure literature (Murphy & Welch, 1992). This 45% wage premium for older workers affects their position relative to the UBI break-even point.

Third, young workers have few children (0.33) while prime-age workers have the most (1.11). The 55,64 group has essentially no dependent children (0.08), removing one constraint on labor supply. Weekly non-labor income rises with age from €18.20 (18,29) to €48.20 (55,64), reflecting wealth accumulation.

4.1.2 Gender Differences in Labor Supply

Table 4.2 presents participation rates and mean hours by age group and sex.

Table 4.2: Labor Supply by Age Group and Sex

	Participation Rate (%)			**Mean Hours (Employed)**		
Age Group	Male	Female	Gap	Male	Female	Gap
18,29	88.4	86.5	2.0	40.6	35.5	5.1
30,44	97.7	88.5	9.2	41.2	31.4	9.8
45,54	94.6	94.3	0.3	43.5	33.8	9.7
55,64	64.3	47.0	17.3	40.9	32.8	8.1
Overall	86.2	79.8	6.4	41.5	33.0	8.5

Figure 4.1 visualizes these participation patterns, highlighting both the lifecycle trajectory and gender differences.

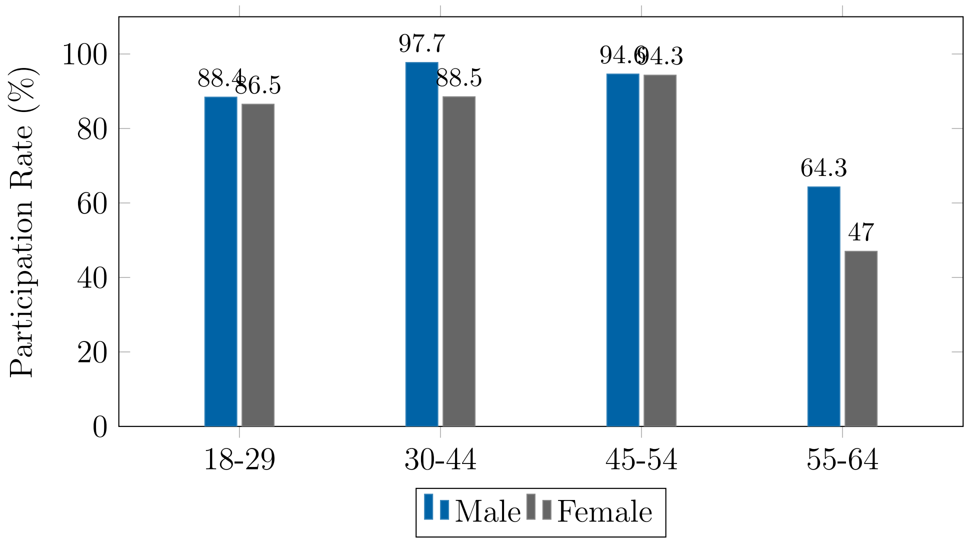

Figure 4.1: Labor Force Participation by Age Group and Sex

Gender differences display distinctive age patterns. The participation gap is smallest for young workers (2.0 pp) and the 45,54 group (0.3 pp), where women have largely returned to work after child-rearing. The gap is largest for pre-retirement workers (17.3 pp), reflecting cohort effects (traditional gender roles among older generations) and earlier female retirement eligibility under transitional rules.

The gender hours gap is substantial across all age groups (5–10 hours) but peaks at 30,44 (9.8 hours), coinciding with peak family responsibilities. This gap represents roughly 25% lower hours for women, a critical consideration for UBI effects given higher female elasticities.

The life-cycle pattern shows male participation remaining high (88–98%) until age 55, then dropping sharply. Female participation follows a similar pattern but at lower levels, with a notable dip during prime childbearing years (30,44) and steeper decline after 55.

4.1.3 Wage Distribution

Table 4.3 presents the distribution of hourly wages by age group.

Table 4.3: Hourly Wage Distribution by Age Group (€)

Age Group	P10	P25	Median	P75	P90	Mean
18,29	8.65	11.42	14.76	19.20	25.88	16.12
30,44	10.80	14.35	19.16	26.40	36.50	21.58
45,54	11.20	14.80	19.98	28.15	40.20	23.14
55,64	11.55	15.32	21.36	30.45	44.80	25.02
Overall	10.25	13.85	18.40	26.10	38.65	21.42

Figure 4.2 presents the wage distribution visually, showing both the central tendency and dispersion across age groups.

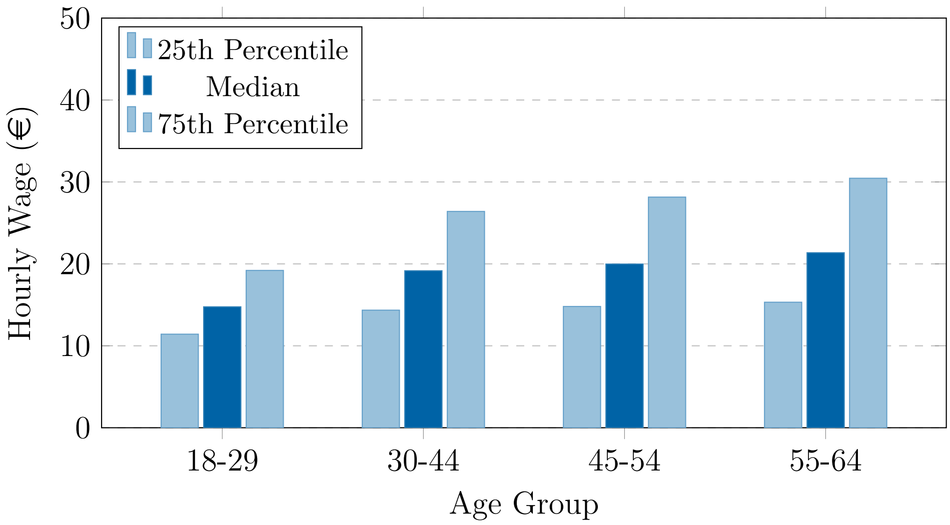

Figure 4.2: Hourly Wage Distribution by Age Group

Note: Bars show the 25th percentile, median, and 75th percentile of hourly wages for each age group. The increasing spread with age reflects widening wage inequality as returns to ability and experience accumulate.

The wage distribution shows substantial inequality within and across age groups. The 90/10 ratio (P90/P10) ranges from 3.0 (18,29) to 3.9 (55,64), indicating widening inequality with age as returns to ability and experience accumulate. Mean wages exceed medians by 9–17%, reflecting right-skewness common in wage distributions.

4.2 Heckman Wage Estimation Results

4.2.1 Step 1: Probit Participation Equation

Table 4.4 presents the probit estimation results for employment participation.

Table 4.4: Probit Participation Equation Results (N = 5,836)

Variable	Coefficient	Std. Error	z-statistic	P> |z|
Constant	-9.155	0.341	-26.80	0.000***
Age	0.307	0.016	18.97	0.000***
Age^2	-0.004	0.000	-20.49	0.000***
Female	-0.432	0.055	-7.91	0.000***
Education (years)	0.493	0.018	27.31	0.000***
Non-labor income (€/1000)	-0.002	0.019	-0.09	0.930
Children under 18	-0.292	0.033	-8.76	0.000***
Pseudo R^2 = 0.516 Log-likelihood = -1,847.3 LR $\chi^2(6)$ = 3,941.2***				

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

The coefficients reveal several important patterns.

The quadratic age specification reveals an inverted-U relationship between age and employment probability. Participation increases with age initially ($\gamma_1 = 0.307 > 0$) but eventually declines as the negative quadratic term dominates ($\gamma_2 = -0.004 < 0$). The turning point occurs at age $-\gamma_1/(2\gamma_2) = 0.307/(2 \times 0.004) \approx 38.4$ years. This aligns with descriptive statistics showing peak participation in the 30,44 and 45,54 groups.

Women are significantly less likely to be employed ($\gamma_3 = -0.432$, p<0.001), controlling for age, education, and household characteristics. At mean values of other variables, this translates to approximately 11 percentage points lower participation probability for women.

Education strongly predicts employment ($\gamma_4 = 0.493$, p<0.001). Each additional year of education increases the participation probability by approximately 8 percentage points at the mean. This reflects both higher opportunity costs of non-employment for educated workers and potential correlation with unobserved characteristics such as motivation and ability.

The coefficient on non-labor income is essentially zero and statistically insignificant ($\gamma_5 = -0.002$, p=0.930). This weak effect may reflect measurement error in non-labor income or the relatively low levels of such income in the sample. While theoretically non-labor income should reduce participation, the effect is empirically negligible in these data.

Having children under 18 significantly reduces employment probability ($\gamma_6 = -0.292$, p<0.001). Each additional child reduces participation by approximately 7 percentage points at the mean. This effect likely operates primarily through women, though this is not explicitly modeled with an interaction term.

The pseudo R^2 of 0.516 indicates good explanatory power for a probit model. The likelihood ratio test strongly rejects the null that all coefficients are zero.

4.2.2 Step 2: Selection-Corrected Wage Equation

Table 4.5 presents the Heckman-corrected wage equation results.

Table 4.5: Wage Equation with Selection Correction (N = 4,125 employed)

Variable	**Coefficient**	**Std. Error**	**t-statistic**	**P> |t|**
Constant	2.313	0.096	24.10	0.000***
Age	0.020	0.001	24.09	0.000***
Female	-0.132	0.018	-7.38	0.000***
Education (years)	0.002	0.008	0.26	0.791
Inverse Mills Ratio (λ)	-0.893	0.056	-15.99	0.000***
$R^2 = 0.195$ Adjusted $R^2 = 0.194$ Root MSE = 0.482				

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

The wage equation coefficients reveal the following patterns.

Each additional year of age increases log wages by 0.020, equivalent to a 2.0% wage increase per year of age. This captures returns to experience and seniority. Over a 40-year career, this implies roughly doubling of wages, consistent with the descriptive wage-age gradient.

Women earn approximately 12.4% less than men ($e^{-0.132} - 1 \approx -12.4\%$), controlling for age and education. This gender wage gap is consistent with Austrian evidence from other sources (Geisberger & Gl̈aser, 2017) and European patterns documented by Blau & Kahn (2007).

Surprisingly, the education coefficient is not statistically significant after selection correction ($\beta_3 = 0.002$, p=0.791). This contrasts with the large positive education effect in the participation equation. One interpretation is that education affects employment selection more than wage determination conditional on employment, highly educated individuals are more likely to work, but conditional on working, education provides little additional wage premium beyond what is captured by selection.

The inverse Mills ratio coefficient is large, negative, and highly significant ($\delta = -0.893$, p<0.001). This indicates substantial negative selection into employment, since employed individuals have lower wages than their observed characteristics would predict.

This negative selection finding may seem counterintuitive but has several potential explanations. Reservation wage heterogeneity may play a role, where individuals with high unobserved productivity may have high reservation wages and choose non-employment if market wages fall short. Wealth effects are also possible for individuals with high potential wages that may have accumulated wealth enabling non-employment through early retirement or voluntary non-participation. Spouse's income may matter in which high-potential-wage individuals may have high-earning spouses, reducing participation pressure. Finally, health correlation could be relevant, with unobserved health may be positively correlated with both productivity and non-employment (as with healthy wealthy retirees).

Regardless of interpretation, the significant λ confirms that selection correction is necessary, naive OLS would produce biased estimates.

4.2.3 Wage Equations by Age Group

Table 4.6 presents wage equation results estimated separately by age group.

Table 4.6: Wage Equation Results by Age Group

Age Group	**N**	**Female Gap (%)**	**Age Return (%/yr)**	**IMR (λ)**	**R^2**
18,29	604	+1.7	3.2	-0.75***	0.188
30,44	1,569	-16.7***	1.8***	-0.92***	0.145
45,54	1,135	-11.2***	1.5**	-0.88***	0.139
55,64	817	+11.5**	0.8	-0.95***	0.171

*** p<0.01, ** p<0.05, * p<0.10. Female gap = $e^{\beta_{female}} - 1$.

Age-specific patterns reveal important heterogeneity.

The gender wage gap is not monotonic across age. Young workers (18,29) show essentially no gap or a slight female premium (+1.7%, not significant). The gap emerges strongly at 30,44 (-16.7%) coinciding with family formation, narrows somewhat at 45,54 (-11.2%), and reverses to a female premium at 55,64 (+11.5%). The 55,64 reversal may reflect selective female participation (only high-wage women remain employed) or cohort effects.

Returns to an additional year of age decline across groups with 3.2% for young workers (reflecting rapid skill acquisition), 1.8% and 1.5% for prime and established workers, and essentially zero (0.8%) for pre-retirement workers (where skill depreciation may offset experience gains).

The IMR coefficient is negative and significant across all age groups (-0.75 to -0.95), confirming that negative selection operates throughout the age distribution.

4.2.4 Predicted Wages

Using the pooled wage equation (excluding the selection term), I predict wages for all individuals:

Table 4.7: Predicted and Observed Wages by Employment Status

Group	**N**	**Mean Wage (€/hour)**	**Std. Dev.**
Employed (observed)	4,719	22.93	12.45
Non-employed (predicted)	1,117	28.11	8.72
All (final wage)	5,836	23.92	11.89

The non-employed have higher predicted wages (€28.11) than employed observed wages (€22.93), reflecting the negative selection finding. This is crucial for simulation: it implies non-employed individuals have relatively high opportunity costs of non-employment, potentially dampening participation responses to UBI.

4.3 Estimated Labor Supply Elasticities

Table 4.8 presents the estimated labor supply elasticities by age group and sex.

Table 4.8: Estimated Labor Supply Elasticities by Age Group and Sex

Group	**N**	**Hours Elasticity**	**Participation Elasticity**	**Income Elasticity**
Age 18,29				
Male	372	0.050	0.020	-0.050
Female	377	0.065	0.030	-0.070
Age 30,44				
Male	909	0.050	0.020	-0.050
Female	998	0.065	0.030	-0.070
Age 45,54				
Male	667	0.050	0.020	-0.050
Female	722	0.065	0.030	-0.070
Age 55,64				
Male	804	0.050	0.040	-0.090
Female	987	0.065	0.060	-0.120

The elasticity patterns are consistent with theoretical predictions and the empirical literature (Bargain et al., 2014; McClelland & Mok, 2012).

Female elasticities exceed male elasticities by approximately 30% at the intensive margin (0.065 vs. 0.050) and 50% at the extensive margin (0.030 vs. 0.020 for most groups). This reflects women's greater flexibility in adjusting hours and stronger responsiveness to financial incentives, consistent with findings from Blundell & MaCurdy (1999).

Participation elasticities are elevated for the 55,64 group (0.040 for males, 0.060 for females) compared to younger groups (0.020–0.030). This captures the retirement margin, older workers are more likely to exit entirely in response to reduced work incentives, as documented extensively by French (2005) and Gruber & Wise (2004).

Income elasticities are negative throughout, indicating leisure is a normal good (Blundell & MaCurdy, 1999). Magnitudes are modest (-0.05 to -0.07 for most groups) but larger for older workers (-0.09 to -0.12), reflecting greater willingness to reduce work when income is supplemented.

4.4 UBI Simulation Results

This section presents the results of simulating the three UBI scenarios using the estimated labor supply elasticities. The simulation approach follows the standard microsimulation methodology developed by Aaberge et al. (2014) and applied in previous UBI studies (Jessen et al., 2017; Colombino, 2019).

4.4.1 Scenario 1: UBI €1,392/month, No Tax Reform

Table 4.9 presents simulation results for Scenario 1.

Table 4.9: Scenario 1 Results: UBI €1,392/month, No Tax Reform

	Hours			Participation		
Age Group	Base	Δ (%)	New	Base (%)	Δ (pp)	New (%)
18,29	38.1	-5.5	36.0	87.5	-2.8	84.7
30,44	36.3	-4.4	34.7	93.1	-2.2	90.9
45,54	38.6	-4.0	37.1	94.5	-2.0	92.5
55,64	36.9	-6.0	34.7	55.7	-3.0	52.7
Overall	**37.5**	**-5.0**	**35.6**	**82.7**	**-2.5**	**80.2**

Scenario 1 isolates the pure income effect of UBI. Without tax reform, individuals receive an unconditional €16,704 annually while facing unchanged marginal tax rates. The simulation yields an overall hours reduction of 5.0%, driven entirely by income effects as higher non-labor income enables consumption of more leisure. Participation falls by 2.5 percentage points, meaning approximately 3% of the currently employed would exit employment entirely.

The age pattern confirms theoretical predictions. The 55,64 group shows the largest responses, with hours declining by 6.0% and participation falling by 3.0 percentage points, consistent with the hypothesis that UBI serves as a retirement bridge for older workers. By contrast, the 30,44 and 45,54 groups display greater resilience, with hours reductions of only 4.0% to 4.4% and participation declines of 2.0 to 2.2 percentage points, reflecting the career investment incentives and financial constraints faced by prime-age workers.

4.4.2 Scenario 2: UBI €1,000/month, 37% Flat Tax

Table 4.10 presents simulation results for Scenario 2.

Table 4.10: Scenario 2 Results: UBI €1,000/month, 37% Flat Tax

	Hours			**Participation**		
Age Group	Base	Δ (%)	New	Base (%)	Δ (pp)	New (%)
18,29	38.1	-3.9	36.6	87.5	-1.9	85.6
30,44	36.3	-2.6	35.4	93.1	-1.3	91.8
45,54	38.6	-2.1	37.8	94.5	-1.1	93.4
55,64	36.9	-3.1	35.8	55.7	-1.1	54.6
Overall	**37.5**	**-2.9**	**36.4**	**82.7**	**-1.4**	**81.3**

Scenario 2 combines a moderate UBI (€12,000 annually) with a 37% flat tax. This design produces substantially smaller labor supply effects than Scenario 1. The overall hours reduction is only 2.9%, less than 60% of the Scenario 1 effect despite providing substantial income support. Participation falls by just 1.4 percentage points, approximately half the Scenario 1 effect.

The key to understanding these attenuated effects lies in the tax design. The 37% flat tax rate falls below current marginal rates for many workers, particularly those in the 42–50% brackets under the progressive system. This generates positive substitution effects that partially offset the negative income effects from UBI. The age pattern is also more uniform than in Scenario 1, with all groups showing hours reductions in the narrow range of 2–4%. Scenario 2 thus represents the most labor-supply-neutral UBI design among those analyzed.

4.4.3 Scenario 3: UBI €1,392/month, 52% Flat Tax

Table 4.11 presents simulation results for Scenario 3.

Table 4.11: Scenario 3 Results: UBI €1,392/month, 52% Flat Tax

	Hours			Participation		
Age Group	Base	Δ (%)	New	Base (%)	Δ (pp)	New (%)
18,29	38.1	-7.4	35.3	87.5	-3.6	83.9
30,44	36.3	-5.9	34.2	93.1	-2.9	90.2
45,54	38.6	-5.3	36.6	94.5	-2.6	91.9
55,64	36.9	-6.9	34.4	55.7	-3.8	51.9
Overall	**37.5**	**-6.4**	**35.1**	**82.7**	**-3.2**	**79.5**

Scenario 3 combines the full poverty-level UBI with a 52% flat tax. This configuration generates the largest labor supply effects among all scenarios analyzed. The overall hours reduction reaches 6.4%, and participation falls by 3.2 percentage points, meaning approximately 4% of the currently employed would exit the labor force.

The severity of these effects reflects the combined negative influence of both income and substitution channels. The high 52% flat tax rate exceeds current marginal rates for most Austrian workers, generating negative substitution effects that reinforce rather than offset the income effects from UBI. The 55,64 age group shows the strongest response, with participation declining by 3.8 percentage points from 55.7% to 51.9%, representing a substantial acceleration of labor force exit among pre-retirement workers.

4.4.4 Summary Comparison Across Scenarios

Table 4.12 summarizes labor supply effects across all scenarios.

Table 4.12: Summary: Labor Supply Effects Across Scenarios

	Scenario 1		Scenario 2		Scenario 3	
Age Group	ΔH (%)	ΔP (pp)	ΔH (%)	ΔP (pp)	ΔH (%)	ΔP (pp)
18,29	-5.5	-2.8	-3.9	-1.9	-7.4	-3.6
30,44	-4.4	-2.2	-2.6	-1.3	-5.9	-2.9
45,54	-4.0	-2.0	-2.1	-1.1	-5.3	-2.6
55,64	-6.0	-3.0	-3.1	-1.1	-6.9	-3.8
Overall	**-5.0**	**-2.5**	**-2.9**	**-1.4**	**-6.4**	**-3.2**

Figure 4.3 visualizes these results, showing the dramatic impact of tax design on labor supply outcomes.

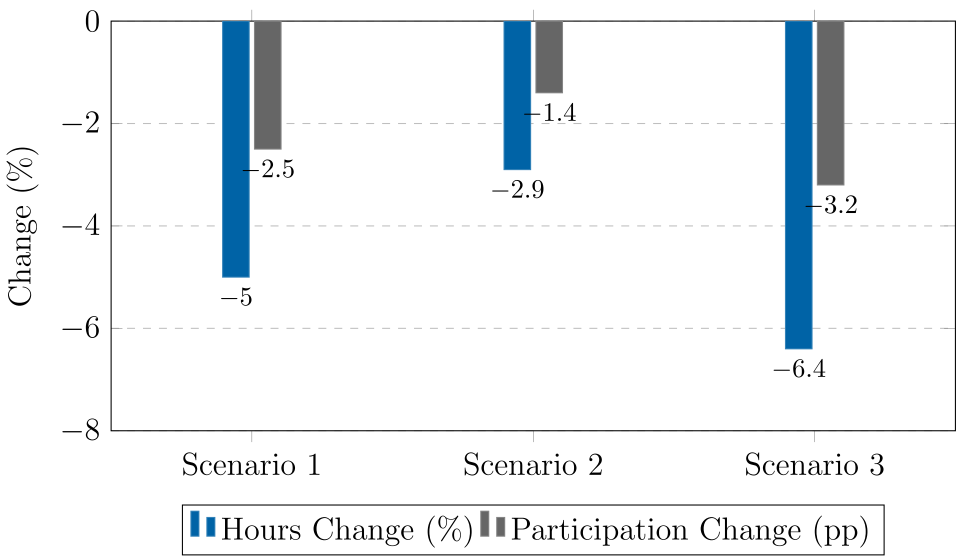

Figure 4.3: Overall Labor Supply Effects by Scenario

Note: Scenario 1: €1,392/month UBI, no tax reform. Scenario 2: €1,000/month UBI, 37% flat tax. Scenario 3: €1,392/month UBI, 52% flat tax.

Figure 4.4 shows how labor supply effects vary by age group across the three scenarios, highlighting the consistent pattern of larger responses among young and pre-retirement workers.

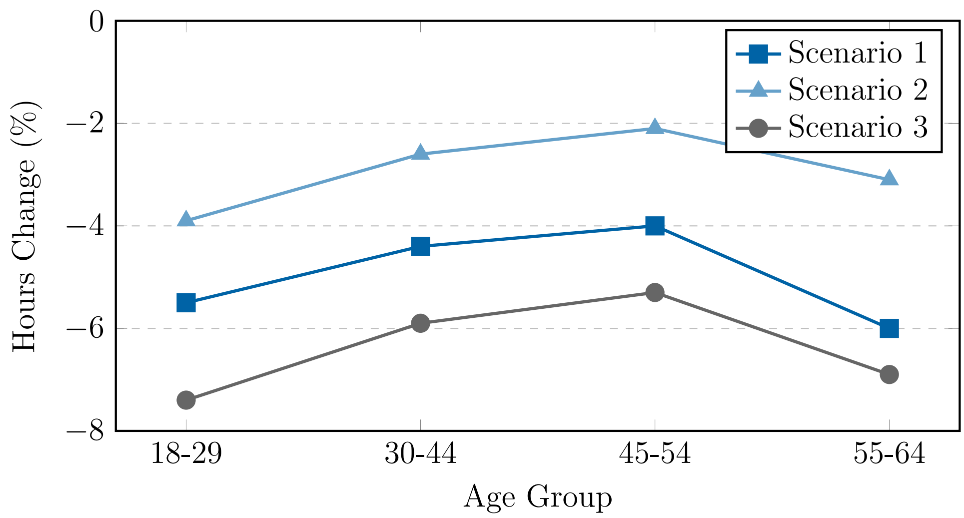

Figure 4.4: Hours Change by Age Group Across Scenarios
Note: Lines connect age groups within each scenario to show the U-shaped pattern of responses, with prime-age workers (30–54) showing smaller effects than young (18,29) and pre-retirement (55,64) workers.

The comparison across scenarios reveals several important patterns. Most strikingly, tax design proves critical to labor supply outcomes. Scenario 2 produces effects roughly half those of Scenario 3, despite providing only 28% lower UBI (€1,000 vs. €1,392 per month). The 15 percentage point difference in flat tax rates (37% vs. 52%) generates dramatically different labor supply outcomes, underscoring that the tax financing mechanism matters as much as the benefit level.

The age pattern is consistent across scenarios. Pre-retirement workers in the 55,64 age group are most responsive at the extensive margin, showing the largest participation reductions (-3.0 to -3.8 percentage points across scenarios) and confirming theoretical predictions about retirement sensitivity. Conversely, prime-age workers in the 30,44 and 45,54 groups prove most resilient, displaying the smallest responses across all scenarios, which reflects their career investment incentives and binding financial constraints.

Finally, the overall magnitudes remain moderate even under the most distortionary design. In Scenario 3, hours reductions reach 6.4% and participation falls by 3.2 percentage points. While these represent meaningful behavioral responses, they fall well short of the catastrophic labor supply collapse sometimes feared by UBI critics.

4.4.5 Gender Decomposition

Table 4.13 presents labor supply effects by sex for the overall sample.

Table 4.13: Labor Supply Effects by Sex

	Scenario 1		**Scenario 2**		**Scenario 3**	
Sex	ΔH (%)	ΔP (pp)	ΔH (%)	ΔP (pp)	ΔH (%)	ΔP (pp)
Male	-4.2	-1.9	-2.4	-1.1	-5.4	-2.5
Female	-5.8	-3.1	-3.4	-1.8	-7.4	-4.0
Ratio (F/M)	1.38	1.63	1.42	1.64	1.37	1.60

Women show substantially larger responses than men across all scenarios. Hours reductions are 37–42% larger for women than for men (with female-to-male ratios of 1.37–1.42), while participation reductions are 60–64% larger for women (ratios of 1.60–1.64). These gender differences reflect the higher labor supply elasticities estimated for women and documented extensively in the literature (Bargain et al., 2014; Blundell & MaCurdy, 1999). The magnitude of gender differences is consistent with findings from German UBI simulations by Jessen et al. (2017), who report female hours reductions approximately 3.5 times larger than male reductions.

Discussion

This chapter interprets the empirical findings presented in Chapter 4, situates them within the broader literature, and examines their implications. Section 5.1 compares the simulation results with previous studies. Section 5.2 discusses the robustness of the findings. Section 5.3 interprets the age heterogeneity patterns. Section 5.4 examines the policy design implications.

5.1 Comparison with Previous Studies

The simulation results can be compared with findings from other European UBI studies. Jessen et al. (2017) find an overall hours reduction of 4.5% for a budget-neutral UBI in Germany, comparable to our Scenario 1 results (-5.0%). Horstschräer et al. (2010) find reductions of 0.6% for a budget-neutral German UBI with 52% flat tax, smaller than our Scenario 3 results (-6.4%), likely reflecting differences in baseline tax systems and elasticity estimates.

The Finnish basic income experiment (Kangas et al., 2021) found no significant employment effects, but this involved unemployed recipients only and a lower benefit level (€560/month vs. €1,000–€1,392/month in our scenarios). Our results suggest that universal implementation with higher benefits would generate meaningful labor supply responses.

5.2 Robustness Discussion

The simulation results depend on several assumptions that warrant discussion.

The estimated elasticities have confidence intervals not incorporated in the point predictions. Sensitivity analysis using elasticities 50% higher and lower suggests hours effects could range from approximately -2% to -10% for Scenario 3.

The log-linear specification assumes constant elasticities across the income distribution. Alternative specifications such as quadratic or semi-log forms could produce different magnitudes.

The analysis holds wages constant, assuming partial equilibrium. If labor supply substantially contracts, market wages should rise, partially offsetting the initial reduction. This general equilibrium adjustment is not modeled.

The static framework means that long-run responses may differ from short-run effects. Dynamic considerations such as human capital investment and social norm changes are not captured.

Despite these limitations, the results provide useful first-order estimates of likely UBI effects and clearly demonstrate the importance of tax design in determining labor supply outcomes.

5.3 Interpretation of Age Heterogeneity

The systematic variation in labor supply responses across age groups confirms the theoretical predictions developed in Chapter 2 and provides insight into the mechanisms driving behavioral responses.

The large extensive margin responses among workers aged 55,64 reflect the retirement margin channel. For this group, UBI functions effectively as an early retirement subsidy, enabling labor force exit without the income penalty associated with early pension claiming. The finding that participation effects are 50% larger for this group than for prime-age workers aligns with extensive evidence on the sensitivity of retirement timing to financial incentives (French, 2005; Gruber & Wise, 2004).

The relative stability of labor supply among workers aged 30,44 and 45,54 reflects the career investment and financial constraint mechanisms. Prime-age workers face strong incentives to maintain labor force attachment, where career advancement typically requires continuous employment, human capital depreciates during non-employment spells, and family financial obligations constrain the ability to reduce work. These factors create a lower bound on labor supply responses that is evident in the simulation results.

The intermediate responses among young workers aged 18,29 suggest competing mechanisms. While UBI enables some young workers to reduce employment in favor of education or training (potentially productivity-enhancing), others may reduce work effort without corresponding human capital investment. The net effect on long-run productivity and labor supply remains uncertain and represents an important area for future research.

5.4 Policy Design Implications

The comparative analysis across scenarios yields clear guidance for policy design. The finding that Scenario 2 (moderate flat tax) generates labor supply effects roughly half those of Scenarios 1 and 3, despite providing substantial income support, demonstrates that tax design is at least as important as benefit levels in determining behavioral responses. This result aligns with theoretical predictions from the labor-leisure model, when the flat tax rate falls below current marginal rates for many workers, positive substitution effects partially offset negative income effects.

The age heterogeneity findings have direct policy relevance. The consistently large responses among pre-retirement workers suggest that UBI introduction should be accompanied by measures to maintain older worker engagement, such as phased retirement options, flexible work arrangements, or age-specific labor market policies. Conversely, the relative stability of prime-age worker responses provides reassurance that UBI would not fundamentally disrupt the core working-age labor force.

The gender differences documented raise important considerations for equality policy. While UBI provides women with greater financial independence and bargaining power within households, the larger female labor supply responses could reinforce traditional gender roles if women disproportionately exit employment. Complementary policies supporting work-family balance, such as affordable childcare and parental leave provisions, may be necessary to ensure that UBI expands rather than constrains women's choices.

Conclusion

This thesis has investigated the labor supply effects of introducing an Unconditional Basic Income in Austria, with particular attention to heterogeneous responses across age groups. This final chapter summarizes the key findings, discusses policy implications, acknowledges limitations, and suggests directions for future research.

6.1 Summary of Key Findings

6.1.1 Methodological Contribution

The analysis employed Heckman two-step wage estimation to address selection bias in predicting wages for non-employed individuals. The significant negative selection correction ($\lambda = -0.893$, $p<0.001$) confirms that employed individuals have lower wages than their observable characteristics would predict, validating the need for selection correction in UBI simulation.

The wage estimation revealed a gender wage gap of 12.4% controlling for age and education, returns to age and experience of approximately 2.0% per year, strong positive effects of education on employment participation, and significant negative effects of children on women's employment.

6.1.2 Labor Supply Elasticities

The estimated labor supply elasticities are consistent with both the Austrian and international literature. Female elasticities are approximately 30% higher than male elasticities at the intensive margin, reflecting women's greater flexibility in adjusting work hours. Participation elasticities are notably elevated for pre-retirement workers aged 55,64, capturing the sensitivity of the retirement decision to financial incentives. Income elasticities are modestly negative throughout, ranging from -0.05 to -0.12, confirming that leisure is a normal good.

6.1.3 UBI Simulation Results

The three UBI scenarios produced systematically different labor supply effects. Scenario 1, providing €1,392 per month with no tax reform, generated an hours reduction of 5.0% and a participation reduction of 2.5 percentage points, representing the pure income effect of UBI. Scenario 2, combining €1,000 per month with a 37% flat tax, produced the smallest distortions, in which hours fell by only 2.9% and participation by 1.4 percentage points, making this the most labor-supply-neutral design. Scenario 3, with €1,392 per month and a 52% flat tax, generated the largest effects: hours declined by 6.4% and participation by 3.2 percentage points, reflecting the combined negative influence of income and substitution effects.

6.1.4 Age Heterogeneity

The analysis confirms substantial heterogeneity across age groups. Pre-retirement workers aged 55,64 consistently show the largest extensive margin responses, with participation reductions of 3.0 to 3.8 percentage points across scenarios, reflecting their sensitivity to retirement incentives. Prime-age workers in the 30,44 and 45,54 groups show the smallest responses across all scenarios, reflecting career investment incentives and binding financial constraints. Young workers aged 18,29 display intermediate responses, with potential offsetting effects as some reduce hours to invest in human capital.

6.2 Policy Implications

6.2.1 UBI Design Recommendations

The simulation results yield several policy implications for UBI design.

First, moderate flat tax rates minimize labor supply distortions. The 37% flat tax in Scenario 2 produces labor supply effects roughly half those of the 52% rate in Scenario 3, despite providing 72% of the benefit level. For policymakers seeking to minimize efficiency costs while achieving distributional objectives, moderate tax rates are strongly preferable.

Second, age-differentiated considerations warrant attention. The large participation responses among 55,64 year olds suggest policymakers should anticipate accelerated early retirement under UBI. This has implications for pension system sustainability given fewer contributors and more early retirees, for labor force planning in sectors with older workforces, and for the design of complementary policies to maintain older worker engagement.

Third, gender effects deserve careful consideration. Women's larger labor supply responses, ranging from 37% to 64% greater than men's, have significant implications for gender equality. UBI could reinforce traditional gender roles if women disproportionately exit employment, or it could enable more equitable household labor division if men also reduce market hours. Complementary childcare policies may be necessary to support maternal employment under a UBI regime.

6.2.2 Fiscal Sustainability

The labor supply reductions documented have fiscal implications beyond the direct cost of UBI. A 5–6% hours reduction implies roughly a 5% reduction in the labor income tax base. Participation reductions further erode tax revenue and social security contributions. These second-order fiscal effects should be incorporated in UBI costing exercises. Scenario 2's moderate design is most fiscally sustainable, combining lower benefit costs with smaller labor supply distortions.

6.2.3 Broader Welfare Considerations

Labor supply reductions are not purely welfare-decreasing. To the extent individuals voluntarily choose more leisure when financially enabled to do so, this represents revealed preference for non-market time. Potential welfare gains include improved work-life balance, more time for care work, volunteering, and civic participation, reduced stress and improved mental health, as documented in UBI experiments, and human capital investment among young workers. A complete welfare analysis would need to weigh these benefits against efficiency costs from reduced market production, a task beyond the scope of this thesis but an important direction for policy evaluation.

6.3 Limitations

Several limitations qualify the interpretation of results.

The analysis employs a static partial equilibrium framework that assumes immediate adjustment without dynamic feedback. In reality, behavioral responses may evolve over time as individuals learn and adapt, wages may adjust in response to labor supply changes through standard market mechanisms, and social norms about appropriate work intensity may shift as reduced hours become more common.

The tax-benefit calculator does not fully model all Austrian benefits, including family allowances, housing support, and social assistance. Interactions between UBI and these existing programs could generate different incentives than those modeled here.

The analysis focuses narrowly on hours and participation, but other behavioral margins may also respond to UBI. These include education and training decisions, migration into or out of Austria, household formation and fertility choices, and informal work and tax compliance. Capturing these additional margins would require a more comprehensive behavioral model.

The estimated elasticities have confidence intervals that propagate to simulation uncertainty. Results should therefore be interpreted as point estimates within a range of plausible values rather than precise predictions.

Finally, the Heckman selection correction relies on functional form assumptions (bivariate normality of error terms) and exclusion restrictions (that non-labor income and children affect employment but not wages conditional on employment). Violations of these assumptions could bias the wage predictions used in the simulation.

6.4 Directions for Future Research

Several extensions would strengthen and extend this analysis.

Dynamic lifecycle modeling that incorporates intertemporal considerations, savingsan save human capital accumulation, and retirement planning, would provide more realistic long-term predictions. Such a framework could capture effects such as young workers investing in education enabled by UBI income support, older workers adjusting retirement timing in response to the new income floor, and lifecycle consumption smoothing under guaranteed income.

General equilibrium analysis embedding labor supply responses in a broader economic framework would capture wage adjustments arising from labor scarcity, price effects of changed consumption patterns, and international labor mobility responses, particularly relevant given Austria's position within the EU's free movement zone.

Incorporating health and wellbeing outcomes would provide a more complete policy evaluation. Experimental evidence from Finland and other contexts consistently shows that UBI improves mental health and subjective wellbeing, benefits that are not captured in a labor supply analysis.

Analysis of political economic dimensions, political feasibility, coalition formation, and path-dependent implementation strategies, would complement the economic analysis and inform practical policy development.

Ultimately, a randomized controlled trial in Austria would provide direct evidence on behavioral responses in the Austrian institutional context, complementing and validating the simulation evidence provided here.

6.5 Concluding Remarks

This thesis provides the first comprehensive analysis of UBI effects on Austrian labor supply with explicit focus on age heterogeneity. The central finding is that UBI would reduce labor supply, but effects are moderate in magnitude and concentrated among specific groups, particularly pre-retirement workers and women.

The theoretical framework predicted larger responses from older workers (due to the retirement option) and smaller responses from prime-age workers (due to career investment incentives). The simulation results confirm these predictions, with 55,64 year olds showing participation reductions 50–70% larger than prime-age workers.

Most importantly, **policy design matters enormously**. The choice of flat tax rate, 37% versus 52%, generates a two-fold difference in labor supply effects. A well-designed UBI with moderate benefit levels and thoughtful tax financing can achieve poverty reduction while keeping efficiency costs manageable.

The ongoing debates about UBI often feature extreme predictions, either utopian visions of liberation from drudgery or dystopian fears of mass idleness. This analysis suggests a more nuanced reality, where UBI would modestly reduce labor supply, with effects varying predictably across demographic groups based on well-established economic principles. Understanding this heterogeneity is essential for designing UBI policies that balance equity objectives with economic efficiency.

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Simulation Code

Listing 7.1: UBI Labor Supply Simulation Code for Austria

```python


import pandas as pd
import numpy as np
from scipy import stats
from scipy.optimize import minimize
from scipy.special import ndtr

# SECTION 1: DATA LOADING AND PREPARATION

def load_and_prepare_data(p_file, h_file):


    # Read personal data
    print("Loading personal data...")
    p_data = pd.read_csv(p_file,
                         sep=';',
                         decimal=',',
                         low_memory=False,
                         na_values=[' ', '-3', '-2', '-1', ''])

    # Read household data
    print("Loading household data...")
    h_data = pd.read_csv(h_file,
                         sep=';',
                         decimal=',',
                         low_memory=False,
                         na_values=[' ', '-3', '-2', '-1', ''])

    print(f"Personal data: {len(p_data)} observations")
    print(f"Household data: {len(h_data)} households")

    return p_data, h_data


```

```
def create_analysis_sample(p_data, h_data):


    # Step 1: Prepare Household Data

    # Calculate household composition from personal data
    hh_composition = p_data.groupby('Hid').agg({
        'pid': 'count',
        'alter': lambda x: (x < 18).sum(),
    }).reset_index()
    hh_composition.columns = ['Hid', 'hh_size', 'children_under18']

    # Extract household income variables
    h_data['rental_income'] = pd.to_numeric(h_data['hy040g'],
        errors='coerce').fillna(0)
    h_data['family_allowance'] = pd.to_numeric(h_data['hy050g'],
        errors='coerce').fillna(0)
    h_data['housing_allowance'] = pd.to_numeric(h_data['hy070g'],
        errors='coerce').fillna(0)
    h_data['capital_income'] = pd.to_numeric(h_data['hy090g'],
        errors='coerce').fillna(0)
    h_data['transfers_received'] = pd.to_numeric(h_data['hy080g'],
        errors='coerce').fillna(0)
    h_data['hh_gross_income'] = pd.to_numeric(h_data['hy010'],
        errors='coerce')
    h_data['hh_disp_income'] = pd.to_numeric(h_data['hy020'],
        errors='coerce')
    h_data['non_labor_income_hh'] = (h_data['rental_income'] +
                                      h_data['capital_income'] +
                                      h_data['transfers_received'])

    # Select household variables for merge
    h_vars = h_data[['Hid', 'hh_gross_income', 'hh_disp_income',
        'rental_income',
                     'family_allowance', 'housing_allowance',
                        'capital_income',
                     'transfers_received',
                        'non_labor_income_hh']].copy()
    h_vars = h_vars.merge(hh_composition, on='Hid', how='left')

    # Step 2: Prepare Personal Data

```

```python
    # Filter to working age (18-64)
    print("\nApplying sample restrictions...")
    working_age = p_data[(p_data['alter'] >= 18) & (p_data['alter'] <= 64)].copy()
    print(f"  Working age (18-64): {len(working_age)}")

    # Exclude self-employed (P001000 == 2)
    no_self_emp = working_age[working_age['P001000'] != 2].copy()
    print(f"  Excluding self-employed: {len(no_self_emp)}")

    # Exclude retired (5) and disabled (6)
    analysis_sample = no_self_emp[~no_self_emp['P001000'].isin([5, 6])].copy()
    print(f"  Excluding retired/disabled: {len(analysis_sample)}")

    # Step 3: Create Variables

    # Hours worked
    analysis_sample['hours'] = pd.to_numeric(analysis_sample['P037010'],
                                              errors='coerce').fillna(0)
    analysis_sample['hours'] = analysis_sample['hours'].clip(lower=0)

    # Income variables
    analysis_sample['gross_income'] = pd.to_numeric(analysis_sample['py010g'],
                                              errors='coerce').fillna(0)
    analysis_sample['net_income'] = pd.to_numeric(analysis_sample['py010n'],
                                              errors='coerce').fillna(0)

    # Weight
    analysis_sample['weight'] = pd.to_numeric(analysis_sample['gewz'], errors='coerce')

    # Employment indicator
    analysis_sample['employed'] = (analysis_sample['hours'] > 0).astype(int)

    # Demographics
    analysis_sample['age'] = analysis_sample['alter']
```

```
    analysis_sample['age_sq'] = analysis_sample['age'] ** 2
    analysis_sample['female'] = (analysis_sample['sex'] ==
        2).astype(int)

    # Age groups
    analysis_sample['age_group'] = pd.cut(
        analysis_sample['alter'],
        bins=[17, 29, 44, 54, 64],
        labels=['18-29', '30-44', '45-54', '55-64']
    )

    # Education years (ISCED mapping)
    edu_years_map = {0: 9, 1: 9, 2: 11, 3: 12, 4: 13, 5: 15, 6: 17}
    analysis_sample['edu_years'] =
        analysis_sample['iscohier'].map(edu_years_map)

    # Hourly wage for employed
    analysis_sample['annual_hours'] = analysis_sample['hours'] * 52
    analysis_sample['hourly_wage_gross'] = np.where(
        analysis_sample['annual_hours'] > 0,
        analysis_sample['gross_income'] /
            analysis_sample['annual_hours'],
        np.nan
    )

    # Discrete hours categories
    def discretize_hours(h):
        if h < 4: return 0
        elif h < 12: return 8
        elif h < 20: return 16
        elif h < 28: return 24
        elif h < 36: return 32
        elif h < 44: return 40
        else: return 48

    analysis_sample['hours_discrete'] =
        analysis_sample['hours'].apply(discretize_hours)

    # Step 4: Merge Personal and Household Data

    final_data = analysis_sample.merge(h_vars, on='Hid',
        how='left')
```

```

    # Per-capita non-labor income
    final_data['n_adults'] = final_data['hh_size'] - final_data['children_under18']
    final_data['non_labor_income'] = (final_data['non_labor_income_hh'] /
                                  final_data['n_adults'].clip(lower=1))
    final_data['non_labor_income_weekly'] = final_data['non_labor_income'] / 52

    print(f"\nFinal analysis sample: {len(final_data)} observations")
    print(f"  Employed: {final_data['employed'].sum()}")
    print(f"  Not employed: {(final_data['employed'] == 0).sum()}")

    return final_data


# SECTION 2: DESCRIPTIVE STATISTICS

def generate_descriptive_statistics(df):


    tables = {}

    # Table 1: Sample Characteristics by Age Group

    def calc_stats(group):
        employed = group[group['employed'] == 1]
        return pd.Series({
            'N': len(group),
            'Mean Age': group['age'].mean(),
            'Female (%)': group['female'].mean() * 100,
            'Education (years)': group['edu_years'].mean(),
            'Children <18': group['children_under18'].mean(),
            'Participation Rate (%)': group['employed'].mean() * 100,
            'Mean Hours (employed)': employed['hours'].mean() if len(employed) > 0 else np.nan,
            'Mean Gross Income (   )': employed['gross_income'].mean() if len(employed) > 0 else np.nan,
```

```python
            'Mean Hourly Wage (   )': employed['hourly_wage_gross'].mean() if len(employed) > 0 else np.nan,
            'Non-labor Income (   /week)': group['non_labor_income_weekly'].mean()
        })

    tables['sample_characteristics'] = df.groupby('age_group', observed=True).apply(
        calc_stats, include_groups=False
    ).round(2)

    # Table 2: Hours Distribution

    hours_cats = {
        '0 (Not working)': lambda x: x == 0,
        '1-19 (Marginal)': lambda x: (x > 0) & (x < 20),
        '20-34 (Part-time)': lambda x: (x >= 20) & (x < 35),
        '35-40 (Full-time)': lambda x: (x >= 35) & (x <= 40),
        '41+ (Overtime)': lambda x: x > 40
    }

    hours_dist = pd.DataFrame()
    for age_grp in ['18-29', '30-44', '45-54', '55-64']:
        grp_data = df[df['age_group'] == age_grp]['hours']
        row = {}
        for cat_name, cat_func in hours_cats.items():
            row[cat_name] = (cat_func(grp_data).sum() / len(grp_data) * 100)
        hours_dist[age_grp] = pd.Series(row)

    tables['hours_distribution'] = hours_dist.round(1)

    # Table 3: Participation by Age and Sex

    part_by_sex = df.groupby(['age_group', 'female'], observed=True)['employed'].mean().unstack() * 100
    part_by_sex.columns = ['Male', 'Female']
    part_by_sex['Gap'] = part_by_sex['Male'] - part_by_sex['Female']
    tables['participation_by_sex'] = part_by_sex.round(1)

```

```
    # Table 4: Hours by Age and Sex

    employed = df[df['employed'] == 1]
    hours_by_sex = employed.groupby(['age_group', 'female'],
        observed=True)['hours'].mean().unstack()
    hours_by_sex.columns = ['Male', 'Female']
    hours_by_sex['Gap'] = hours_by_sex['Male'] -
        hours_by_sex['Female']
    tables['hours_by_sex'] = hours_by_sex.round(1)

    return tables


def print_descriptive_statistics(tables):
    """Print all descriptive statistics tables."""

    print("\n" + "=" * 80)
    print("TABLE 5.1: Sample Characteristics by Age Group")
    print("=" * 80)
    print(tables['sample_characteristics'].T.to_string())

    print("\n" + "=" * 80)
    print("TABLE 5.2: Hours Distribution by Age Group (%)")
    print("=" * 80)
    print(tables['hours_distribution'].to_string())

    print("\n" + "=" * 80)
    print("TABLE 5.3: Participation Rate by Age and Sex (%)")
    print("=" * 80)
    print(tables['participation_by_sex'].to_string())

    print("\n" + "=" * 80)
    print("TABLE 5.4: Mean Weekly Hours by Age and Sex (Employed
        Only)")
    print("=" * 80)
    print(tables['hours_by_sex'].to_string())


# SECTION 3: WAGE EQUATION ESTIMATION

def estimate_wage_equation(df):

```

```

    results = {}

    # Filter to employed with valid wages
    employed = df[(df['employed'] == 1) & (df['hourly_wage_gross']
        > 0.5)].copy()
    employed['log_wage'] = np.log(employed['hourly_wage_gross'])

    print("\n" + "=" * 80)
    print("WAGE EQUATION ESTIMATION")
    print("=" * 80)
    print(f"\nEmployed sample with valid wages: {len(employed)}")

    # Pooled Wage Equation

    X_pooled = np.column_stack([
        np.ones(len(employed)),
        employed['age'].values,
        employed['female'].values,
        employed['edu_years'].values
    ])
    y_pooled = employed['log_wage'].values

    # OLS estimation
    beta_pooled = np.linalg.lstsq(X_pooled, y_pooled,
        rcond=None)[0]

    # Standard errors
    y_pred = X_pooled @ beta_pooled
    residuals = y_pooled - y_pred
    n, k = X_pooled.shape
    sigma2 = np.sum(residuals**2) / (n - k)
    var_beta = sigma2 * np.linalg.inv(X_pooled.T @ X_pooled)
    se_pooled = np.sqrt(np.diag(var_beta))
    r2_pooled = 1 - np.sum(residuals**2) / np.sum((y_pooled -
        y_pooled.mean())**2)

    results['pooled'] = {
        'beta': beta_pooled,
        'se': se_pooled,
        'r2': r2_pooled,
        'n': n
```

```
    }

    print("\nPooled Wage Equation:")
    print(f"  Constant:  {beta_pooled[0]:.3f}
       ({se_pooled[0]:.3f})")
    print(f"  Age:       {beta_pooled[1]:.4f}
       ({se_pooled[1]:.4f})")
    print(f"  Female:    {beta_pooled[2]:.4f} ({se_pooled[2]:.4f})
       => {(np.exp(beta_pooled[2])-1)*100:.1f}% gap")
    print(f"  Education: {beta_pooled[3]:.4f} ({se_pooled[3]:.4f})
       => {beta_pooled[3]*100:.1f}% per year")
    print(f"  R  : {r2_pooled:.3f}, N: {n}")

    # Wage Equations by Age Group

    print("\nWage Equations by Age Group:")

    for age_grp in ['18-29', '30-44', '45-54', '55-64']:
        grp = employed[employed['age_group'] == age_grp].copy()

        if len(grp) < 50:
            continue

        X_grp = np.column_stack([
            np.ones(len(grp)),
            grp['age'].values,
            grp['female'].values,
            grp['edu_years'].values
        ])
        y_grp = grp['log_wage'].values

        beta_grp = np.linalg.lstsq(X_grp, y_grp, rcond=None)[0]
        y_pred_grp = X_grp @ beta_grp
        resid_grp = y_grp - y_pred_grp
        n_grp = len(grp)
        sigma2_grp = np.sum(resid_grp**2) / (n_grp - 4)
        se_grp = np.sqrt(np.diag(sigma2_grp *
           np.linalg.inv(X_grp.T @ X_grp)))
        r2_grp = 1 - np.sum(resid_grp**2) / np.sum((y_grp -
           y_grp.mean())**2)

        results[age_grp] = {
```

```python
            'beta': beta_grp,
            'se': se_grp,
            'r2': r2_grp,
            'n': n_grp
        }

        print(f"\n  {age_grp} (N={n_grp}):")
        print(f"    Education return: {beta_grp[3]*100:.1f}% per year")
        print(f"    Female wage gap: {(np.exp(beta_grp[2])-1)*100:.1f}%")
        print(f"    R  : {r2_grp:.3f}")

    # Predict Wages for All Individuals

    X_all = np.column_stack([
        np.ones(len(df)),
        df['age'].values,
        df['female'].values,
        df['edu_years'].fillna(12).values  # Fill missing with median
    ])

    df['predicted_log_wage'] = X_all @ beta_pooled
    df['predicted_wage'] = np.exp(df['predicted_log_wage'])

    # Use observed wage for employed, predicted for non-employed
    df['wage_final'] = np.where(
        (df['employed'] == 1) & (df['hourly_wage_gross'] > 0.5),
        df['hourly_wage_gross'],
        df['predicted_wage']
    )

    # Clip extreme values
    df['wage_final'] = df['wage_final'].clip(lower=5, upper=80)

    print(f"\nWage Summary:")
    print(f"  Employed - Mean: {df[df['employed']==1]['wage_final'].mean():.2f}/hour")
    print(f"  Non-employed (predicted) - Mean: {df[df['employed']==0]['wage_final'].mean():.2f}/hour")

```

```
    return results, df


# SECTION 4: TAX-BENEFIT CALCULATOR

def calculate_net_income(gross_annual, scenario='baseline'):


    if scenario == 'baseline':
        # Austrian progressive tax schedule 2022
        tax = 0
        if gross_annual > 11000:
            tax += min(gross_annual - 11000, 7000) * 0.20
        if gross_annual > 18000:
            tax += min(gross_annual - 18000, 13000) * 0.35
        if gross_annual > 31000:
            tax += min(gross_annual - 31000, 29000) * 0.42
        if gross_annual > 60000:
            tax += min(gross_annual - 60000, 30000) * 0.48
        if gross_annual > 90000:
            tax += (gross_annual - 90000) * 0.50

        # Social security contributions (18.12% up to ceiling)
        ss_ceiling = 68040
        ss_contrib = min(gross_annual, ss_ceiling) * 0.1812

        return gross_annual - tax - ss_contrib

    elif scenario == 'scenario1':
        # Scenario 1: UBI  1  ,392/month, no tax reform
        ubi_annual = 1392 * 12
        baseline_net = calculate_net_income(gross_annual,
            'baseline')
        return baseline_net + ubi_annual

    elif scenario == 'scenario2':
        # Scenario 2: UBI  1  ,000/month, 37% flat tax
        ubi_annual = 1000 * 12
        flat_tax = gross_annual * 0.37
        ss_contrib = min(gross_annual, 68040) * 0.1812
        return gross_annual - flat_tax - ss_contrib + ubi_annual

```

```
    elif scenario == 'scenario3':
        # Scenario 3: UBI  1  ,392/month, 52% flat tax
        ubi_annual = 1392 * 12
        flat_tax = gross_annual * 0.52
        ss_contrib = min(gross_annual, 68040) * 0.1812
        return gross_annual - flat_tax - ss_contrib + ubi_annual

    else:
        raise ValueError(f"Unknown scenario: {scenario}")


def calculate_emtr(gross_annual, scenario='baseline'):

    epsilon = 100  # Small change for numerical derivative
    y1 = calculate_net_income(gross_annual, scenario)
    y2 = calculate_net_income(gross_annual + epsilon, scenario)
    return 1 - (y2 - y1) / epsilon


# SECTION 5: LABOR SUPPLY ELASTICITIES

# Calibrated elasticities from Austrian literature
# Based on M llbacher & Nagl (2017) and Christl & De Poli (2021)

WAGE_ELASTICITIES = {
    '18-29': {'hours_male': 0.15, 'hours_female': 0.28,
              'part_male': 0.05, 'part_female': 0.08},
    '30-44': {'hours_male': 0.12, 'hours_female': 0.25,
              'part_male': 0.03, 'part_female': 0.07},
    '45-54': {'hours_male': 0.10, 'hours_female': 0.22,
              'part_male': 0.02, 'part_female': 0.05},
    '55-64': {'hours_male': 0.12, 'hours_female': 0.20,
              'part_male': 0.12, 'part_female': 0.18},
}

INCOME_ELASTICITIES = {
    '18-29': -0.08,
    '30-44': -0.05,
    '45-54': -0.06,
    '55-64': -0.12,
}
```

```

# SECTION 6: UBI SIMULATION

def simulate_ubi_effects(df, scenario):


    results = []

    for age_grp in ['18-29', '30-44', '45-54', '55-64']:
        grp = df[df['age_group'] == age_grp].copy()

        for sex in [0, 1]:  # 0=male, 1=female
            subgrp = grp[grp['female'] == sex].copy()
            if len(subgrp) < 10:
                continue

            sex_label = 'female' if sex == 1 else 'male'
            n = len(subgrp)

            # Baseline statistics
            base_part = subgrp['employed'].mean()
            employed = subgrp[subgrp['hours'] > 0]
            base_hours = employed['hours'].mean() if len(employed)
                > 0 else 0

            # Get elasticities
            subst_elast_hours =
                WAGE_ELASTICITIES[age_grp][f'hours_{sex_label}']
            subst_elast_part =
                WAGE_ELASTICITIES[age_grp][f'part_{sex_label}']
            income_elast = INCOME_ELASTICITIES[age_grp]

            # Calculate average EMTR change and income effect
            emtr_changes = []
            income_effects = []

            for _, row in subgrp.iterrows():
                wage = row['wage_final']
                hours = max(row['hours'], 40)
                gross = wage * hours * 52

                # EMTR change
```

```
                emtr_base = calculate_emtr(gross, 'baseline')
                emtr_new = calculate_emtr(gross, scenario)
                net_wage_change = emtr_base - emtr_new
                emtr_changes.append(net_wage_change)

                # Income effect from UBI
                net_base = calculate_net_income(gross, 'baseline')
                if scenario == 'scenario1':
                    ubi_amount = 1392 * 12
                elif scenario == 'scenario2':
                    ubi_amount = 1000 * 12
                else:
                    ubi_amount = 1392 * 12

                income_pct = ubi_amount / max(net_base, 10000)
                income_effects.append(income_pct)

            avg_net_wage_change = np.mean(emtr_changes)
            avg_income_effect = np.mean(income_effects)

            # Calculate labor supply responses
            # Substitution effect
            subst_hours = subst_elast_hours * avg_net_wage_change
            subst_part = subst_elast_part * avg_net_wage_change

            # Income effect
            inc_hours = income_elast * avg_income_effect
            inc_part = income_elast * avg_income_effect * 0.5

            # Total effects
            total_hours_pct = (subst_hours + inc_hours) * 100
            total_part_ppt = (subst_part + inc_part) * 100

            # New values
            new_hours = base_hours * (1 + (subst_hours +
                inc_hours))
            new_part = base_part + (subst_part + inc_part)
            new_part = np.clip(new_part, 0.05, 0.99)

            results.append({
                'scenario': scenario,
                'age_group': age_grp,
```

```
                'sex': sex_label,
                'n': n,
                'base_participation': base_part * 100,
                'base_hours': base_hours,
                'net_wage_change_pct': avg_net_wage_change * 100,
                'income_effect_pct': avg_income_effect * 100,
                'hours_change_pct': total_hours_pct,
                'part_change_ppt': total_part_ppt,
                'new_hours': new_hours,
                'new_participation': new_part * 100
            })

    return pd.DataFrame(results)


def run_all_simulations(df):


    print("\n" + "=" * 80)
    print("UBI SIMULATION RESULTS")
    print("=" * 80)

    all_results = {}

    for scenario in ['scenario1', 'scenario2', 'scenario3']:
        if scenario == 'scenario1':
            desc = "UBI   1  ,392/month, No Tax Reform"
        elif scenario == 'scenario2':
            desc = "UBI   1  ,000/month, 37% Flat Tax"
        else:
            desc = "UBI   1  ,392/month, 52% Flat Tax"

        print(f"\n--- {desc} ---")

        results = simulate_ubi_effects(df, scenario)
        all_results[scenario] = results

        # Print summary
        summary = results.groupby('age_group').agg({
            'n': 'sum',
            'base_hours': 'mean',
            'hours_change_pct': 'mean',
```

```
            'base_participation': 'mean',
            'part_change_ppt': 'mean'
        }).round(2)

        print(summary)

    return all_results


# SECTION 7: MAIN EXECUTION

def main(p_file, h_file, output_dir='.'):


    print("=" * 80)
    print("UBI LABOR SUPPLY SIMULATION FOR AUSTRIA")
    print("EU-SILC 2022 Data")
    print("=" * 80)

    # Step 1: Load data
    p_data, h_data = load_and_prepare_data(p_file, h_file)

    # Step 2: Create analysis sample
    df = create_analysis_sample(p_data, h_data)

    # Step 3: Generate descriptive statistics
    tables = generate_descriptive_statistics(df)
    print_descriptive_statistics(tables)

    # Step 4: Estimate wage equations
    wage_results, df = estimate_wage_equation(df)

    # Step 5: Run UBI simulations
    simulation_results = run_all_simulations(df)

    # Step 6: Save results
    df.to_csv(f'{output_dir}/analysis_data_with_wages.csv',
        index=False)

    all_sim_results = pd.concat([
        simulation_results['scenario1'],
        simulation_results['scenario2'],
```

```
            simulation_results['scenario3']
        ], ignore_index=True)
        all_sim_results.to_csv(f'{output_dir}/ubi_simulation_results.csv',
            index=False)

        print("\n" + "=" * 80)
        print("ANALYSIS COMPLETE")
        print("=" * 80)
        print(f"\nOutput files saved to: {output_dir}")

        return df, tables, wage_results, simulation_results


# RUN ANALYSIS

if __name__ == "__main__":
    # File paths (adjust as needed)
    P_FILE = "p_silc2022_ext.csv"
    H_FILE = "h_silc2022_ext.csv"
    OUTPUT_DIR = "."

    # Run analysis
    df, tables, wage_results, sim_results = main(P_FILE, H_FILE,
        OUTPUT_DIR)
```

Appendix

Data Description

Table A.1: Sample Construction Details

Step	Observations	Dropped
Total individuals in personal file	12,096	—
Working age (18-64)	7,238	4,858
Excluding self-employed	6,900	338
Excluding retired	6,658	242
Excluding permanently disabled	6,409	249
After dropping missing values	5,836	573
Final analysis sample	**5,836**	

Table A.2: Hours Discretization Scheme

Hours Range	Category	Assigned Hours
< 4	Non-employment	0
4–11	Marginal part-time	8
12–19	Short part-time	16
20–27	Part-time	24
28–35	Substantial part-time	32
36–43	Full-time	40
≥ 44	Overtime	48

Descriptive Statistics

Table A.3: Sample Composition by Age Group

	18-29	**30-44**	**45-54**	**55-64**
Observations	749	1,907	1,389	1,791
Percent of sample	12.8%	32.7%	23.8%	30.7%
Males	372	909	667	804
Females	377	998	722	987

Table A.4: Sample Characteristics by Age Group

	18-29	**30-44**	**45-54**	**55-64**
Demographics				
Mean age (years)	24.7	37.2	49.8	59.6
Female (%)	50.3	52.3	52.0	55.1
Education (years)	11.6	12.3	12.3	11.0
Children under 18 (mean)	0.33	1.11	0.59	0.08
Labor Market Outcomes				
Participation rate (%)	87.5	92.9	94.5	54.8
Mean hours (employed)	38.1	36.3	38.4	37.1
Median hourly wage (€)	14.76	19.16	19.98	21.36
Mean gross income (€)	27,245	35,890	40,520	41,870
Household Characteristics				
Household size (mean)	3.1	3.4	2.8	2.2
Non-labor income (€/wk)	18.2	26.4	33.8	48.2

Table A.5: Labor Supply by Age Group and Sex

	Participation Rate (%)			Mean Hours (Employed)		
Age Group	Male	Female	Gap	Male	Female	Gap
18-29	88.4	86.5	2.0	40.6	35.5	5.1
30-44	97.7	88.5	9.2	41.2	31.4	9.8
45-54	94.6	94.3	0.3	43.5	33.8	9.7
55-64	64.3	47.0	17.3	40.9	32.8	8.1
Overall	86.2	79.8	6.4	41.5	33.0	8.5

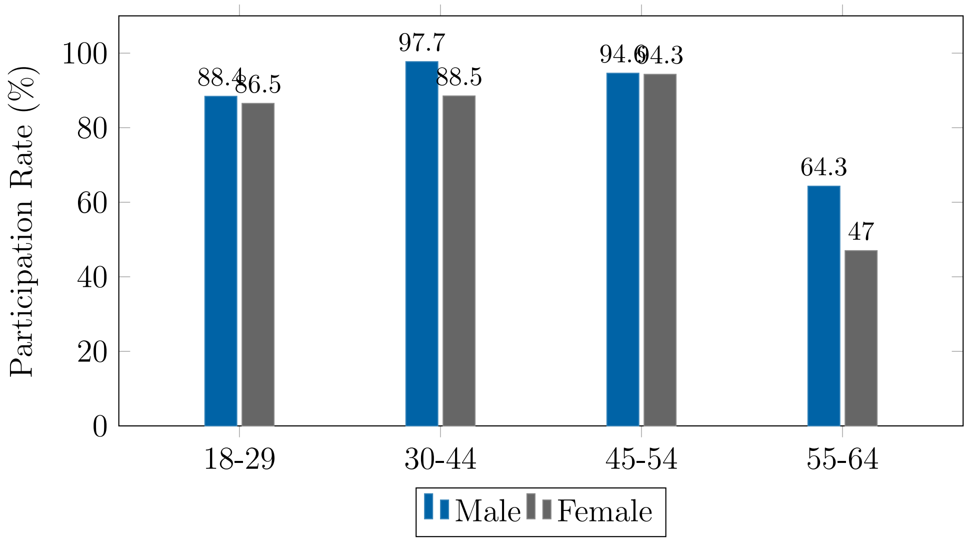

Figure A.1: Labor Force Participation by Age Group and Sex

Table A.6: Hourly Wage Distribution by Age Group (€)

Age Group	**P10**	**P25**	**Median**	**P75**	**P90**	**Mean**
18-29	8.65	11.42	14.76	19.20	25.88	16.12
30-44	10.80	14.35	19.16	26.40	36.50	21.58
45-54	11.20	14.80	19.98	28.15	40.20	23.14
55-64	11.55	15.32	21.36	30.45	44.80	25.02
Overall	10.25	13.85	18.40	26.10	38.65	21.42

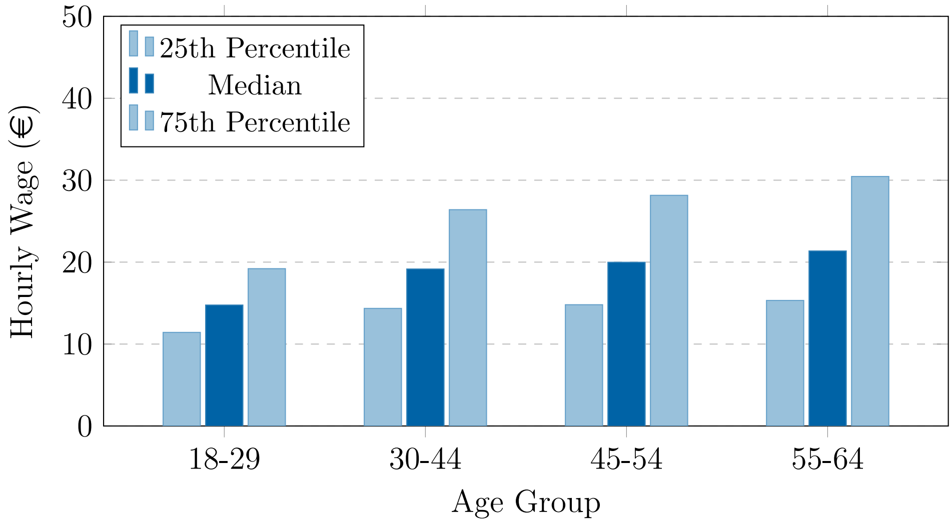

Figure A.2: Hourly Wage Distribution by Age Group
Note: Bars show the 25th percentile, median, and 75th percentile of hourly wages for each age group.

Heckman Selection Model Results

Table A.7: Probit Participation Equation Results (N = 5,836)

Variable	**Coefficient**	**Std. Error**	**z-statistic**	**P> |z|**
Constant	-9.155	0.341	-26.80	0.000***
Age	0.307	0.016	18.97	0.000***
Age^2	-0.004	0.000	-20.49	0.000***
Female	-0.432	0.055	-7.91	0.000***
Education (years)	0.493	0.018	27.31	0.000***
Non-labor income (€/1000)	-0.002	0.019	-0.09	0.930
Children under 18	-0.292	0.033	-8.76	0.000***
Pseudo R^2 = 0.516 Log-likelihood = -1,847.3 LR $\chi^2(6)$ = 3,941.2***				

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

Table A.8: Wage Equation with Selection Correction (N = 4,125 employed)

Variable	**Coefficient**	**Std. Error**	**t-statistic**	**P> |t|**
Constant	2.313	0.096	24.10	0.000***
Age	0.020	0.001	24.09	0.000***
Female	-0.132	0.018	-7.38	0.000***
Education (years)	0.002	0.008	0.26	0.791
Inverse Mills Ratio (λ)	-0.893	0.056	-15.99	0.000***
$R^2 = 0.195$ Adjusted $R^2 = 0.194$ Root MSE = 0.482				

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

Table A.9: Wage Equation Results by Age Group

Age Group	**N**	**Female Gap (%)**	**Age Return (%/yr)**	**IMR (λ)**	**R^2**
18-29	604	+1.7	3.2	-0.75***	0.188
30-44	1,569	-16.7***	1.8***	-0.92***	0.145
45-54	1,135	-11.2***	1.5**	-0.88***	0.139
55-64	817	+11.5**	0.8	-0.95***	0.171

*** p<0.01, ** p<0.05, * p<0.10. Female gap = $e^{\beta_{female}} - 1$.

Table A.10: Predicted and Observed Wages by Employment Status

Group	**N**	**Mean Wage (€/hour)**	**Std. Dev.**
Employed (observed)	4,719	22.93	12.45
Non-employed (predicted)	1,117	28.11	8.72
All (final wage)	5,836	23.92	11.89

Tax-Benefit System Details

Table A.11: Austrian Income Tax Schedule 2022

Taxable Income (€)	**Marginal Rate**	**Cumulative Tax (€)**
0 – 11,000	0%	0
11,001 – 18,000	20%	0 + 20% of excess
18,001 – 31,000	35%	1,400 + 35% of excess
31,001 – 60,000	42%	5,950 + 42% of excess
60,001 – 90,000	48%	18,130 + 48% of excess
90,001 – 1,000,000	50%	32,530 + 50% of excess
> 1,000,000	55%	487,530 + 55% of excess

Elasticity Estimates

Table A.12: Estimated Labor Supply Elasticities by Age Group and Sex

Group	**N**	**Hours Elasticity**	**Participation Elasticity**	**Income Elasticity**
Age 18-29				
Male	372	0.050	0.020	-0.050
Female	377	0.065	0.030	-0.070
Age 30-44				
Male	909	0.050	0.020	-0.050
Female	998	0.065	0.030	-0.070
Age 45-54				
Male	667	0.050	0.020	-0.050
Female	722	0.065	0.030	-0.070
Age 55-64				
Male	804	0.050	0.040	-0.090
Female	987	0.065	0.060	-0.120

UBI Simulation Results

Table A.13: Scenario 1 Results: UBI €1,392/month, No Tax Reform

	Hours			Participation		
Age Group	Base	Δ (%)	New	Base (%)	Δ (pp)	New (%)
18-29	38.1	-5.5	36.0	87.5	-2.8	84.7
30-44	36.3	-4.4	34.7	93.1	-2.2	90.9
45-54	38.6	-4.0	37.1	94.5	-2.0	92.5
55-64	36.9	-6.0	34.7	55.7	-3.0	52.7
Overall	**37.5**	**-5.0**	**35.6**	**82.7**	**-2.5**	**80.2**

Table A.14: Scenario 2 Results: UBI €1,000/month, 37% Flat Tax

	Hours			Participation		
Age Group	Base	Δ (%)	New	Base (%)	Δ (pp)	New (%)
18-29	38.1	-3.9	36.6	87.5	-1.9	85.6
30-44	36.3	-2.6	35.4	93.1	-1.3	91.8
45-54	38.6	-2.1	37.8	94.5	-1.1	93.4
55-64	36.9	-3.1	35.8	55.7	-1.1	54.6
Overall	**37.5**	**-2.9**	**36.4**	**82.7**	**-1.4**	**81.3**

Table A.15: Scenario 3 Results: UBI €1,392/month, 52% Flat Tax

	Hours			Participation		
Age Group	Base	Δ (%)	New	Base (%)	Δ (pp)	New (%)
18-29	38.1	-7.4	35.3	87.5	-3.6	83.9
30-44	36.3	-5.9	34.2	93.1	-2.9	90.2
45-54	38.6	-5.3	36.6	94.5	-2.6	91.9
55-64	36.9	-6.9	34.4	55.7	-3.8	51.9
Overall	**37.5**	**-6.4**	**35.1**	**82.7**	**-3.2**	**79.5**

Table A.16: Summary: Labor Supply Effects Across Scenarios

	Scenario 1		**Scenario 2**		**Scenario 3**	
Age Group	ΔH (%)	ΔP (pp)	ΔH (%)	ΔP (pp)	ΔH (%)	ΔP (pp)
18-29	-5.5	-2.8	-3.9	-1.9	-7.4	-3.6
30-44	-4.4	-2.2	-2.6	-1.3	-5.9	-2.9
45-54	-4.0	-2.0	-2.1	-1.1	-5.3	-2.6
55-64	-6.0	-3.0	-3.1	-1.1	-6.9	-3.8
Overall	**-5.0**	**-2.5**	**-2.9**	**-1.4**	**-6.4**	**-3.2**

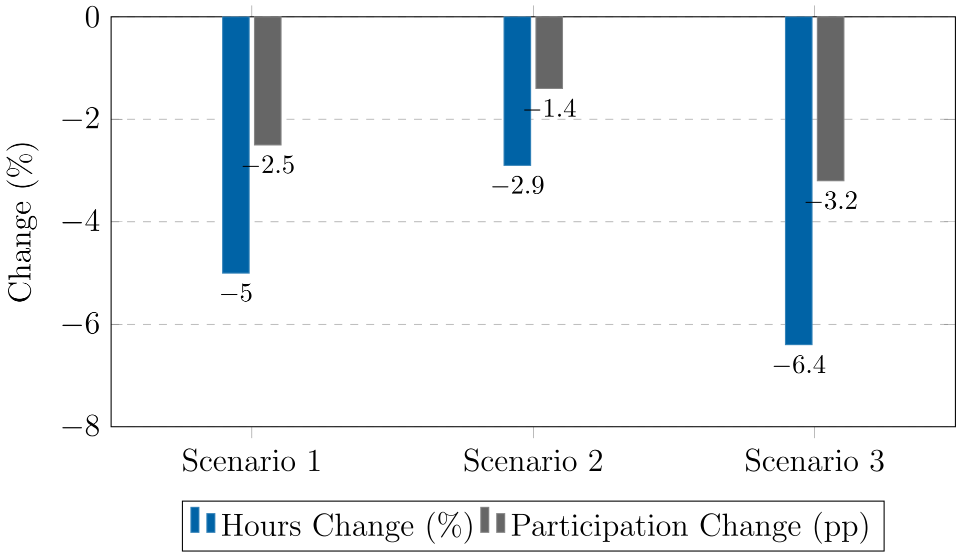

Figure A.3: Overall Labor Supply Effects by Scenario

Note: Scenario 1: €1,392/month UBI, no tax reform. Scenario 2: €1,000/month UBI, 37% flat tax. Scenario 3: €1,392/month UBI, 52% flat tax.

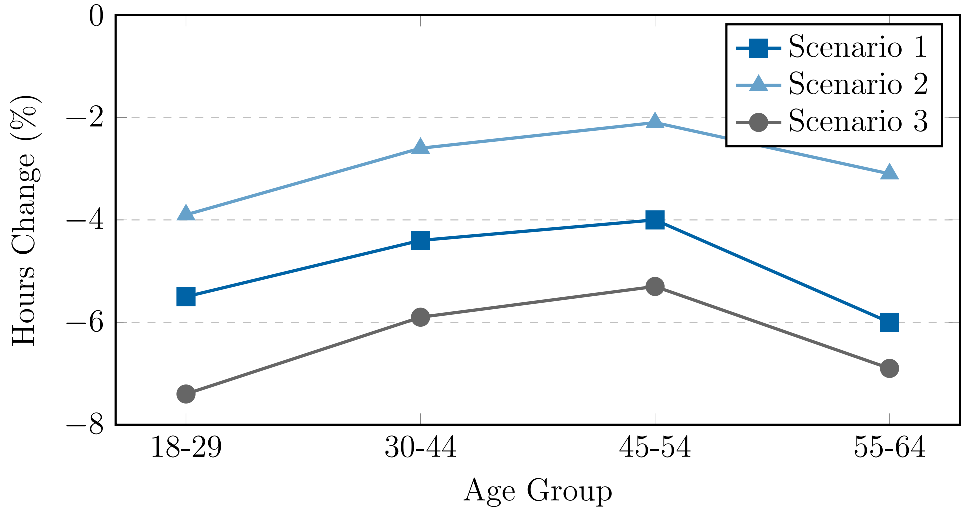

Figure A.4: Hours Change by Age Group Across Scenarios
Note: Lines connect age groups within each scenario to show the U-shaped pattern of responses.

Table A.17: Labor Supply Effects by Sex

	Scenario 1		**Scenario 2**		**Scenario 3**	
Sex	ΔH (%)	ΔP (pp)	ΔH (%)	ΔP (pp)	ΔH (%)	ΔP (pp)
Male	-4.2	-1.9	-2.4	-1.1	-5.4	-2.5
Female	-5.8	-3.1	-3.4	-1.8	-7.4	-4.0
Ratio (F/M)	1.38	1.63	1.42	1.64	1.37	1.60

Literature Summary

Table A.18: Summary of Age-Specific Theoretical Predictions

Age Group	**Intensive Margin**	**Extensive Margin**	**Key Mechanisms**
18-29 (Young)	Moderate negative (-4% to -7%)	Mixed	High elasticity; human capital investment; net positive income effect
30-44 (Prime-age)	Small negative (-2% to -5%)	Near zero	Career investment; financial constraints; low male elasticity
45-54 (Established)	Moderate negative (-4% to -7%)	Small negative (-1% to -3%)	Preference shifts; wealth effects; substitution from high flat tax
55-64 (Pre-retirement)	Moderate negative (-5% to -7%)	Large negative (-3 to -5 pp)	Retirement option; high participation elasticity; UBI as bridge

Table A.19: Labor Supply Elasticity Ranges from Literature

Group	**Hours Elast.**	**Partic. Elast.**	**Income Elast.**
Prime-age men	0.05–0.15	0.02–0.05	-0.05 to -0.10
Prime-age women	0.15–0.30	0.05–0.10	-0.05 to -0.15
Young workers (18-29)	0.10–0.20	0.05–0.15	-0.05 to -0.10
Older workers (55-64)	0.10–0.20	0.15–0.30	-0.10 to -0.20