Hours-Biased Technological Change*

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Abstract

Aggregate evidence in the United States points to a long-term decline in working hours. In contrast, cross-sectional evidence indicates that high-wage workers work increasingly longer hours than low-wage workers. This rising inequality in working hours coincided in time with the well-documented increase in wage inequality. To jointly explain these facts, this paper proposes a matching model of the labor market in which hours worked are endogenous. The theory shows how the hours decision can amplify or dampen sorting and inequality, depending on the trade-off between the income effect in preferences and the complementarities in production. The model is estimated to the US data to quantitatively analyze the impact of technological advancements on income inequality. The results suggest that a new type of technological change – the rising returns to long hours for skilled workers – explains about a quarter of the rise in wage inequality, and accounts for the entire increase in the hours-wage correlation. Additionally, technological change is responsible for the recent increase in average working hours in the US.

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1 Introduction

Over the last century, hours worked have declined substantially. For example, the average American worker now spends 20% less time at work than she did a century ago. Given that sustained economic growth has increased productivity and wages, this suggests that workers devote more time to leisure (and less to work) as they grow richer.

However, cross-sectional evidence suggests that *who* spends more time at work changes as countries develop. In the US of the 1950s, for example, those with the lowest incomes worked the longest hours. Nowadays, this correlation has reversed: it is CEOs, top lawyers, and other high-wage workers who work the longest. This observation is hard to explain in light of the long-run evidence: If higher wages induce to work less, why is it the case that higher-wage workers work more, and increasingly so?

In this paper, I propose a new mechanism to reconcile these facts. I build on the observation that changes in the hours-wage correlation have been accompanied by unprecedented technological progress. It has long been recognized that technological change has been behind changes in the wage structure over the past decades. But new technologies also affect working hours; for example, smartphones and laptops make it easier to adjust the work schedule by allowing workers to work extra hours if required. Moreover, these changes are unlikely to affect all workers equally: a late-night online meeting between the top managers of a ride-sharing company brings more value to the firm than an additional ride from one of the drivers.

This project provides a framework to study how technological change affects working hours – and the associated implications for inequality and the macroeconomy. In doing so, I make two contributions: First, I build a matching model of the labor market in which workers sort into jobs based on skill as well as how their time is valued in that job. In the model, an income effect induces high-skill workers to work fewer hours; at the same time, complementarities in production raise the returns to hours worked for the high-skill workers, making them willing to work more. The key insight is that the endogenous hours decision can amplify or dampen sorting, and as result inequality, depending on the strength of the income effect in preferences relative to the complementarities in production.

Second, I estimate the model to US data and find that well-known forces, such as Skill-Biased Technological Change, have been accompanied by a change in the relative value of hours worked across skills, a phenomenon I label Hours-Biased Technological Change (HBTC). Counterfactual experiments reveal that HBTC is key driver of income inequality: it explains about a fourth of the rise in wage dispersion, and fully accounts for the rise in hours-wage correlation. The estimated technological changes have important aggregate effects: absent the estimated increases in returns to working longer hours, the working week for the average american worker would be almost one day shorter than it is nowadays.

I start by documenting in detail the key facts motivating the analysis. The first fact is that from an aggregate, long-term perspective, hours per worker tend to decline as countries grow. This is true both in US and across developed countries. At the beginning of the 20th century, the average American worker used to work 24% more than now (roughly 50 hours per week, compared to the modern 38 hours per week). These facts can be well explained by models of the labor supply in which the utility function is such that the income effect dominates the substitution effect; when this is the case, rising productivity (and hence wages) for the typical household imply more leisure time[1].

While this preference-based explanation for hours worked does a good job in explaining long run trends, the second cross-sectional fact of how hours relate to wages reveals there is more to the story. During the 1960's and 1970's, low wage workers in US used to work the longest hours. Nowadays, it is the highest wage workers who spend more time working[2]. This implies that the cross-sectional correlations between hours and wages turned from negative to positive[3]. This pattern is not unique to the US. As documented by Bick *et al.* (2018), as countries grow, the cross-sectional hours-wage correlation becomes less and less negative and turns positive for the richest countries, suggesting a link between this correlation and the level of technology. This changing correlation coincided in time with the well-documented increase in income inequality in the US and elsewhere[4]. These cross-sectional facts are hard to reconcile in light of the aggregate evidence: if income effects dominate substitution effects, this would suggest that high skill workers work *less*, not more (and increasingly so)[5].

I then propose a model of the labor market featuring heterogeneous workers and firms, which match one to one in a competitive labor market. Crucially, the model departs from most existing assortative matching models in that it explicitly features an endogenous hours choice by the worker[6]. Hence, not only skills, but also time input are a determinant component of sorting in equilibrium. I find a new condition for positive sorting that highlights the

[1]For a thorough account of how income effects affect hours in balanced growth models, see Boppart and Krusell (2020)).

[2]The fact that the rich used to consume more leisure has attracted the attention of sociologists since at least the end of the 19th century: Veblen (1899) discusses how the wealthiest were spending large parts of their time in leisure activities, while low-class people worked long hours. Recently, Jacobs and Gerson (2005) discuss the consequences of the growing 'time divide' between the increasingly working elite and the idle middle class.

[3]These patterns have been documented before for the US in Costa (2000) and in Heathcote *et al.* (2010).

[4]The phenomenon of increasing wage inequality motivated the voluminous literature on Skill Biased Technological Change (see Katz and Murphy (1992), Krusell *et al.* (2000), Autor and Acemoglu (2011), among many others).

[5]The fact that high-wage workers work increasingly more than their low-wage counterparts is especially puzzling in light of the increase in wage inequality happening in US over the same period.

[6]A framework featuring endogenous hours with sorting is Michelacci and Pijoan-Mas (2015), but I abandon here the assumption of balanced growth and focus on cross-sectional heterogeneity in hours and wages. For a summary of sorting models of the labor market, see Chade *et al.* (2017).

importance of skill-job complementarities (as in, for instance, Autor and Acemoglu (2011)) together with skill-hours complementarities (i.e., the relative value of hours worked across skills). At the heart of the model mechanism is the interaction between the income effect coming from preferences, and the heterogeneous substitution effect, coming from the properties of the production function. On the one hand, higher wages decrease working hours. On the other hand, due to hours complementarities in production, hours of work affect wages in a non-linear fashion.

The model rationalizes the evidence precisely through the interaction of the preference channel and the technology channel: hours worked can amplify or dampen income inequality because of complementarities in production between skills and jobs. If income effects are sufficiently strong or hours enter the earnings function linearly (as in most existing models), high skill workers will be induced to choose lower hours. This will induce a negative relationship between hours worked and wages both in the cross-section as well as in the aggregate, similarly to the pre-1980's period in the US. If earnings are non-linear in hours due to complementarities in production, high skill workers may decide to work longer hours, reverting the cross-sectional relationship between hours and wages, thus amplifying inequality. An important theoretical contribution of this paper is to theoretically characterize for which preferences and technology class each force dominates.

To quantitatively assess the relative importance of these channels, I structurally estimate the model using US data for the recent decades (1980-2016). The estimation results reveal that, in addition to an increase in the complementarity between skills and jobs (commonly referred to as Skill Biased Technological Change, SBTC), other technological changes have marked the U.S. experience. In particular, I estimate that hours and skills (in addition to hours and jobs) have become more complementary. This implies that SBTC has been accompanied by HBTC: the value of an extra hour worked is now higher for the high skilled.

I examine the implications of these estimated technological changes for the evolution of inequality and hours worked in the US. Through counterfactual exercises, I find that both SBTC and HBTC increased income inequality in the US. However, they do so through different channels: while SBTC is more important in explaining the increased dispersion in wages, HBTC is key in driving up the correlation between hours and wages, thus amplifying overall income inequality. In equilibrium, I find that HBTC and SBTC interact in interesting ways: Without HBTC, the correlation between hours and wages would have gone down: high skilled workers would have decreased their hours due to their higher wages and the resulting income effect. Without SBTC, the effect of HBTC on wages and hours would have been lower: the increased value of working hours for the high skilled is amplified if these high skilled workers work in top jobs. Overall, HBTC played a quantitatively meaningful role in the increase in income inequality, accounting for about a quarter of the increase in wage dispersion, and fully accounting for the increase in the observed hours-wage correlation.

I then study the evolution of aggregate hours worked in US. In the 1980's, average hours worked in US have flattened out (and even slightly increased), following a decades-long decline. Through counterfactuals, I show that the estimated technological changes affecting returns to long hours are behind the trend reversal in hours worked. Absent these changes, the average US worker would work roughly five hours less per week. This counterfactual result reconciles the long-run declines in hours worked (and the implied existence of strong income effects in preferences) with the relatively flat pattern of hours worked in the US[7]. This is potentially very important for our understanding of the parameters that govern our desire to work[8] and shows that accounting for heterogeneity is key to understand aggregate outcomes. Finally, the result suggests a new perspective on the future of hours worked, complementing existing studies focusing on taxation, income effects, and structural change[9].

I conclude by discussing how the current framework can be used to shed new light on issues where the decision to work longer hours is important. The reason is that they key feature of the model - that hours worked translate non-linearly in earnings for skilled workers - implies that hours constraints can have heterogeneous effects across workers. Moreover, the mechanism I propose implies that technological change magnified over time the potential costs associated with hours constraints. In sum, this paper provides a framework to analyze how the hours decision affects the allocation of workers to jobs, and the implications for inequality. Moreover the framework serves as a useful starting point to think about how distortions to hours worked (e.g., social norms) affect misallocation between workers and jobs, and the resulting adverse consequences for the macroeconomy.

Literature Review In proposing a new force for increasing income inequality, as well as a new determinant for aggregate hours worked, the paper brings together two main literatures: a macro literature on the aggregate relationship between wages and hours, and a micro literature, focused on the determinants of increasing sorting and inequality in labor market outcomes.

Among macroeconomic models of balanced growth, King *et al.* (1988) is a seminal contribution in specifying a preference class that implies constant hours worked along the growth path. The perceived need to work with preferences that imply constant hours was due to the fact that hours per capita are approximately constant in the US. However, as shown in several papers, the roughly constant level of hours worked in the post-war period masks

[7]It is precisely the relatively flat series of aggregate hours worked in US in the post-war period that first motivated the use of preferences where income and substitution effects cancel out, see King *et al.* (1988).

[8]These parameters are crucial for a number of issues, for example the study of optimal tax policies. See e.g. Piketty and Saez (2013).

[9]For the latter, and a discussion on recent perspectives on the future of hours worked, see Bick *et al.* (2022b).

significant heterogeneity, most notably reflecting increasing participation rates for women. Boppart and Krusell (2020) provide a theoretical analysis of aggregate hours worked, and a general preference class in which income effects dominate substitution effects, and they show it can account for the intensive margin of hours worked in the US and elsewhere. Relatedly, Bick *et al.* (2018) and Bick *et al.* (2022b) also present evidence pointing towards strong income effects in the aggregate, while highlighting the role of structural change in accounting for patterns of hours worked along the development spectrum. Rachel (2021) and Kopytov *et al.* (2021) propose theories to explain the decline in hours worked based on improvements in leisure technologies. Relative to all these papers, this study argues that technological complementarities in production can shed new light on the evolution of the aggregate labor supply. With respect to macroeconomic models that aim to explain aggregate patterns of hours worked, this model is new in that it allows for hours of work to impact wages differently for different workers. Hence not only preferences, but also technological *complementarities* become a crucial determinant of aggregate hours worked.

The sorting literature has studied how technological complementarities are crucial in determining sorting patterns in equilibrium, and how these complementarities interact with other features of the labor market (see for example, Lindenlaub (2014), Chade and Lindenlaub (2022), Eeckhout and Kircher (2018), Eeckhout and Sepahsalari (2018), Vereshchagina (2021)). With respect to models of sortins, this paper models explicitly the hours decision, which helps building a comprehensive picture of increasing inequality: not only in wages, but also in hours worked (and the interaction between the two). Thus, the framework nests several existing models as special cases. The following contributions are closest to this framework: Calvo *et al.* (2021), Michelacci and Pijoan-Mas (2015) and Shao *et al.* (2021). The first studies how the interplay between marriage and labor market decisions, shaped by the endogenous hours decision, affects inequality and hours in equilibrium. The second provides a competitive growth model where the pace of technological progress affects hours and the sorting of workers to jobs. The third studies the role of hours complementarities in production on the size distribution of firms, and their impact on sorting and earnings inequality. Relative to these papers, I contribute theoretically by characterizing the sorting pattern for a general class of production and utility functions. Moreover, I differ in the quantitative application of the paper, in that I estimate how the production technology has changed over time, with a particular particular focus on how enters in production[10].

This paper also closely relates to the literature that has attempted to explain diverging trends in labor market outcomes between high and low skilled, with a focus on employment rates and hours worked. Wolcott (2021) proposes a model to explain the diverging trends in

[10] Another related paper is Erosa *et al.* (2022), which develop a Roy-style model of occupational choice to study the implications of gender differences in home production possibilities for the gender wage gap.

employment rates across skills. Boppart and Ngai (2021) reconcile diverging trends in leisure and increasing inequality with a mechanism based on intertemporal substitution. Heathcote *et al.* (2010) analyze the macroeconomic and welfare implications of rising wage inequality and increasing hours-wage correlation. Relative to these papers, I contribute theoretically by highlighting a new mechanism through which inequality can stem from hours and skills, and quantitatively by disentangling the different forces of rising inequality in the data.

Outline Section 2 presents the main facts motivating the analysis. In section 3, I outline and characterize the model implications, with an emphasis on the new insights and the how the model links to the previous literature. I estimate the model to US data in Section 4; Section 5 presents the main results of the quantitative application and the resulting implications. Section 6 concludes and suggests some avenues for further research.

2 Motivating Evidence

In this section, I present two sets of facts (one aggregate and one cross-sectional) that motivate the theoretical analysis below[11].

Data

The main data source I use for hours worked in US is CPS, which contains detailed information on hours worked and wages for the period of interest. I complement hours data from CPS with hours data from Kendrick (1961) and Kendrick (1973) to be able to trace total hours worked back in time[12]. In Appendix A, I show that the main messages delivered by the analysis below are very similar across other datasets of hours worked (e.g. ATUS). To construct a real wage index, I use labor productivity divided by hours worked and complement it with series from Kendrick (1973)[13]. Finally, for hours worked across countries, I use Penn World Tables 9.0.

Facts

Aggregate Decline In Hours Worked The first fact I highlight the long-run behavior of hours per worker[14]. The series is weekly hours worked per worker, and is plotted in Figure 1, together with an index of real average wages.

The key message from the figure, it is evident that the data exhibit a clear downward trend, except for the most recent decades, where hours worked are relatively stable. On the other hand, the index for real wages has risen steadily over the period.

These simple patterns, interpreted through the lens of neoclassical models of labor supply, point towards preferences where - along the balanced growth path - income effects are stronger than substitution effects, so that an increase in *average* wages due to productivity implies lower hours worked[15]. This is the main intuition behind models that aim to characterize the forces behind long-run declines in hours worked, as in Boppart and Krusell (2020)

[11] Since the quantitative application will use data from US, I will only present the facts for the latter; however, previous literature has shown that the main messages hold across several countries (see Appendix A).

[12] The latter datasets have been used extensively in the labor supply literature to capture long-run trends in hours worked (see e.g. Francis and Ramey (2009) and Cociuba *et al.* (2018))

[13] The same approach is used by Kopytov *et al.* (2021).

[14] Since the focus of the paper is on the intensive margin, the relevant measure to be considered is hours per worker. Moreover, as noted in Boppart and Krusell (2020), long run movements in hours worked per worker (the *intensive* margin) are more important than participation rates (the *extensive* margin). Nevertheless, a similar picture emerges if we consider hours per capita over the very long term (see also Francis and Ramey (2009)).

[15] Moreover, these trends are consistent with papers using time use data, which show that hours worked have declined (and leisure time increased) in US, as in Aguiar and Hurst (2007).

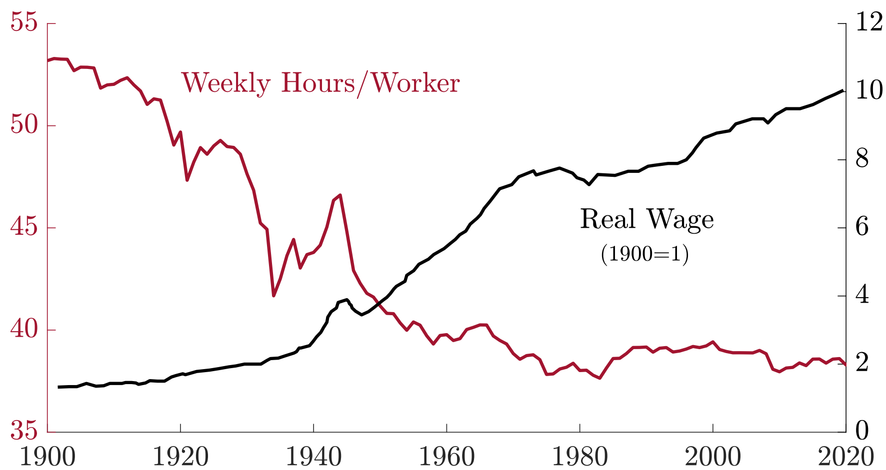

Figure 1: Hours per Worker and Wages (US).

Notes: Average weekly hours worked per employed worker in the US (colored line). Real wage index, constructed as real labor prodictivity divided by total hours (black line). Source: Kendrick (1961), Kendrick (1973), CPS, FRED and own calculations.

and Bick *et al.* (2022b)[16]. Overall, the main takeaway from this figure is that, from an aggregate perspective and over the long term, hours per worker have decreased in US, suggesting an aggregate *negative* relationship between wages and hours worked[17].
As noted before, this downward trend in average hours worked per worker is by no means a phenomenon specific to US. Figure 2 plots average hours worked over time for a selected group of developed countries. Similarly to US, hours worked fall over time. Interestingly, the trajectory is not uniform and for several countries, hours worked are nearly flat in more recent decades, again reminiscent of the US experience.

Further evidence that hours decline as countries grow is presented in Bick *et al.* (2018): they showthat, along the development spectrum, hours per worker decline with GDP per capita, and that these pattern does not reflect systematic differences in age, educational attainment or sectoral composition across countries. Further evidence is also provided in Kopytov *et al.* (2021), where show that the overall decrease of hours as wages grow is a trend that characterizes all OECD countries in the post-war period.

Increasing Hours-Wage Correlation The second fact motivating the analysis concerns the crosssection data on hours worked. As first noted in Costa (2000), the US experience is

[16]The idea that, over long run periods of productivity and wages growth, people would dedicate more time to leisure activities traces back at least to Keynes (1930)

[17]In Appendix A, I provide further evidence that the pattern of declining hours per worker is not at all a phenomenon specific to US: using data from Bick *et al.* (2018), a clear pattern of declining hours per worker emerges when considering middle income and high income countries. See in particular Figure A.5.

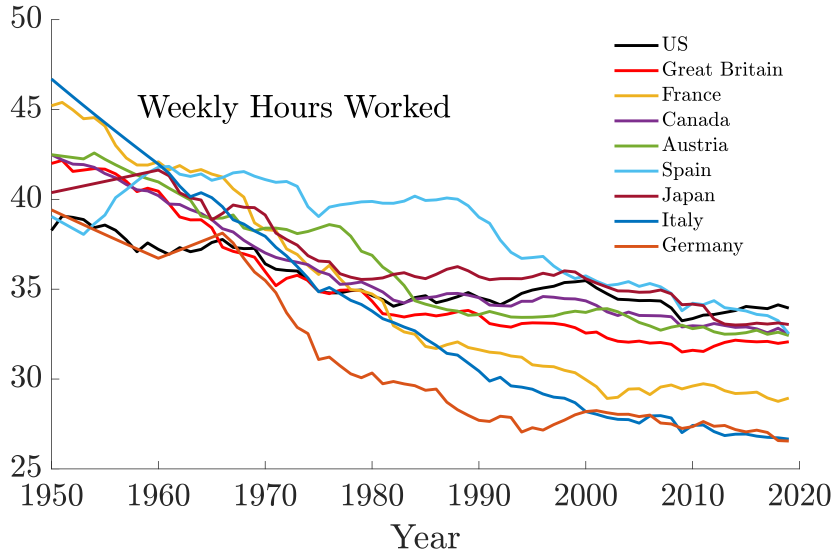

Figure 2: Hours per Worker - Selected Countries

Notes: Average weekly hours worked per employed worker in selected developed countries. Source: Penn World Tables 9.0.

characterized by a sign reversal in the hours-wage elasticity, from negative to positive: low wage workers used to work the longest hours in 1960's and 1970's; starting from the 1980's, however, high wage workers work significantly more hours than low wage workers.

I now update the analysis first conducted in Costa (2000) to more recent years, using the same specification as in her paper, and also adopted in Bick *et al.* (2018). In particular, I analyze the cross-sectional hours-wage elasticity by running the following regression year by year, in CPS data:

$$log(h_i) = \alpha + \beta log(w_i) + X_i + \epsilon, \tag{1}$$

where h_i is individual hours worked, w_i is individual wages, and X_i are demographic controls[18]. The coefficient β describes the relationship between hours and wages in the cross-section. I plot the resulting coefficient in Figure 3. At the beginning of the sample, and consistent with Costa (2000)'s results, the coefficient is negative; starting from the 1980's, it turns significantly positive and increasing, with a mild decrease only in the most recent years in the sample[19].

Importantly, Bick *et al.* (2018) note that across the development spectrum, the hours-wage elasticity is negative for low income countries, while it gets progressively smaller and even positive for high income countries; this is very much in line with the US experience that I

[18]In the baseline specification, I consider age and age squared as controls to account for the systematic variation in hours worked across the life-cycle.

[19]In 2005, the coefficient β almost perfectly overlaps with the result in Bick *et al.* (2018).

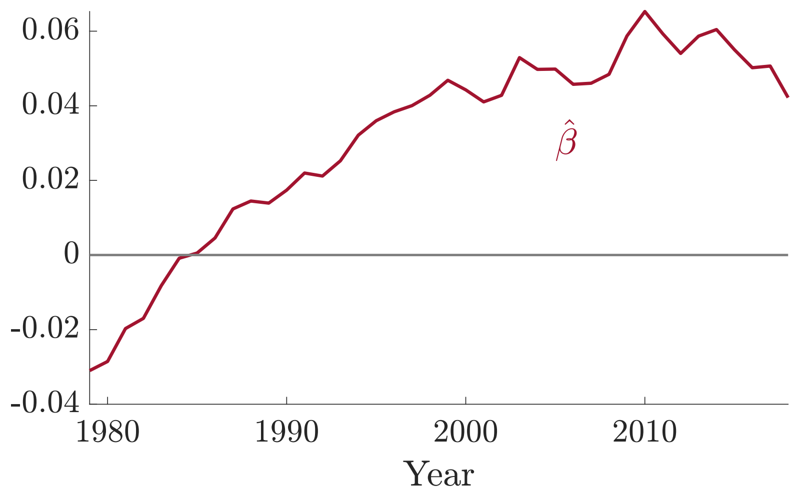

Figure 3: Hours-Wage Elasticity in the Cross Section (US).

Notes: The figure displays the coefficient β from regression (1), run separately for each year in the sample. Source: CPS-ORG and own calculations.

uncover here. Moreover, data from time use sources (see in particular Aguiar and Hurst (2007)) are broadly consistent with the evidence presented thus far: starting from the mid-1980's, leisure time has increased for the low skilled workers more than for the high skilled workers (while importantly, it increased uniformly across skill categories between 1965 and 1985).

The key message is that, starting from the 1980's, high wage workers have worked progressively longer hours than their low-wage counterparts. Thus, the negative aggregate hours-wage relationship that we highlighted in the previous paragraph does not translate in the cross-section, where the relationship at the individual level has turned positive in the last recent years.

Summary and Implications The aggregate data presented so far, namely a decreasing trend in hours worked, suggests the need of using models of the labor supply where preferences are such that income effects are larger than substitution effects (as in Boppart and Krusell (2020)). This approach does a good job in describing aggregate data in the long run. However, cross-sectional data for more recent years seem to point to a richer picture; in fact, high wage workers working increasingly longer hours seem to suggest that, if we analyze a shorter time span, other forces might be at play.

It is important to note that, starting from roughly the same period, another phenomenon has been widely documented and studied: increasing wage inequality (see among many others Song *et al.* (2018)). In other words, leisure inequality has been accompanied by a widening wage inequality. The evidence presented thus far calls for a framework that takes into ac-

count aggregate, long run trend of decreasing hours worked and - at the same time - is able to account for increasing cross sectional dispersion in wages and hours worked in the last few decades.
The next section provides a parsimonious matching framework that accounts for these trends, and aims at shedding more light on the consequences of technological progress onthe *joint* determination of wages and hours worked across workers of different skills.

3 Theory

Motivated by the evidence of the previous section, this section develops an assignment framework, with the key feature that workers sort in the labor market based on skills and hours. After characterizing the theory, I show how it relates to the literature and in particular, how it includes several models of the labor supply as special cases. Finally, I do comparative statics to introduce the quantitative analysis carried in the next section.

3.1 Framework

Setup I consider a competitive labor market, composed of heterogeneous workers $x \sim H$ and firms $y \sim G$, where H and G are the distribution of workers and firms[20], respectively. Individuals are endowed with one unit of time to be allocated between market work and leisure (there is no home production)[21]. Workers and firms match in a one-to-one fashion to produce output $f(x, y, h)$.

Firms' problem Firms choose type x to maximize output net of income w to be paid to the worker[22]:

$$\max_{x} f(x, y, h) - w \tag{2}$$

The choice of worker type x by the firm will determine, in equilibrium, the assignment function μ that maps workers to firms as well as income and profit functions (commonly referred to as hedonic price schedules).

Household problem Households choose time allocation taking income w as given:

$$\max_{h} \quad u(c, h) \quad s.t. \quad c = w \tag{3}$$

This determines optimal choice of hours h as a function of skill, $h^*(x)$. Hours choice is the key link between worker problem and firms problem. With no hours choice and transferable utility (TU), this is a standard assignment game between workers and firms Becker (1973).

[20] For the theoretical section, I will refer to y as firms and jobs, interchengeably, as the model allows for both interpretations; when I take the model to the data, I will interpret y as jobs.

[21] While home production can be an important determinant of inequality, see e.g. Boerma and Karabarbounis (2021), I choose to abstract from home production as it does not display diverging trends across households. Moreover, doing so allows for a more direct comparison with macro models based on preferences, which typically abstract from this margin.

[22] To save on notation, I use w as income but it should be understood that income is a function of the matched pair x, y and the hours choice, i.e. $w = w(x, y, h)$.

Market clearing The model is closed by specifying a market clearing condition, essentially requiring that the workers and firms match in a measure-preserving way. Market clearing can be written as, under PAM[23]:

$$\int_{\mu(x)}^{\bar{y}} g(s)ds = \int_{x}^{\bar{x}} h(s)ds$$

Equilibrium We are now ready to define a competitive equilibrium of this economy.

Definition 1 *A competitive equilibrium of this economy is a tuple of functions (w, μ, h) such that:*

- *w and h solve problems (1) and (2) (optimality)*
- *equation (3) holds (market clearing)*

3.2 Assortative Matching

Towards a complete characterization of the equilibrium of this economy, we want to seek for conditions under which assortative matching arises. To do so, we can rewrite the *joint* maximization problem of the worker and the firm as a single maximization problem, by substituting the wage in the worker problem (3) using the definition of profits from (2). This becomes effectively a matching problem with non-linear Pareto frontiers (see Legros and Newman (2007)):

$$U(x, y, V) = \max_{y,h} \quad u\left(f(x, y, h) - V, h\right) \tag{4}$$

where V is the hedonic price schedule (in this case, profits) that arises in equilibrium and U is the value to a worker x matched to a job y to which he leaves the value V.
The FOCs for hours and firm choice are, respectively:

$$u_c f_h + u_h = 0 \tag{5}$$
$$u_c(f_y - V_y) = 0 \tag{6}$$

Equation (5) is akin to the standard labor-leisure choice, the main difference being that f_h is now allowed to depend on hours, implying that hours can have a non-linear effect on

[23] Here and throughout the text, I refer to PAM as Positive Assortative Matching, indicating that better workers are matched in equilibrium with better firms (analogously for Negative Assortative Matching, NAM).

earnings; importantly, this effect varies across skills due to complementarities in production[24].

Equation (6) is equivalent to one arising from the first order condition of the standard assignment model with transferable utility, where workers choose firms[25].

In this case, the sorting condition can be derived from the second order condition of (4) and it is equal to[26]:

$$U_{xy} - U_{Vx}\frac{U_y}{U_V} > 0 \tag{7}$$

In the case of transferable utility (TU), $U_{xy} = f_{xy}$ (i.e., complementarity between firm and worker type) is the only determinant of assortative matching; in this ITU setting, however, what matters for sorting is also how the surplus of the match varies across worker-firm pairs, which in turn depends on the complementarity between worker type and partner's (firm's) utility, captured by U_{Vx}. Intuitively, the easier it is for higher x to transfer utility to firms, the more likely it is they will match with these high type firms. In my setting, this will depend on both characteristics of preferences (income effects) and on technological complementarities between hours, firms and worker types. By writing explicitly the expressions U_{xy}, U_{Vx}, U_y and U_V in (7), the next proposition states this explicitly in terms of primitives of the model (preferences and technology)[27].

Proposition 1 *A necessary condition on primitives to have Positive Assortative Matching (PAM) for any distribution of types is*

$$f_{xy} + f_{hy}h_x > 0 \tag{8}$$

where $h_x = \frac{\partial h}{\partial x}$.

Proof: see Appendix B. ■

[24] In the textbook model of labor supply, f_h would be replaced by w, wage for efficiency units of labor. This is because earnings $w \cdot h$ are linear in hours.

[25] Typically, the standard assignment model with TU is solved from the perspective of the firm; however, it is easy to show that the conditions under which assortative matching arises are identical to those arising from the dual problem, in which workers choose firms. In this case, the FOC is precisely equal to (6).

[26] This condition is equivalent to the one used by Eeckhout (2018)- Section 2.2. There, the problem of the firm is: $\max_x \phi(x, y, u)$ where $u(x)$ is the utility of the worker. Analogously, we can interpret $\max_x \phi(x, y, u)$ as the problem of a worker y and a firm x where $u(x)$ is the utility of the firm (V in our case). It is easy to show that the condition under which $\mu'() > 0$ is simply that $\phi_{xy} > \frac{\phi_x}{\phi_u}\phi_{yu}$. In our case, this is equivalent to (7).

[27] Alternatively, the problem can be described as a joint, simultaneous choice of firms and hours by the workers, that gives rise to a multidimensional second order condition; then, PAM/NAM arises depending on conditions derived from the Hessian of the problem, as in Eeckhout and Kircher (2018). I provide the alternative proof in Appendix B, showing it gives rise to identical condition for sorting as described in the main text.

If $f_{hy} > 0$, then $h_x > 0$ or $h_x < 0$ (but not too negative) implies PAM. The intuition here is that if high type jobs require longer hours, it can be that in equilibrium low skilled workers are matched with high type jobs (NAM), if they work sufficiently more than the high skilled to compensate for their lower skill. This can overturn the effect induced by f_{xy}, which pushes towards PAM. The opposite intuition is at work when $f_{yh} < 0$.
Condition (8) expresses the condition under which PAM arises in terms of an endogenous object, h_x. The advantage of this condition is that it's simple and intuitive, but leaves the question of how to interpret positive sorting in this model purely in terms of primitives. For this purpose, we derive the following condition:

Proposition 2 *A necessary condition on primitives to have Positive Assortative Matching (PAM) for any distribution of types is*

$$f_{yx}\phi + f_{hy}(u_{cc}f_x f_h + u_c f_{hx}) > 0 \tag{9}$$

where $\phi > 0$. The opposite inequality provides a condition for Negative Assortative Matching (NAM).

Proof: see Appendix B. ■

Let us inspect this condition. From optimality, we know $(u_{cc}f_h f_h u_c f_{hh} u_{hh}) < 0$ implying $(-u_{cc}f_h f_h - u_c f_{hh} - u_{hh}) > 0$. It is clear that, to obtain PAM ($\mu_y > 0$), f_{yx} is not sufficient. We need the term $f_{hy}(u_{cc}f_x f_h + u_c f_{hx})$ to be positive as well, or not too negative, otherwise the term in parenthesis above will be negative, making it impossible for $\mu_y > 0$ to be an optimal outcome. Assuming f_{hy}, the key term becomes $(u_{cc}f_x f_h + u_c f_{hx})$, which captures the key income and substitution effects contained in the model, respectively. The first term $(u_{cc}f_x f_h$ is a by product of the skill and hours premium $f_x f_h$ combined with income effects coming from preferences, u_{cc}, and is therefore negative. The second term captures the substution effect, which is skill-dependent in this model ($u_c f_{hx}$). This term is positive as long as f_{hx} is positive. Hence, we need this second term to outweight the income effect term for PAM to be an equilibrium outcome, *even if* we assume $f_{yx} > 0$. This discussion highlights the how key forces in the model (hours in production and preferences) play an additional role with respect to known forces in the standard sorting framework (Becker (1973), Eeckhout (2018)).

Hours Choice As the previous paragraph made clear, the key endogenous outcome that shapes equilibrium sorting is the hours choice. We thus analyze more in detail the determinant of hours choice and how sorting and hours affect each other in equilibrium.
We start with the following proposition:

Proposition 3 *In equilibrium, high skill workers choose higher hours* $(h_x > 0)$ *if*

$$(u_{cc} f_h f_x + u_c f_{hx}) > 0 \tag{10}$$

Proof: see Appendix B. ■

Proposition 3 makes it clear that there are several forces at work when it comes to the hours choice by skill type. The term governing the condition, $(u_{cc} f_h f_x + u_c f_{hx})$, is a combination of two effects. The first is an income effect, acting through $u_{cc} < 0$, which push towards $h_x < 0$. Notice that this effect is higher, the higher the marginal product of skill, f_x. The second effect is akin to a substitution effect, acting through f_{xh}, which push towards $h_x > 0$. These opposing forces are similar to those arising in a static labor supply model. The key distinguishing feature here is that substutution effects can be heterogeneous across skills, i.e. the marginal product of one more hour worked is higher across skills (this happens when $f_{xh} > 0$).

To get even more insight, assume - as typical in labor supply models - that preferences are of the CRRA form[28]. The, condition (8) is automatically satisfied if utility is linear, i.e. $u_{cc} = 0$, as long as $f_{xh} > 0$. Inspecting this condition further gives a key result for the rest of the paper. In fact, in standard labor supply models, assuming $\sigma > 1$ ($\sigma < 1$) is enough to determine whether income effects are stronger (weaker) than substitution effects, and hence whether a higher wage pushes towards working more or less. In this model, the crucial feature is that the shape of the production function (in this case, whether log-supermodularity is satisfied) is fundamental to determine who works more. If f_{xh} is sufficiently strong, higher skill work more even though $\sigma > 1$. This result will be key in the quantitative application of the next sections.

As a final observation, note that the PAM condition (8) highlights the complementarities terms f_{xy} and f_{yh} as key drivers of positive sorting. The previous condition completes the derivation by highlighting the further role of f_{xh} in driving sorting, as it pushes higher skills to work more and counteract the negative effect coming from u_{cc}. These complementarity terms act together to drive sorting and the hours decisions. The next section shows this for some functional forms, with the help of numerical simulations.

3.3 Comparative Statics

In this section, I consider some numerical examples (assuming specific functional forms for production and utility functions, as well as distributions) to help clarifying the main forces at play and introduce the quantitative exercise in the next section.

[28]In this case, utility takes the form $u(c,h) = \frac{c^{1-\sigma}}{1-\sigma} + v(h)$ for some function $v(h)$.

Functional Forms I choose a widely used utility function in the macro literature and set

$$u(c,h) = \frac{c^{1-\sigma}}{1-\sigma} - \psi \frac{h^{1+\frac{1}{\theta}}}{1+\frac{1}{\theta}} \tag{11}$$

where I allow σ to vary. Higher σ imply higher income effects. For production, I use

$$f(x,y,h) = A\left(\beta(\alpha x^{\rho} + (1-\alpha)y^{\rho})^{\frac{\gamma}{\rho}} + (1-\beta)h^{\gamma}\right)^{\frac{1}{\gamma}} \tag{12}$$

with $\gamma, \rho < 1$.

This production function captures both effects due to skill-job complementarity (measure by ρ) and effects coming from skill-hours complementarity, which is the key new feature I introduce in this framework. These effects are captured in particular by γ.

Income Effects I first consider an example to highlight the role of income effects (and in general, or preferences) in driving the main outcomes of the model. The key comparative static I focus on is on the aggregate hours-wage elasticity, defined as the average hours worked response to an increase in average wages. I consider two scenarios to illustrate the intuition behind the mechanics of the model. Both are illustrated in Figure 4.

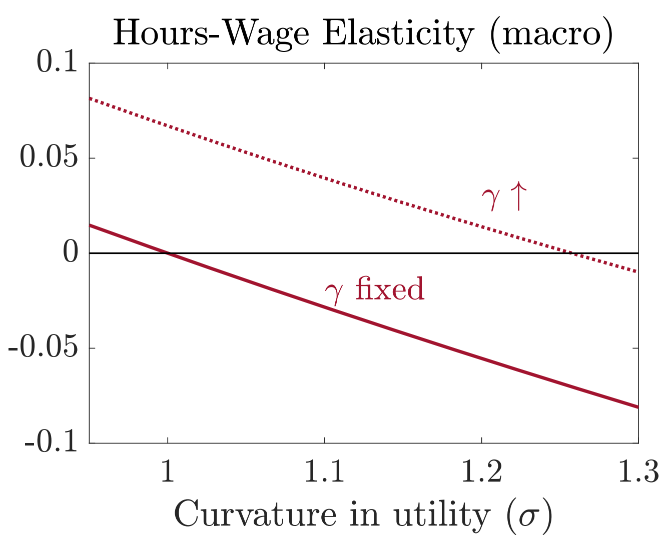

Figure 4: Macro Elasticity with Varying Income Effects.

Notes: Hours-wage elasticity computed as response of average hours worked after an increase in average wages. Solidand dotted lines plot the response following an increase in A (TFP) only and an increase in A and γ (TFP and biased technological change), respectively.

The first message is that increasing σ leads to a smaller hours-wage elasticity. This is the basic force at work in macro models and textbook models of the labor supply: with higher income effects, an increase in average wages (caused in this case by an increase in the TFP A) leads to lower hours worked. With σ sufficiently high, this relationship turns negative, as shown in the figure. This effect is the main explanation for long-run decreases in hours worked in US and across countries (as well as along the development path).

Next, I consider the effects of different technological progress on the macro hours-wage elasticity. When techonological progress is factor-neutral (so that increasing average wages are only driven by an increase in TFP), hours wage elasticity turns negative when σ is larger than one, again in line with standard models (solid line). When progress is also driven by an increase in production complementarities (dotted line), a larger income effect (larger σ) is required to turn the elasticity from positive to negative. This is because an increase in hours complementarities drives up incentives to work for high skill people, hence the same level of σ is not sufficient anymore to reduce their hours.

There are two key takeaways from this. The first takeaway is that in this model, hours-wage elasticity in the aggregate cannot be summarized by a single preference parameter σ, but it depends on the shape of the production function (in particular, the complementarities embedded in it). Hence both preferences and technology are key in driving this elasticity. The second takeaway is that in this model, it is important to recognize what force drives technological progress to understand the *macro* elasticity, and average hours worked in the economy can decrease or stay flat (i.e., displaying zero hours-wage elasticity) depending on *which* force drives up average wages.

Production complementarities In this section I show a simple parametric example to illustrate how technological change can affect the hours decision and wages in equilibrium, taking as given the utility function. I fix σ to be slightly higher than 1, which implies strong income effects. I consider two types of comparative statics, meant to describe the different effects that technological change (understood as a change in the parameter governing the production function) can have in this economy. I consider as before an economy with utility and production function given respectively by (11) and (12). I consider two experiments, reported in Figure 5.

In the panel on the left, I keep all baseline parameters fixed and I vary the importance of skill in production, measured by the parameter α. This captures the idea that is behind the Skill Biased Technological Change literature, that is the marginal product of skill has increased. I plot two model-computed outcomes, the variance of income and the cross-sectional correlation between hours and wages. As expected, a higher α increases the marginal product of skill and increases inequality. Due to high income effects from preferences, this leads high skill workers to work lower hours and decreases the cross-sectional correlation

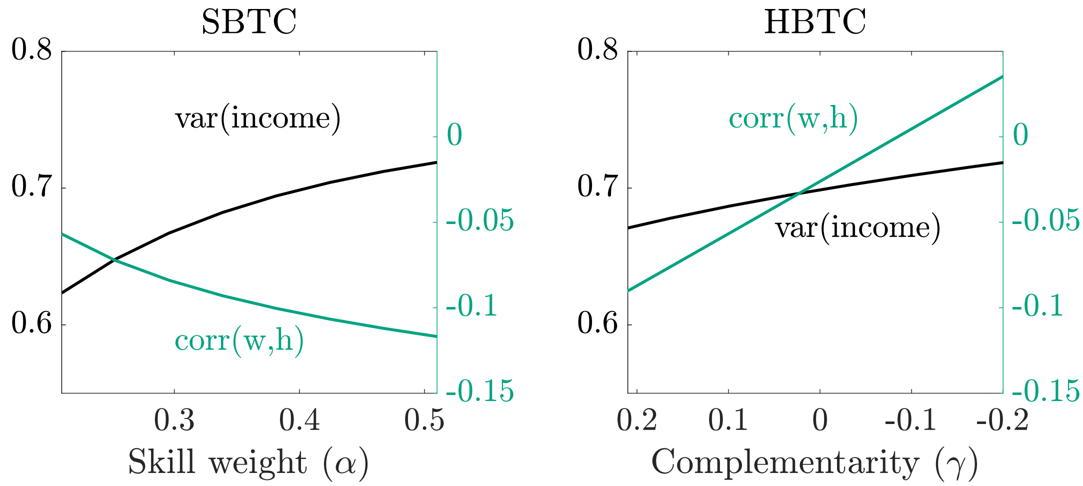

Figure 5: Inequality and Technological Changes.

Notes: Variance of income and hours wage elasticity (measured as model-computed correlation between hours and wages) following two type of comparative statics.

between hours and wages.

In the panel on the right, I consider an experiment where i vary the complementarity in production between skills/jobs and hours, measured by the parameter γ. This is what I refer to in the paper as Hours-Biased Technological Change (HBTC). Decreasing this parameter has two effects on the model economy: it increases income inequality, but it also increases the hours wage-elasticity in the cross section. The intuition is simple: despite large income effects, increasing γ raises the incentives to work longer hours for the high skilled. Hence, hours worked and wages go up for this group of workers, and the correlation increases as well (in line with the data).

In summary, we note two things from this exercise: first, the way the hours profile reacts to technological change crucially depends on the type of technological change we consider. This, in turn, changes wage inequality in different ways. Second, and equally important, not only HBTC changes the *macro* elasticity (as considered in the previous section) but also the micro-elasticity. This is a key insight for the model, and will come back later when analyzing model-based counterfactuals.

3.4 Special Cases and Relationship to the Literature

The purpose of this section is to discuss how my framework relates to existing models, deriving the latter as special cases whenever possible. Special emphasis will be put on the two extremes: the macro framework that focused on preferences (King *et al.* (1988), Boppart and Krusell (2020)), and the assignment framework that has largely abstracted from the labor supply decision (with important exceptions discussed in detail below).

Models with Linear Earnings The standard labor supply model used in the literature implicitly assumes that earnings are linear in hours worked. In other words, the earning function e is such that $e = w \cdot h$, where w is the hourly wage rate, independent of hours worked. My framework allows for a more general earnings function: earnings are allowed to depend on the sorting patterns and on hours worked by skill, as well as the interaction between the two.

Convex Earnings A key feature of this framework is that earnings are non-linear in hours worked. Thus, the model in this paper is in close connection to the works by French (2005) and its generalization in Bick *et al.* (2022a) and Erosa *et al.* (2022) . In these models, earnings $e(h)$ typically take the form $e(h) = x \cdot h^{\theta}$, where θ is the elasticity of earnings with respect to hours[29]. My framework can be seen as a more general version of these models, in that I allow for complementarities between skills and jobs. To see this, notice that the earnings function in these models[30], which is $e(h) = x \cdot h^{\theta}$, can be microfounded in this framework by a production function where there is no skill-jobor hours-job complementarity ($f_{xy} = 0, f_{yh} = 0$), but where skills and hours can potentially interact ($f_{xh} \neq 0$). Recall the condition to have $h_x > 0$:

$$u_{cc} f_h f_x + u_c f_{hx} > 0 \tag{13}$$

Assuming the functional form for earnings $e(h) = x \cdot h^{\theta}$ and $u(c) = \frac{c^{1-\sigma}}{1-\sigma}$ - as typically done in this class of models - and substituting terms in (13), it is easy to prove that high skill workers work longer (shorter) hours if $\sigma = -c\frac{u_{cc}}{u_c} < 1 (> 1)$. Of course, since $f_{xy} = 0, f_{yh} = 0$, hours worked affect wages and inequality only through their interaction of skills, and not through the equilibrium sorting patterns.

Models with Effective Labor A few models in the literature have been using a production function where skills and hours are 'bundled' together; in these models, therefore, only the bundle $g(x, h)$ enters the production function, so that f becomes $f = f(g(x, h), y)$. In other words, the firm only cares about the composite between hours and skills. In these cases, it is easy to show that Condition 9 is always satisfied (so that positive sorting always obtains) as long as g is such that $g_{hh} < \frac{g_h}{g_x} g_{xh}$ [31].

[29] θ is typically estimated to match the empirical earnings function; French (2005) assumes this elasticity is constant across the hours distribution, i.e. $\theta_h = \bar{\theta}$; Bick *et al.* (2022a) allow for a more general specification, where θ_h can vary across the hours distribution.

[30] Or the more general version $e(h) = x \cdot g(h)$.

[31] A similar point arises in a model with sorting and taxation but with risk-neutral workers, as shown in Vereshchagina (2021).

Hours Worked in Balanced Growth Models Balanced growth models have been used to describe long-run behavior of hours worked, specifying utility functions such that - together with rising productivity - a given pattern of hours worked is obtained along the balanced growth path. Leading examples are King *et al.* (1988) and Boppart and Krusell (2020), which specify general utility functions that imply constant and decreasing hours worked, respectively[32]. In these frameworks, the basic labor-leisure choice is summarized by the first order condition[33]:

$$MRS = -\frac{u_c}{u_h} = w, \tag{14}$$

where w is the wage rate[34], to be equal to the Marginal Rate of Substitution (MRS). Boppart and Krusell (2020) derive a class of utility functions such that, in equilibrium:

$$\frac{u_c}{u_h} = c^{\frac{1}{1-\nu}} q(hc^{\frac{\nu}{1-\nu}}),$$

for some function $q()$. Note that the term $q(hc^{\frac{\nu}{1-\nu}})$ will be constant in the long run, which means the MRS in the long run is driven by the term $c^{\frac{1}{1-\nu}}$. The key implication of this model is that whenever $\nu > 0$, consumption will shrink and relatively more time will be devoted to leisure as an economy grows. Importantly, the rate at which this happens depends on ν, a constant[35].

In my framework, due to sorting, there is a tight linke between the $MRS = -\frac{u_c}{u_h}$ and tech-

[32]The use of utility functions that imply constant hours worked along the balanced growth path is paramount in the literature, and was motivated by the fact that total hours worked in US have been roughly stable over the postwar period. However, as noted for example in Boppart and Krusell (2020) and Kopytov *et al.* (2021), constant hours worked are specific to US and Canada, and are mostly driven by the increase hours worked by women, possibly driven by their increase in the labor force participation. Hence, the need of specifying models that are consistent with decreasing work hours over time. The fact that constant hours worked in US reflect opposing trends between men and women hasl also been noted by Browning *et al.* (1999) and Attanasio *et al.* (2018).

[33]Note that the present framework and frameworks such as Boppart and Krusell (2020) differ in several aspects; in particular, they use of models specified in BGP to speak to long-run data (post-war period or even more). Moreover, they specify not only an intratemporal choice between labor and leisure, but also an intratemporal allocation of consumption and savings. However, both my framework and theirs focus on the intensive margin of hours choice. For this reason, it is sensible to compare the optimal time allocation by workers and how they are related.

[34]I omit the time subscripts as my framework is static, unlike Boppart and Krusell (2020). In the absence of intertemporal decisions (e.g. savings choice), one can compare the two frameworks at a given point in time, i.e. for a given productivity level.

[35]When $\nu = 0$, time devoted to leisure is constant along the balanced growth path (and so are hours worked): this happens for example when preferences are of the form $u(c,h) = log(c) - \psi\frac{h^{1+1/\theta}}{1+1/\theta}$ (see King *et al.* (1988).

nology. In other words, Equation (14) becomes:

$$-\frac{u_c}{u_h} = w_h, \tag{15}$$

where w_h is is the impact of one more unit of time on earnings; importantly, it crucially depends on the complementarities in production between x, y and h and the sorting patterns that obtain in equilibrium. This highlights the crucial point of this discussion: in addition to preferences, my framework makes clear how technology (and in particular, complementarities in production) can play a key role in describing hours worked by skill, and therefore in the aggregate. With respect to existing frameworks, it can therefore speak to both cross-sectional and aggregate patterns thanks to the explicit role of technology and preferences that is at the heart of the proposed framework. Therefore, there is the need of specifying and estimating a production function to capture salient aggregate and cross sectional data, which is what I do in the next section.

4 Quantitative Analysis

The goal of this section is to estimate whether and how the production function, as well as the skill and job types distributions have evolved in recent decades, and assess the quantitative relevance of the mechanism presented in the previous section. As I am primarily focused on the effects of technology on hours worked, I consider the period 1980-2015[36], during which the advances in computer and ICT technologies have advanced most rapidly. I will now make clear how I bring the three building blocks of the model to the data (distributions, preferences, production). The estimation will involve a mix between parameters set to match moments from the data, and parameters taken as input of the model.

4.1 Data

CPS has large sample size and is available for the whole period of interest (1980-2016). Moreover, it contains information on hours worked, earnings, and hourly wages. I therefore make use of CPS as the main dataset used in the estimation. When computing the estimation targets, I will retrict the focus to the population of full-time males, aged 25-64, and not self-employed[37]. I focus on the male population only because the analysis abstracts from participation margin[38]. In the baseline analysis, I compute hours in the data using the variable 'usual hours worked'. As noted in Heathcote *et al.* (2010), the wage-hours correlation trends for US are similar if 'hours worked last week' available in CPS-ASEC is considered instead. All calculations use provided CPS sample weights.

4.2 Functional Forms

Production I assume a production function of the form:

$$f(x,y,h) = A\left(\beta(\alpha x^{\rho} + (1-\alpha)y^{\rho})^{\frac{\gamma}{\rho}} + (1-\beta)h^{\gamma}\right)^{\frac{1}{\gamma}}.$$

The advantage of this functional form is that it allows for complementarities between skills and jobs, captured by the parameter ρ as well as between skill/job and hours, captured by γ.[39] This production function can be thought of a generalization of a production function

[36] I will estimate the model year by year during this period, where parameters for each year are estimated separately using moments specified below.

[37] For a full description of the data used in the estimation, see Appendix A.

[38] Focusing on the male population is a common approach in the labor supply literature tat focuses on the intensive margin choice, see e.g. Bick *et al.* (2022a).

[39] Note that this is a slightly more general version of the multiplicatively separable production function, of the form $f(x,y,h) = A(\alpha x^{\rho} + (1-\alpha)y^{\rho})^{\frac{\beta}{\rho}}h^{1-\beta}$. As noted for example in Chade and Lindenlaub (2022), the latter is perhaps one of the most commonly used production function for empirical applications, and it is a

that takes as input skills x and jobs y, and that interprets the recent rise in wage inequality as captured by an increase in the parameter α (or similarly, a decrease in the parameter ρ). Finally, the weight in production of the skill/job bundle, compared to that of hours, is measured by β.

Preferences I make use of the following utility function (MaCurdy (1981)):

$$u(c,h) = \frac{c^{1-\sigma}}{1-\sigma} - \psi \frac{h^{1+\frac{1}{\theta}}}{1+\frac{1}{\theta}} \tag{16}$$

This preference formulation is a slightly more general version of the preferences typically used in balanced growth path models. This specification has several advantages for the purpose of this paper, most notably that the curvature in consumption is parametrized by σ, and hence from the macroeconomic literature on hours worked, we know that $\sigma > 1$ implies substitution effect being dominated by the income effect, other things being equal[40].

To calibrate this utility function, I take common values for σ and θ from the literature, and employ the normalization $\psi = 1$. In particular, I set $\sigma = 1.4$, which is in the mid-range of values from the literature that aims at matching the overall decline in hours worked, both across time (Boppart and Krusell (2020)) and across the development path (Bick *et al.* (2022b)). The latter study is particularly relevant for the calibration of the utility function employed in this paper, in that they estimate a utility function of the form in (16) to match aggregate data on hours worked. I then follow them and set $\theta = 0.49$; this value is also in the range of commonly used values to calibrate intensive-margin elasticities (see Keane (2011) for a survey).

Notice that the calibration I adopt for the utility function is very close to available estimates of the same functional form from cross-sectional studies; in particular, Heathcote *et al.* (2014) employ a similar specification as in (16) and find values of σ and θ of 1.71 and 0.46, respectively [41]. The important takeaway is that the calibration I use is roughly consistent with structural models that focus on *cross-sectional* data (e.g. Heathcote *et al.* (2014)), as well as very recent studies that aim at explaining long-run, *aggregate* data on hours worked (Bick *et al.* (2022b), Boppart and Krusell (2020)). This is important because it will be the focus of

special case of the production function I employ (in particular, it can be obtained by letting $\gamma \to 0$)

[40]This specification has the additional feature that leisure and consumption are separable, i.e. $u_{ch} = 0$. This formulation is convenient in this paper since - as the ultimate objective is to assess the role of technological complementarities in explaining patterns of hours inequality - it effectively shuts down complementarities between hours and consumption (or income) coming from the utility function, and hence isolates the role of technology in explaining the data.

[41]Of course, the latter study differs in other aspects, e.g. the heterogeneity in ψ (which I assume away) or the presence of ininsurable shocks, as well as the data used (PSID, CEX), and hence are not fully comparable with this paper.

the present study, namely sorting on hours and skills, that will help reconcile cross-sectional data over the entire period considered (1980-2015) and shed new light on the patterns of inequality.

Distributions In order to estimate the model, I need to provide skills and job distributions, $G(y)$ and $H(x)$[42]. In the baseline estimation, I treat both skills and job distribution as unobserved, and hence to be estimated. I assume that skills x and jobs y are distributed according to log-normal distributions $log\mathcal{N}(a_x, b_x)$ and $log\mathcal{N}(a_y, b_y)$, respectively. A similar approach has been used extensively in the literature, see e.g. Lise *et al.* (2016). The advantage of this approach is that one does not need to treat worker and job types as observable, but it comes with additional computational cost since more parameters are to be estimated[43].

4.3 Moments and Identification

I estimate the model by Simulated Method of Moments (Pakes and Pollard (1989), McFadden (1989)). In practice, I pick a set of moments m to identify the set of model parameters θ. The estimation procedure uses a global search algorithm to search for the parameter vector θ that minimizes the weighted square distance between model moments $m(\theta)$ and data moments $\bar{m}$:

$$\min_{\theta} \quad (\bar{m} - m(\theta))'\Omega(\bar{m} - m(\theta)),$$

where Ω is a weighting matrix. Table 1 contains a summary of targeted moments.

Table 1: Targeted Moments

$\mathbb{E}$(h)	Avg. Hours
$\mathbb{E}$(w)	Avg. Wages
w90/w50	Wage inequality (top)
w90/w10	Wage inequality (overall)
Hours-wage Elasticity	Coeff. of reg. $log(h)$ on $log(w)$
std(w)	Wage dispersion

I now discuss how each moment is related to the parameter to be estimated. As typical in these models, each parameter is informed by more than one moment. The TFP level A

[42] I interpret y in my model as jobs rather than firms. This is motivated by the application of the model, and specifically the techonlogical changes at the center of the mechanism. This is a common interpretation in sorting models trying to understand rising inequality, see e.g. Lindenlaub (2014).

[43] A common alternative approach is to estimate worker and job types from available data, as for example in Chade and Lindenlaub (2022) or in Calvo *et al.* (2021), and use them as input in the estimation of the remaining parameters. As a robustness check of the baseline estimation strategy, I follow this alternative approach trating distributions as observed as in Chade and Lindenlaub (2022). Details on the estimation results following this alternative approach are in Appendix C.

informs the income level in the model, as it translates into a level shift of the earnings in the economy. Clearly, given the assumed preference specification, A will also inform the average hours worked in the economy. In particular, it will shift down average hours worked in the economy. Importantly, A affects all workers' hours and wages equally, so has no effect on measures of inequality.

The parameter β informs, too, average hours worked, as it determines the importance of hourse in production (compared do job/skill). The mechanism is however different: β directly shifts up (or down) the marginal product of an hour worked, f_h. Hence, once again is a parameter that has a primary effect of shifting hours worked for all workers in the economy, but not through the effect of wages (and its income effect).

The parameters α, ρ and γ crucially determine the income and hours inequality in the model; however, key to identification is that they do so differently, as the comparative statics in the previous section have shown; in fact, while the former two have a negative effect on the wage/hours elasticity, the latter increases wage/hours elasticity in the cross section[44]; in sum, they have an opposite effect on the moment. Moreover, α and ρ inform inequality at different points in the income distribution. The former increases overall inequality, while the latter governs the convexity in the wage function (recall that the model features a competitive labor market, and hence it features a tight link between the production function and the shape of the income function). Finally, I estimate the worker and job distributions by assuming that they have mean 0, i.e. $a_x = a_y = 0$. Moreover, since in this model the matching function is defined as $\mu(x) = G^{-1}H(x)$ where G, H are the distributions of workers and jobs, I estimate the ratio of dispersions σ_x/σ_y. With this identification strategy, there are in total six parameters to be estimated: two from the production function (A, α, β, γ, ρ) and one from the distributions of worker and job types (b_x)[45]. Table 2 contains a summary of the parameters to be estimated.

Table 2: Endogenous, estimated parameters (time-varying)

Parameter	Meaning
A	Total Factor Productivity (TFP)
β	Importance of hours in production
α	Importance of skill in production (relative to job type)
γ	Elasticity of substitution between hours and skill/job
ρ	Elasticity of substitution between skill and job
b_x	Variance of distribution of skill types

[44] Again, the assumed preference specification is crucial to this result.

[45] I also employ, as a robustness check, a different strategy for identifying skills and job distribution, finding similar parameter estimates for the production function. See footnote 43 and Appendix C for details.

4.4 Estimation Results

Model Fit I plot the model and data moments targeted in the estimation in Figure C.1. The model, despite being parsimonius, exhibits a good fit of the data. Key for the counterfactual exrcises is that is captures both the slightly increasing (and overall, flat) pattern in hours over the period considered, despite assuming $\sigma = 1.4$ which implies, coupled with rising average productivity over the period, large income effects operating in the model. Moreover, the model matches almost perfectly the increase in hours-wage correlation observed over the period, and can accomodate well both the negative and the significantly posiitive elasticity over the period. The ability of the model to match inequality measures is reassuring but somewhat less surprising, given that the functional form considered for production is an extended version of those typically considered in models used to explain technological change and inequality (see e.g. Autor and Acemoglu (2011)).

Estimates I now briefly comment on the estimates for the period considered (1980-2016). The estimated parameters are presented in Figure C.2. The estimates reveal several interesting patterns, some new to this model, and some common given previous work focused on understanding the determinants of inequality in US.

First, there has been Skill Biased Tehcnical Change, defined as an increase in the complementarity between skills x and jobs y (ρ has decreased). The marginal product of skill in production, capture by α, has increased. These patterns are at least qualitatively similar to what the literature on wage inequality in US has found[46].

However, the estimation reveals that other technological changes have taken place. In particular, the estimated model reveals that the complementarity between skills/jobs and hours (captured by γ) has also increased (i.e., γ decreased). Intuitively, this can be interpreted as an increase in the marginal product of one more hour of work for the high skilled workers (independently of the job they are matched with). Besides being conceptually different from parameters governing skill-biased technical change (α, ρ), a decrease in γ will have first order implications for our understanding of inequality, a result I will show in the next section through counterfactual experiments. Finally, the estimation results reveal that β, the weight of skill/job in production relative to those of hours, has decreased slightly. This has crucial implications for the aggregate labor supply movements in US, something I analyze in detail in the counterfactual section.

[46] For example, estimating a version of her model with one-dimensional skills, Lindenlaub (2014) finds that returns to skill have increased (see Table 18 in her paper).

5 Results

In light with the estimated technology parameters, I focus on two sets of counterfactuals: the first related to the change in inequality and in the hours-wage elasticity. The second counterfactual relates to the aggregate labor supply: we ask how much aggregate hours would have evolved absent the observed technological changes in production.

5.1 Counterfactuals

Inequality A key advantage of this model is that rising income inequality can be studied in all three components. In fact, taking the variance of income as a measure of inequality, we have the decomposition: $var(income) = var(wage) + var(hours) + 2 \cdot cov(wages, hours)$. This model is suitable to study how counterfactual inequality would have evolved, absent the technological changes I estimate through the model. This is particularly true in this setting as all three components are endogenous outcomes of the model. Figure 6 plots the evolution of income inequality in US, and shows which drivers are important in its observed increase. It is clear from the figure that all components have had a significant increase and they all contributed to the increase in income inequality. Of course, the share of each component is not equal, hence the key driver of the increase in income inequality has been the increase in the variance of wages, followed by the increase in the covariance between wages and hours.

The estimated model lends itself to an exercise in which we fix one estimated parameter to the 1980 level, and we analyze the evolution of inequality and its component in this counterfactual economy (i.e., we fix one parameter at its 1980 estimated level and compute model-menerated moments feeding the model with all other parameters as estimated over time). Since - as shown in the comparative statics section - different parameters impact inequality in a different way, we perform this exercise for several parameters of interest. In particular, given the big changes in the estimated parameters α, ρ and γ (measuring, respectively, the weight of skills vs job in production, and the complementarity of skills and hours), I focus on these two[47]. I refer to Skill-Biased Technological Change (SBTC) the changes in parameters α and ρ, since they affect the productivity of skilled workers without changing (at least, directly) the productivity of their hours. Viceversa, I refer to Hours-Biased Technological Change (HBTC) the changes in γ, as the latter changes the marginal product of one hour worked for the high skilled. The two counterfactual economies (one where HBTC did not happen, one where SBTC did not happen) and the evolution of the variables in the data

[47] Figure C.3 in Appendix C contains an alternative decomposition using all model parameters.

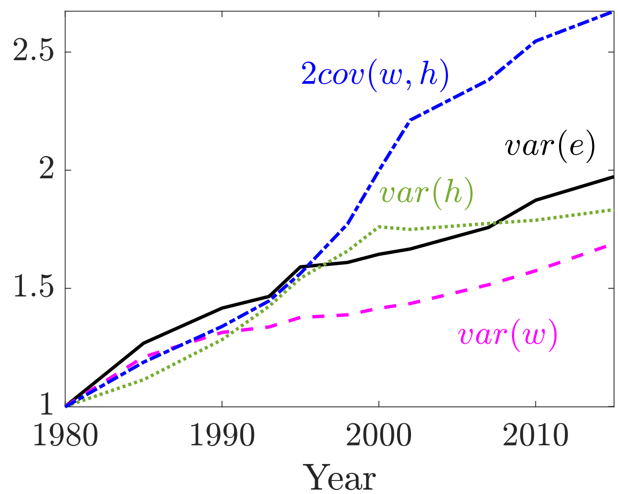

Figure 6: Income Inequality in the Data (US).

Notes:The figure displays income inequality defined as the variance of log income (black line). Moreover, it plots the three components of income inequality (variance of log wages, variance of log hours, and twice the covariance between the two. Variables are normalized to be 1 in the first year of the sample. All series are plotted with 5-years moving average. Source: CPS and own calculations.

are plotted in Figure 7.

Several results emerge. Focusing on Panel A., we notice that both SBTC and HBTC caused an increase in the variance of wages. In fact, if each of them did not happen, the variance of wages in the economy would be significantly lower. Quantitatively, the effect is larger for SBTC since the counterfactual variance gows down. The mechanism is that SBTC increases hourly wages by increasing the marginal product of skill, while HBTC increases the returns to working long hours for high skilled workers.

Panel B. shows that the dispersion in hours would have increased greatly absent HBTC, while SBTC did not have a very big effect in the hours dispersion. The reason this happens is that without HBTC, SBTC would have led the high skill workers to work even less (recall that at the beginning of the sample, the correlation was negative). Hence it would have increased even more the dispersion in hours.

Finally, Panel C. (in line with the predictions of the theory) show that the two estimated parameter changes have had opposite effects on the counterfactual relationship between hours and wages: due to income effects in preferences, SBTC leads to high skill people work less (due to their higher wages); the implication is that the hours-wage correlation would have increased. Viceversa, without HBTC, increases their return to work long hours would be absent and hence the covariance would have decreased significantly due to the combination of SBTC and large income effects in preferences.

The key message is simple, but powerful: the estimate technology changes have had qualitatively and quantitatively different effects on the different drivers of inequality. To the best of my knowledge, this is a new result that has profound implications for our understanding of the deep causes of inequality. It also complements the literature on Skill Biased Technical Change in that it shows that - in addition to the increased importance of skills in production - how these skills perform with more hours of work has first order implications for inequality trends.

For completeness, in Figure C.3, I plot the counterfactuals with respect to all parameters changes[48]. What the figure shows is that the estimated hours weight in production (given by $1-\beta$) has relatively small effects on inequality. However, I show in the next section that it will be crucial to understand the aggregate effect of technological changes on the labor supply.

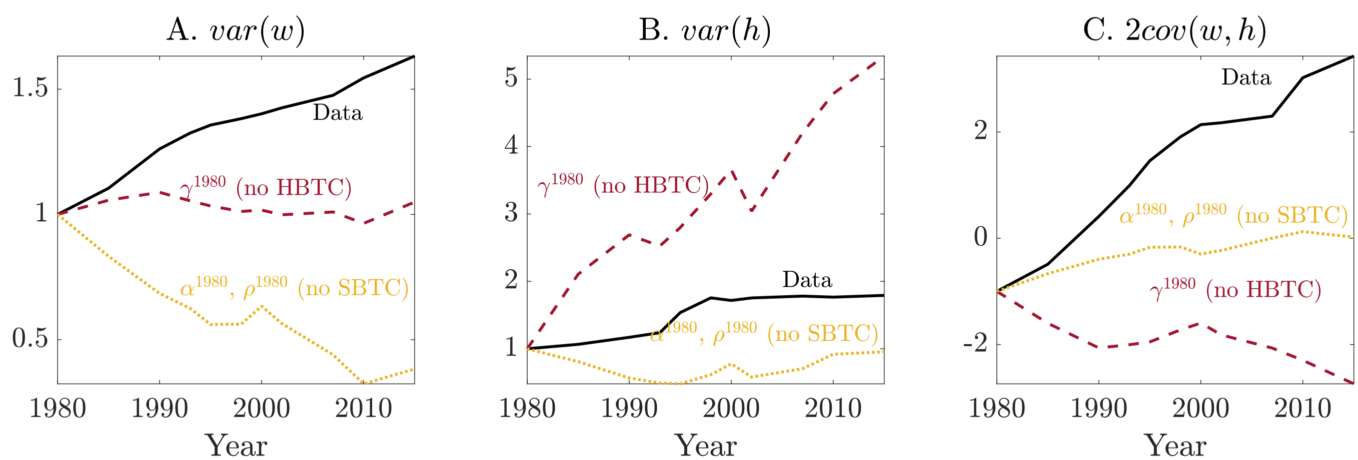

Figure 7: Income Inequality: Counterfactuals.

Notes: Panel A., B., and C. plots respectively the variance of wages, hours and the covariance between the two (the black lines represent these statistics in the data; the yellow dotted line represents the model-generated statistics when all the estimated parameters are fed to the model, except α and ρ, which are fixed at their 1980 values; the dashed brown line does the analogous exercise, but the estimated parameter γ at its 1980 level. Model and data moments are computed using 5-years moving average.

Total Hours Worked The estimated changes in the model not only have implications for inequality but, as I show in this section, they have first-order implciations for aggregate hours worked. I key question in macroeconomics is how to characterize the relationship between hours worked and productivity (or wages). The answer to this question not only has implications for the future of hours worked, but also for our understanding of the deep forces that shape preferences at the individual and at the aggregate level. Hence, a correct understanding of the relationship between hours and wages is informative for a range of

[48]I do not plot the counterfactual with respect to the TFP level A since it does not affect inequality measures, as explained in the identification section.

other issues, not least the effect of taxation on hours worked. I now show that the estimated model can shed light on the evolution on hours worked in US.

Since the key parameter that governs *average* hours worked in the model is $1-\beta$, I focus my counterfactual on this parameter. The estimated changes on β, as discussed in the rpevious section, reveal that the marginal product of hours worked in the economy has increase (β has decreased).

The counterfactual exercise is shown in Figure 8. From the figure, is evident the pre-1980 declining trend in average hours worked. This trend flattened out in the period starting from 1980. The dashed line shows average hours model, *absent* the estimated changes in the marginal product of hours worked (β). Hours worked in this counterfactual economy decrease subtantially, reaching roughly 33 hours worked per week. Most importantly, the counterfactual decline in hours worked is (roughly, at least) in line with thre pre-1980 trend. The key takeaway is that the estimated model has implications for average hours worked in the economy: through the role of technological change, the model can explain the flattening of hours worked in the economy[49].

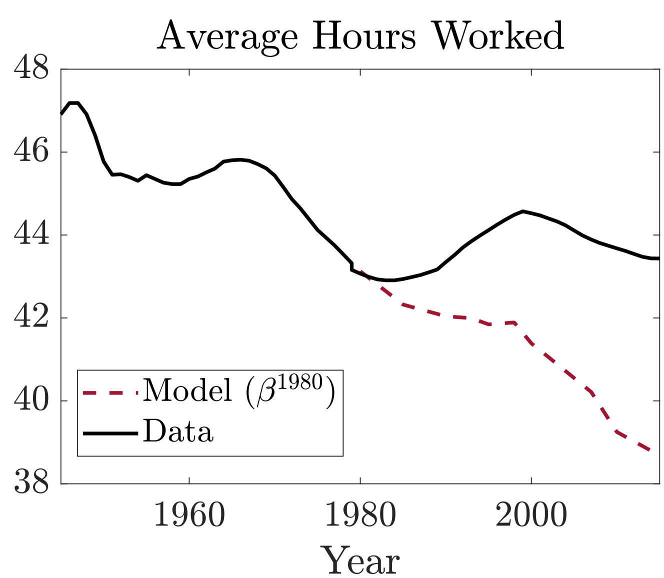

Figure 8: Hours Worked: Counterfactual.

Notes: The figure plots average hours worked per worker in US (black line) and the estimated counterfactual hours worked in the model, keepin the parameter β fixed at its estimated level in the 1980. Model and data moments are computed using 5-years moving average.

These last counterfactual experiment closely relate to those in, for example, Bick *et al.* (2022b). Like in this paper, they consider what forces could determine aggregate hours

[49]For an alternative, though related explanation of increasing hours worked in US, see Michelacci and Pijoan-Mas (2012). In particular, they explain the rise in hours worked in the US through rising wage inequality and a mechanism intertemporal subtitution of labor.

worked in addition to preferences, and highlight structural transformation as one such force; this paper joins this literature in concluding that that the prediction on the future of hours worked (tracing back at least to Keynes (1930)) rely heavily on other forces (namely, technology), and that such forces are crucial to formulate predictions on the future of work. Importantly, this counterfactual also provides a potential explanation for why hours worked in US have become flat after the 1970's; rather than interpreting hours worked with models where income and substitution effects cancel out, this paper shows that an alternative interpretation is one where income effects prevailed in the 1960's and 1970's; starting from the 1980's, technological change increased the importance of substitution effects, and these two roughly cancel out in the aggregate. In other words, the patterns of hours worked in the aggregate mask substantial heterogeneity.

5.2 Robustness

I consider several robustness exercises on the model and estimation assumptions to assess the generality of the results presented so far[50].

The first robustness exercise is to consider different nesting for the production function $f(x,,y,h)$. In the baseline estimation and comparative statics exercise, I offer a particular nesting that relies on a clear interpretation of the different technological forces that this paper uncover. However, it is useful to consider the robustness of the estimation to different nests. I report the estimated alternative formulations in Table C.1 and Table C.2. Although each nest offers a different interpretation of technological changes related to hours worked, both alternative specification imply an increase in the complementarity between hours and skill/jobs, which is the key new result I also highlight in the baseline specification (for example, Table C.1 shows that the complementarity between skill and jobs/hours has gone up - γ is more negative).

The second robustness exercise I consider concerns income effects. In the baseline exercise, I assume $\sigma = 1.4$, in the mid-range of macro studies. I consider an alternative estimation exercise, where all moments and estimation is identical to the baseline, but I adopt a lower value for σ (1.2). I report the estimates in Table C.3. While (not suprisingly) the level of the parameters change, we broadly observe the same parameter *changes* across the two periods: α increases while ρ decreases significantly (SBTC); γ decreases significantly (HBTC). Hence, we conclude that the choice of σ, while relevant, does not fundamentally affect the interpretation of the model of increasing inequality and changes in hours worked.

I next conduct a robustness exercise on the distribution of skills and jobs, G and H. In the

[50]For simplicity, instead of estimating the model year by year, I consider only the intial and end year of the estimation.

baseline estimation, I assume they follow a log-normal distribution. To show the robustness of the results to this assumption, I repeat the estimation results assuming that skills and jobs follow a Beta distribution (a similar assumption has been employed, for rexample, in Lise *et al.* (2016)). Results are reported in Table C.4. As for theprevious robustness exercises, we observe parameter changes similar to those in the baseline estimation. Hence we conclude that even in this alternative specification, the model interprets changes in the key moments in very similar ways.

5.3 Implications

I now show that the framework developed in this paper has implications for the design of income tax progressivity and for our understanding of the gender gap in wages[51].

Income taxation The labor-leisure trade off, and the forces shaping it, are at the heart of the literature on income taxation. In particular, a key question the literature is trying to answer is whether and how income progressivity should respond in US to the widening income inequality (see for instance the recent contributions in Heathcote *et al.* (2021) and Ferriere *et al.* (22)). While the model in this paper does not provide an answer to it, I argue that the view proposed in this paper can be potentially useful on this matter.

To see why, notice that the classic equity-efficiency tradeoff that determines the optimal level of progressivity is typically governed by preference parameters, and in particular the elasticity of labor supply. This framework potentially adds to this literature by showing that a complete understanding of how hours enter in production is an equally important driver; in fact, complementarities in production of different nature determine how sensitive the hours choice of each worker is and, as such, they may impact the level of progressivity for a given social welfare function. In other words, understanding whether rising income inequality is ultimately driven by x, y or x, h complementarities may matter for the responsiveness of hours to tax progressivity and hence, for the optimal determination of tax progressivity.

The intuition behind this argument is illustrated in Figure 9. It plots the returns to working higher hours across skills (i.e. the heterogeneous subsitution effects that arise in this model). Higher γ (in the model, higher complementarity between skills/jobs and hours give rise to more convex returns to long hours across skills. This effectively implies that a given increase in the marginal tax faced by a worker will trigger a higher (negative) response in hours worked, and hence a higher distortionary effect of a more progressive tax schedule. Similar effects arise in models that study taxation in presence of sorting in the labor market

[51] Fully developing on exploring these implications is well beyond the scope of this paper, but I am developing them as separate projects.

(see e.g. Scheuer and Werning (2017), Vereshchagina (2021))[52].

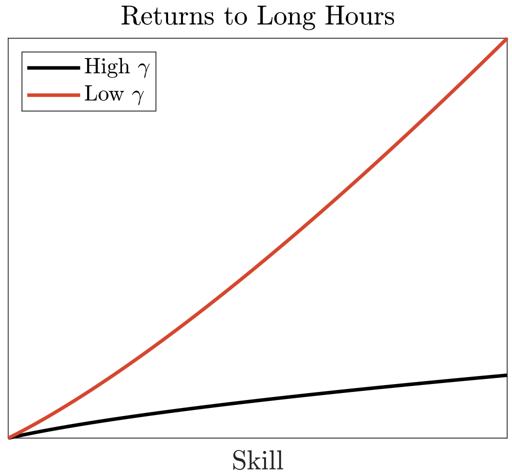

Figure 9: Returns to Long Hours

Gender Gap and Flexible Hours The framework I develop in this paper has potential first-order implications for the evolutions of the gender wage gap, defined as wage differential between men and women. A number of authors have emphasized how the gender gap has been declining at a slower rate, especially for the high skilled (see Goldin (2014) and Cortés and Pan (2019)). The same literature has noted how measures of gender gap are clearly correlated with how earnings respond to hours in the cross-section, as Figure A.13 shows.

The fundamental insight of this paper - that technological change shape how income responds to hours worked - may help us understand why the gender wage gap has stalled in the 1990's, especially for the high skilled- high wage workers. The intuition is that the adverse effects on wages of social norms or external constraints that prevent women for working longer hours might be have been magnified by technological change. In other words, one lower hour worked for a woman in a top occupation might result in bigger output and earning losses than for a woman in a low-skill occupation, thus preventing the forces that point towards convergence in earnings between men and women to fully close the gap. Thus, the model can potentially rationalize the evolution of the gender gap through two dinstinct forces: if on one hand, social norms and constraints that affect women have been reduced, on the other hand technology amplifies the adverse effects of those constraints on earnings and wages.

The additional implication is that misallocation and output costs of hours constrains can be severely understated if we do not consider the non-linear nature of income in hours worked.

[52]These papers, unlike mine, focus on the assignment problem between CEOs/managers and firms.

6 Concluding Remarks

Motivated by aggregate and cross-sectional evidence, this paper provides a new framework to study the allocation of workers and hours across jobs, and uses it to study the aggregate, as well as the cross sectional relationship between hours worked and wages. The framework combines the literature on sorting and the allocation of job to skills with the macro literature that attempts to describe the evolution of hours worked across time.

I obtain the following results: on the theory side, I show how hours, sorting and wages depend on the properties of the production function as well as the utility function, and I characterize such forces interact in equilibrium. The key theoretical result is that hours worked can amplify or dampen wage inequality in equilibrium, depending on the strength of the income effect and the properties of the production function. I then quantify the model and analyze how such forces might have contributed to the cross-sectional relationship between hours and wages, and what are the aggregate implications. I find that in addition to technological changes that favoured high skill workers, technology has evolved to favour long hours worked, especially for high skilled. This has increased inequality and has pushed hours worked up, but mostly for the high skilled. Counterfactual experiments show these effects to be quantitatively significant. Additionally, the model provides a rationale for increasing hours worked in the 1980's, which is especially puzzling given long-run evidence on hours worked both in US and across the world.

I conclude that the techological properties of the production function are crucial to have a more complete picture of wage inequality, as well as the future of hours worked. The model has, as I show, first-order implications for the design of optimal progressive taxation and the evolution of the gender gap. In particular, the present framework can be potentially used to understand why the gender wage gap has stalled for the high skilled during the 1980's. This shows how modeling the way hours enter in production can have implications for a wide range of issues related to the labor market.

References

AGUIAR, M. and HURST, E. (2007). Measuring trends in leisure: The allocation of time over five decades. *Quarterly Journal of Economics*, **122** (3), 969–1006.

ATTANASIO, O., LEVELL, P., LOW, H. and SANCHEZ-MARCOS, V. (2018). Aggregating elasticities: Intensive and extensive margins of women's labor supply. *Econometrica*, **86** (6), 2049–2082.

AUTOR, D. H. and ACEMOGLU, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. *Handbook of Labor Economics*, (4), 1043–1171.

BECKER, G. (1973). A theory of marriage l. *Journal of Political Economy*, **81**, 813–846.

BICK, A., BLANDIN, A. and ROGERSON, R. (2022a). Hours and wages. *Quarterly Journal of Economics*.

—, FUCHS-SCHÜNDELN, N. and LAKAGOS, D. (2018). How do hours worked vary with income? cross-country evidence and implications. *American Economic Review*, **108** (1), 170–199.

—, FÜCHS-SCHUNDELN, N., LAGAKOS, D. and TSUJIYAMA, H. (2022b). *Structural Change in Labor Supply and Cross-Country Differences in Hours Worked*. Tech. rep.

BLAU, F. D. and KAHN, L. M. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, **55** (3), 789–865.

BOERMA, J. and KARABARBOUNIS, L. (2021). Inferring inequality with home production. *Econometrica*, **89** (5), 2517–2556.

BOPPART, T. and KRUSELL, P. (2020). Labor supply in the past, present, and future: A balanced-growth perspective. *Journal of Political Economy*, **128** (1), 118–157.

— and NGAI, R. (2021). Rising inequality and trends in leisure. *Journal of Economic Growth*, **26**.

BORJAS, G. (1980). The relationship between wages and weekly hours of work: The role of division bias. *Journal of Human Resources*, **15** (3), 409–423.

BROWNING, M., HANSEN, L. P. and HECKMAN, J. J. (1999). Chapter 8 micro data and general equilibrium models. *Handbook of Macroeconomics*, vol. 1, Elsevier, pp. 543–633.

CALVO, P., LINDENLAUB, I. and REYNOSO, A. (2021). *Marriage Market and Labor Market Sorting*. Tech. rep.

CHADE, H., EECKHOUT, J. and SMITH, L. (2017). Sorting through search and matching models in economics. *Journal of Economic Literature*, **49** (4), 961–1075.

— and LINDENLAUB, I. (2022). Risky matching. *Review of Economic Studies*, **forthcoming**.

COCIUBA, S. E., PRESCOTT, E. C. and UEBERFELDT, A. (2018). Us hours at work. *Economics Letters*, **169**, 87–90.

CORTÉS, P. and PAN, J. (2019). When time binds: Substitutes for household production, returns to working long hours, and the skilled gender wage gap. *Journal of Labor Economics*, **37** (2).

COSTA, D. L. (2000). The wage and the length of the work day: From the 1890s to 1991. *Journal of Labor Economics*, **18** (1), 156–181.

EECKHOUT, J. (2018). Sorting in the labor market. *Annual Review of Economics*, **10**.

— and KIRCHER, P. (2018). Assortative matching with large firms. *Econometrica*, **86** (1), 85–132.

— and SEPAHSALARI, A. (2018). *The Effect of Asset Holdings on Worker Productivity*. Tech. rep.

EROSA, A., FUSTER, L., KAMBOUROV, G. and ROGERSON, R. (2022). Hours, occupations, and gender differences in labor market outcomes. *American Economic Journal: Macroeconomics*, **14** (3), 543–590.

FERRIERE, A., GRUBENER, P., NAVARRO, G. and VARDISHVILI, O. (22). *On the optimal design of transfers and income-tax progressivity*. Tech. rep.

FRANCIS, N. and RAMEY, V. (2009). A century of work and leisure. *American Economic Journal: Macroeconomics*, **1** (2).

FRENCH, E. (2005). The effects of health, wealth, and wages on labour supply and retirement behaviour. *Review of Economic Studies*, **72** (2), 395–427.

GOLDIN, C. (2014). A grand gender convergence: Its last chapter. *American Economic Review*, **104** (4).

GREENWOOD, J. and VANDENBROUCKE, G. (2005). Hours worked (long-run trends). *Economie d'Avant Garde Research Reports 10*.

HEATHCOTE, J., STORESLETTEN, K. and VIOLANTE, G. L. (2010). The macroeconomic implications of rising wage inequality in the united states. *Journal of Political Economy*, **118** (4), 681–722.

—, — and — (2014). Consumption and labor supply with partial insurance: An analytical framework. *American Economic Review*, **104** (7), 2075–2126.

—, — and — (2021). How should tax progressivity respond to rising income inequality? *Journal of the European Economic Association*, **18** (6), 2715–2754.

JACOBS, J. A. and GERSON, K. (2005). The time divide - work, family, and gender inequality.

KATZ, L. F. and MURPHY, K. M. (1992). Changes in relative wages, 1963-1987: Supply and demand factors. *Quarterly Journal of Economics*, **107** (1), 35–78.

KEANE, M. P. (2011). Labor supply and taxes: A survey. *Journal of Economic Literature*.

KENDRICK, J. W. (1961). *Productivity Trends in the United States*. National Bureau of Economic Research, Inc.

— (1973). *Postwar Productivity Trends in the United States, 1948–1969*. National Bureau of Economic Research, Inc.

KEYNES, J. M. (1930). Economic possibilities for our grandchildren.

KING, R. G., PLOSSER, C. I. and REBELO, S. T. (1988). Production, growth and business cycles: I. the basic neoclassical model. *Journal of Monetary Economics*, **21** (2-3), 195–232.

KOPYTOV, A., ROUSSANOV, N. and TASCHERAU-DUMOUCHEL, M. (2021). *Cheap Thrills: the Price of Leisure and the Global Decline in Work Hours*. Tech. rep.

KRUSELL, P., OHANIAN, L., RÍOS-RULL, J. and VIOLANTE, G. L. (2000). Capital-skill complementarity and inequality: A macroeconomic analysis. *Econometrica*, **68** (5), 1029–1053.

LEGROS, P. and NEWMAN, A. F. (2007). Beauty is a beast, frog is a prince: Assortative matching with nontransferabilities. *Econometrica*, **75** (4), 1073–1102.

LINDENLAUB, I. (2014). Sorting multidimensional types: Theory and application. *Review of Economic Studies*, **84** (2), 718–789.

LISE, J., MEGHIR, C. and ROBIN, J.-M. (2016). Matching, sorting, and wages. *Review of Economic Dynamics*, **19**, 63–87.

MACURDY, T. E. (1981). An empirical model of labor supply in a life-cycle setting. *Journal of Political Economy*, **89** (6), 1059–85.

MCFADDEN, D. (1989). A method of simulated moments for estimation of discrete response models without numerical integration. *Econometrica*, **57** (5), 995–1026.

MICHELACCI, C. and PIJOAN-MAS, J. (2012). Intertemporal labour supply with search frictions. *Review of Economic Studies*, **79** (3), 899–931.

— and — (2015). Labor supply with job assignmentunder balanced growth. *Journal of Economic Theory*.

PAKES, A. and POLLARD, D. D. (1989). Simulation and the asymptotics of optimization estimators. *Econometrica*, **57** (5), 1027–1057.

PIKETTY, T. and SAEZ, E. (2013). Optimal labor income taxation. *handbook of Public Economics*, **5**, 391–474.

RACHEL, L. (2021). *Leisure-Enhancing Technological Change*. Tech. rep.

SCHEUER, F. and WERNING, I. (2017). The taxation of superstars. *Quarterly Journal of Economics*, **132** (1), 211–270.

SHAO, L., SOHAIL, F. and YURDAGUL, E. (2021). *Labor Supply and Establishment Size*. Tech. rep.

SONG, J., PRICE, D., GUVENEN, F., BLOOM, N. and VON WACHTER, T. (2018). Firming up inequality. *Quarterly Journal of Economics*, **134** (1), 1–50.

VEBLEN, T. (1899). The theory of the leisure class.

VERESHCHAGINA, G. (2021). *Progressive taxation and sorting of managers across firms*. Tech. rep.

WOLCOTT, E. (2021). Employment inequality: Why do the low-skilled work less now? *Journal of Monetary Economics*, **118**, 166–177.

A Data Appendix

A.1 Data Construction

Overview The main dataset used in the analysis is the Current Popultion Survey (CPS). In particular, I use the Ongoing Rotation Groups (ORG) due to the detailed information on earning and hours worked. In Section 2 also make use of the Annual Social and Economic supplement (ASEC) to obtain a long-run measure of average hours worked in the economy, since CPS-ORG is only available from 1979. However, to obtain cross-sectional wage hours elasticity (as well as in the estimation), I use CPS-ORG as main dataset[53]. Unless otherwise noted, I focus my analysis on males aged 25-64. All statistics are computed using the provided sample weights.

Hours The variable used to compute hours statistic is *hourslw*, which represents hours worked at the main job last week. I drop individuals working part-time (defined as individuals working less than 20 hours per week[54]). As a robustness check, I repeat the computation of the hours-wage elasticity using usual hours worked and find very similar results, both qualitatively and quantitatively.

Wages Real hourly wages are defined as weekly earnings divided by usual weekly hours. Wages are adjusted for inflation using codes for CPI adjustment provided with the dataset[55].

A.2 Additional Evidence

In this section I provide evidence of the two main facts in the analysis (aggregate and cross-sectional) through other data sources. Moreover, I show that the facts presented are not unique to the U.S. experience, but have been shown to hold in several other countries as well.

A.2.1 Hours Worked in US

Aggregate I start by showing that the long-run decline in hours worked in U.S. is present across several datasets. Figure A.1 shows the decline in hours worked in US using an index

[53] The main advantage of using CPS-ORG is that questions on work and hours refer to current pay or usual hours, unlike CPS-ASEC,which use as a reference period of the last week or last year. For details on how variables are extracted and cleaned from CPS, see `https://ceprdata.org/wp-content/cps/CEPR_ORG_Wages.pdf`.

[54] I also considered as robustness other thresholds to define part time workers, e.g. >30 hours per week, obtaining very similar results.

[55] Available at `http://ceprdata.org/cps-uniform-data-extracts/cps-outgoing-rotation-group/`

from FRED/BLS. The decline in weekly hours worked has been between 15 to 20% in the post-war period, roughly in line with the decline in the main figure in the text.

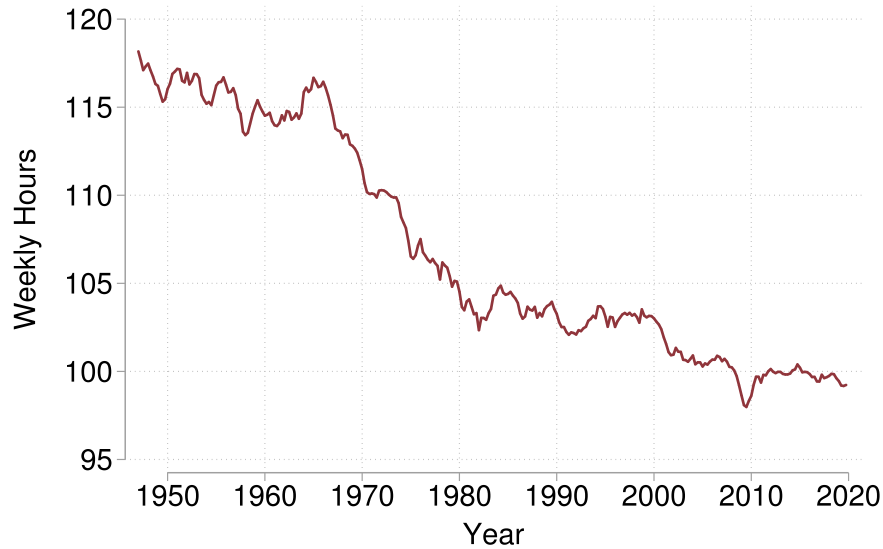

Figure A.1: Weekly hours worked index in US (2012=100).

Notes: Source: Available on the FRED/BLS website (Series PRS85006023).

Figure A.2 shows series for weekly average hours worked in non-farm establishments in US (this corresponds to Figure 2a in Boppart and Krusell (2020). The advantage of this dataset is that it extends back in time until at least 1890 (data before this year are available only every ten years). The figure confirms qualitatively and quantitatively the main figure in the text.

Breakdown by Gender Next, I provide the breakdown for hours worked by gender. This is plotted in Figure A.3. The breakdown by gender reveals substantial heterogeneity: while annual hours worked in US have remained roughly constant, hours for men have overall declined, while hours for women have increased significantly. This is important because it shows that the reason why US exhibit constant annual hours worked is simply the result of opposing trends between men and women. This point has been made, for example, in Kopytov *et al.* (2021).

Intensive vs Extensive Margin Given the focus of this paper, I abstracted in the analysis from the extensive margin of hours worked, i.e. the participation rate (defined as number of employed over total population). Figure A.4 provides a justification for doing so in US: the figure plots the participation rate for the whole 20th century. With the exception of the last

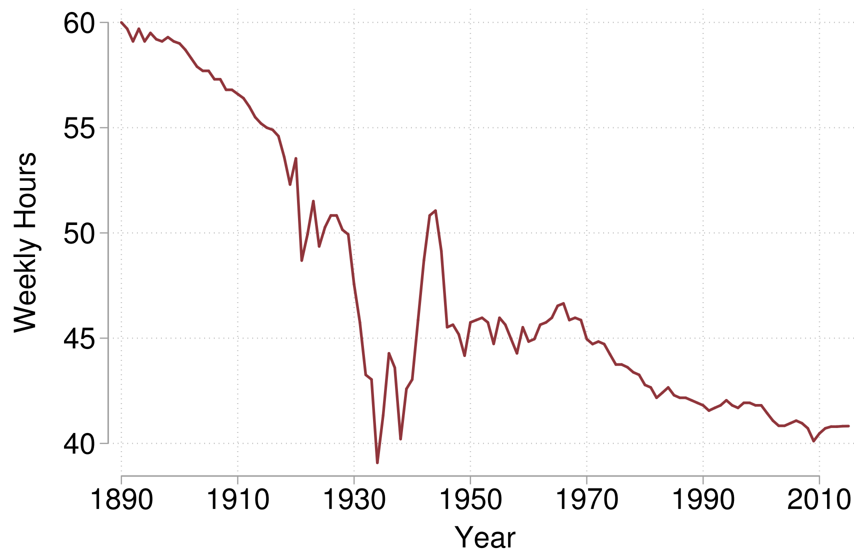

Figure A.2: Weekly hours worked in US.

Notes: Source: Boppart and Krusell (2020), Greenwood and Vandenbroucke (2005). The original data sources are *Historical Statistics of the United States: Colonial Times to 1970* and the *Statistical Abstract of the United States*. See Greenwood and Vandenbroucke (2005) for details.

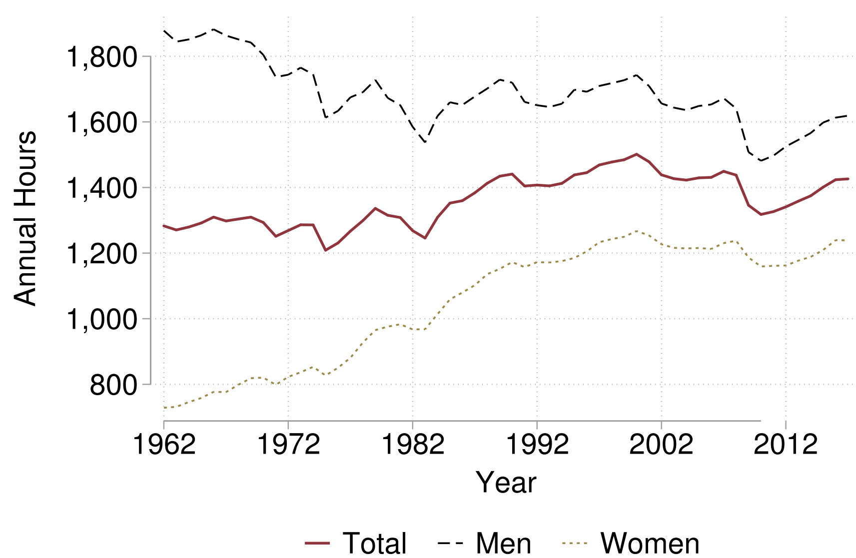

Figure A.3: Annual hours worked in US, by gender.

Notes: Source: Cociuba *et al.* (2018) using CPS/ASEC. See the paper for details on data construction.

20 years (and due to the steep increase in the participation rate for women), the participation rate has been remarkably stable at around 55%. A similar point has been made in Boppart and Krusell (2020), who notice that long-run trends in the intensive margin of hours worked swamp those in the extensive margin of hours worked. Moreover, when comparing the contribution of the extensive vs the intensive margin of hours in driving hours per adult, Bick *et al.* (2018) find that the extensive margin is the main driver in low to middle-income countries; from middle-income to rich countries, viceversa, the main driver is the intensive margin. These arguments are in favor of the approach I take in this paper, which focuses on the intensive margin.

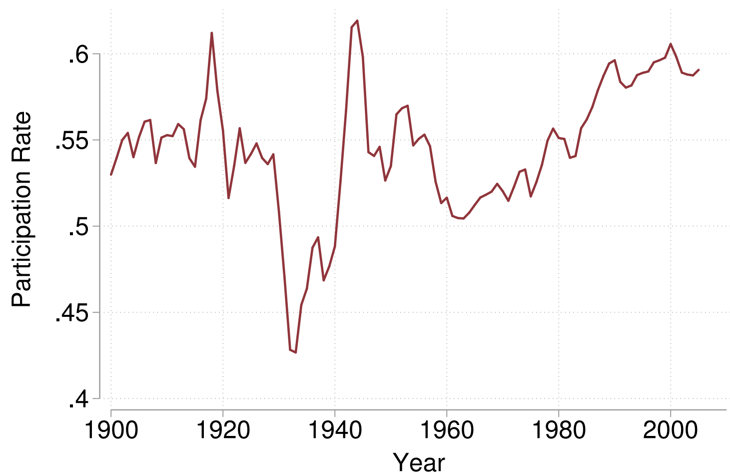

Figure A.4: Participation rate in US.

Notes: Source: Francis and Ramey (2009) using CPS. See the paper for details on data construction.

A.2.2 Hours Worked Across Countries

In this sub-section I provide evidence on the patterns of hours worked across other countries than U.S. The data come from the recent contribution in Bick *et al.* (2018), who collect hours worked data across a large set of countries and describe the patterns I reproduce here[56]. Figure A.5 and Figure A.6 report, for a sample of middle-income and rich countries[57], hours per worker and hours per adult, respectively. The message is similar: hours decline with GDP per capita, similar to the US experience (with the exception, as noted previously, of the post-1980 period).

[56] I refer the reader to that paper for details on data construction.

[57] Unlike Bick *et al.* (2018), I focus in this paper on the US experience; hence I plot hours worked for middle and rich countries, since US in the post-war period has had similar GDP per capita levels as middle-income countries (earlier) and rich countries (in recent years). It should be kept in mind that patterns of extensive and intensive margins measure of hours worked across all countries are even richer, as explained in Bick *et al.*

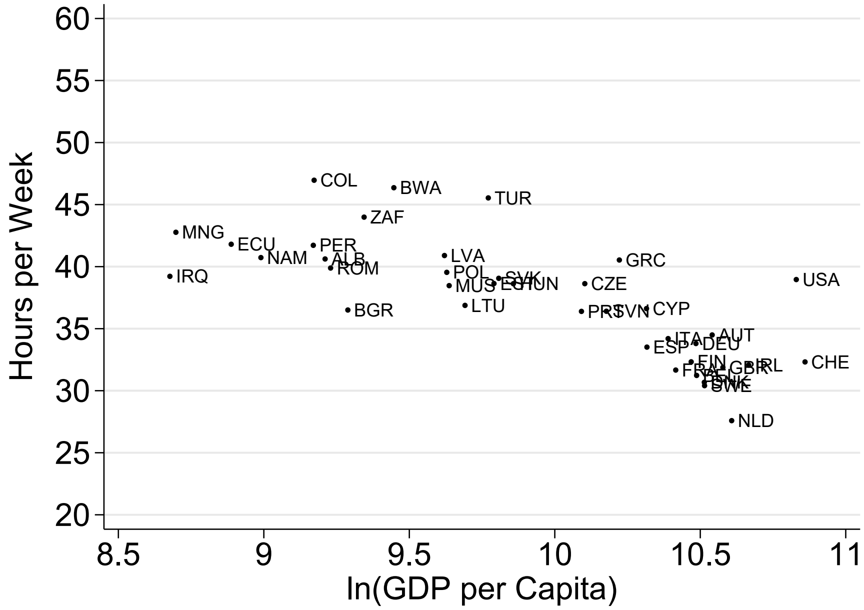

Figure A.5: Hours per worker in middle and rich countries.

Notes: Source: Bick *et al.* (2018) database. See the paper for details on data construction.

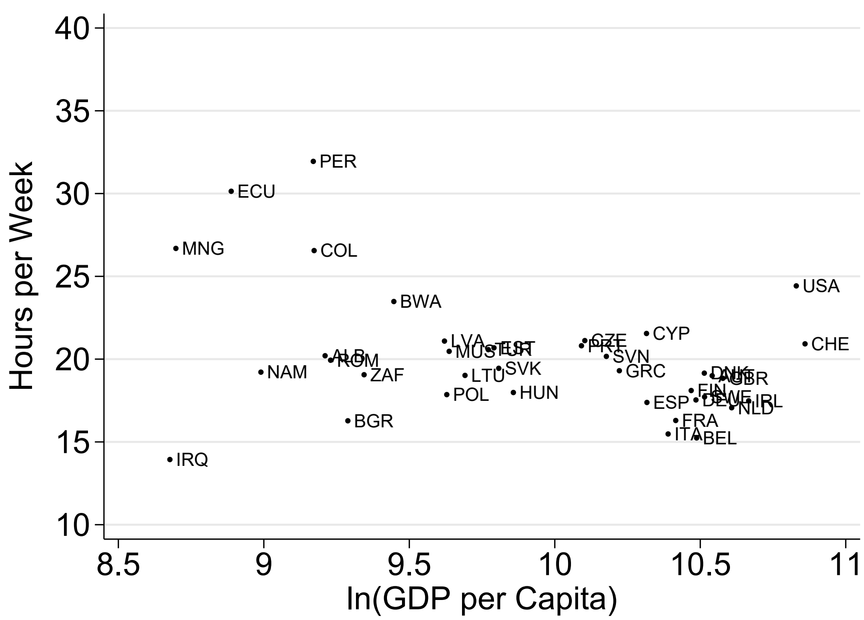

Figure A.6: Hours per adult in middle and rich countries.

Notes: Source: Bick *et al.* (2018) database. See the paper for details on data construction.

A.2.3 Hours Worked - Cross Section

Hours By Wage Decile In figure A.7, I divide the sample of workers in CPS by wage decile (i.e., I compute the wage decile year by year) and plot the average hours worked by each decile. To avoid cluttering, I only plot average hours worked for the top, the bottom, and the middle decile. The figure clearly shows that workers with the lowest wages (black line) decreased their hours worked; workers with highest wages (red, dotted line) increased their hours, albeit the increase is concentrated in the 1980's and 1990's. The figure confirms the results from the main regression exercise in Section 2.

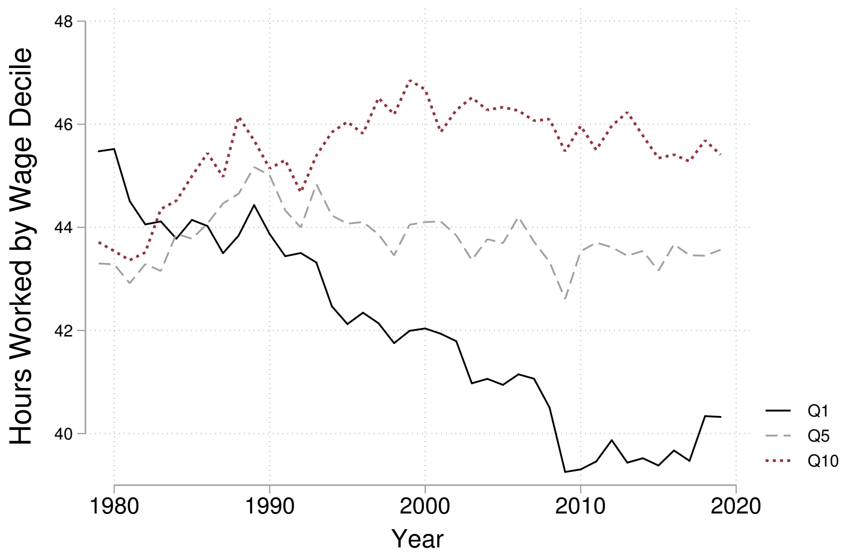

Figure A.7: Hours worked by wage decile (Q1 = decile with lowest wage). Source: CPS and own calculations.

ATUS Next, I turn to another dataset to inspect whether trends in hours worked and leisure by skill category are unique to CPS. I use the American Time Use Survey (ATUS), already used for studies regarding leisure trends, e.g. Aguiar and Hurst (2007).
Following Boppart and Ngai (2021) (see their paper for details on data construction), I plot average hours worked on the market and leisure hours by skill category. I approximate skill by years of education, and I consider four skill categories, from high-school or less (less than 12 years of schooling) to more than college (more than 16 years of schooling). I plot the evolution of leisure hours and market hours (hours worked) by educational category in Figure A.8 and Figure A.9, respectively.
The figures show very interesting patterns. From the beginning of the sample until roughly

(2018) and Bick *et al.* (2022b).

1985, workers of each education category consume more leisure hours and less market hours. Importantly, the movement are almost perfectly parallel along educational categories. Starting from 1985, however, highly educated workers diminsh their leisure hours and increase their market hours; this is not true for low educated workers, who continue to consume more leisure and provide lower market hours as years go by. Hence, evidence from ATUS data confirm the patterns highlighted using CPS: hours worked by skill display divergent trajectories, but only starting from the 1980's. I conclude that data from ATUS is supporting the mechanism and provides additional evidence to motivate the analysis.

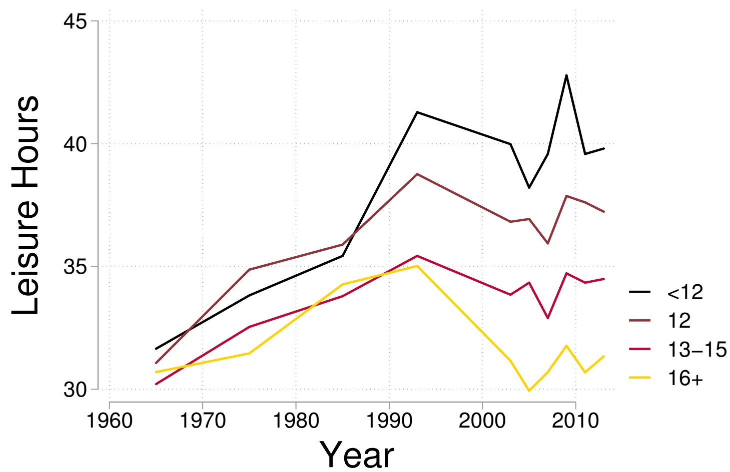

Figure A.8: Leisure hours by education (each line represents an educational category, defined as number of years of education of the individual). Source: ATUS; Boppart and Ngai (2021).

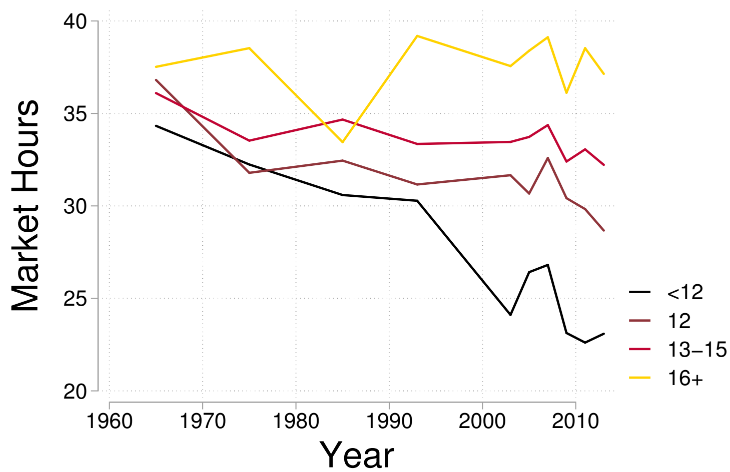

Figure A.9: Hours worked by education (each line represents an educational category, defined as number of years of education of the individual). Source: ATUS; Boppart and Ngai (2021).

ASEC I examine in another dataset the robustness of the cross-sectional evidence presented thus far using CPS-ORG and ATUS. I use the CPS-March Supplement (ASEC), which has the key advantage that it extends back since 1962 for at least some of the variables of interest for this study. In particular, CPS-ASEC contains information on both 'usual weekly hours worked' (from 1976) and 'actual hours worked' (from 1962). I examine the wage-hours correlation using both variables. However, notice that (as highlighted in Heathcote *et al.* (2010)), the variable 'usual weekly hours' should contain a more correct representation of hours worked by workers.
I first compute the hours-wage correlationin ASEC for males, using the variable 'usual hours worked'. I run the same regression as in the main empirical section of the paper, which is specified in regression (1). The resulting estimated coefficient β is plotted in Figure A.10. Not suprisingly, the coefficient exhibits a very similar pattern than CPS-ORG.

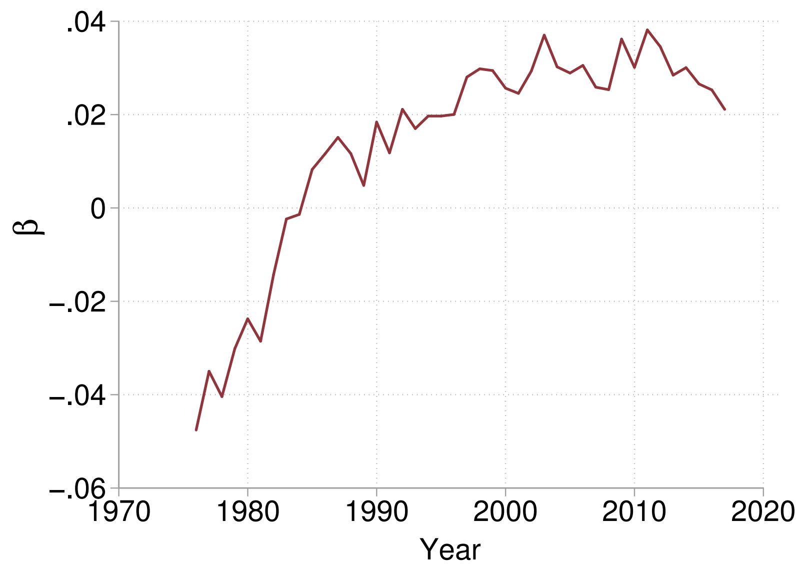

Figure A.10: Cross-sectional hours-wage correlation using 'usual weekly hours worked' from ASEC, 1976-2018, males only. Source: ASEC, own calculations.

Next, I examine using the same dataset the hours-wage correlation using the variable 'actual hours worked' (*ahrsworkt*). This is reported in Figure A.11. Two things are worth noticing. First, throughout the whole sample, the correlation is significantly lower when using actual hours worked, compared to usual hours worked. Second, and reassuringly for the theory, the correlation is clearly upward trending, as in the case for usual hours worked. Notice that the *level* of the correlation could be significantly lower (or higher) depending on the extent of the division bias in computing hourly wages (Borjas (1980)). This is due to the fact that when wages are computed as earnings divided by hours worked, higher reported hours result in a lower computed hourly wage (and viceversa). These considerations are not new, and have been discussed previously in the literature (see e.g. Heathcote *et al.* (2010)). To sum up, while the level of the correlation seems to be affected by the measure of hours worked used, the increasing correlation is a very robust pattern.

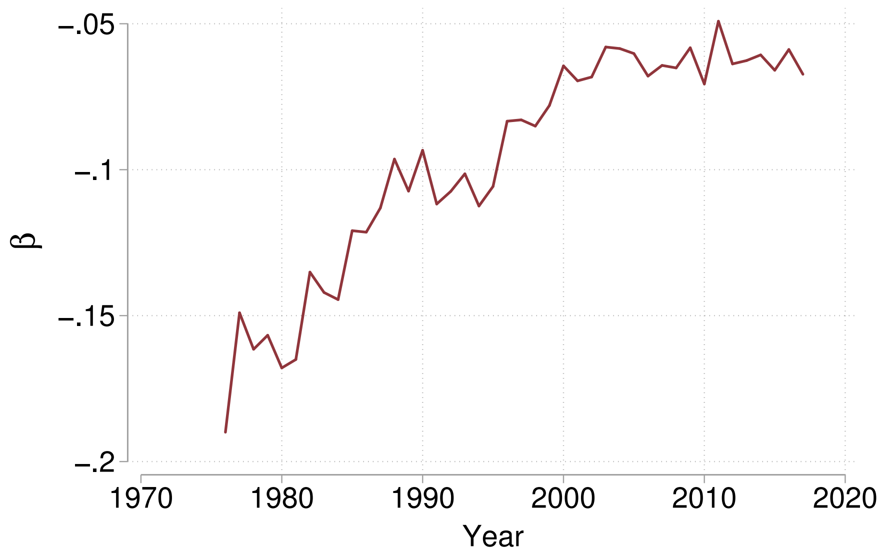

Figure A.11: Cross-sectional hours-wage correlation using 'usual weekly hours worked' from ASEC, 1962-2018, males only. Source: ASEC, own calculations.

By Gender Even though in the main analysis I focus on males, I also report for completeness the hours-wage correlation for females, using CPS-ASEC and usual hours worked. The correlation is reported in Figure A.12. On average, the correlation is bigger than for males. The overall pattern is increasing (i.e., the correlation is significantly lower in 1980 than in 2018) but the steep increasing pattern observed for males is not present for females. Both observations can be explained by the fact that, as women's participation rates and earnings have increased, the associated income effects moderate the wage-hours correlation. A similar point has been made in Heathcote *et al.* (2010). Notice, moreover, that the fact that the hours-wage correlation increases with development is a pattern that is robust for females as well, see Bick *et al.* (2018) (Figure 6, panel B. in their paper). To sum up, I conclude that focusing on males for the analysis provides a way to abstract from changes in participation rates and associated income effects (important for females) but importantly, the patterns that motivate the paper are at least broadly similar between genders.

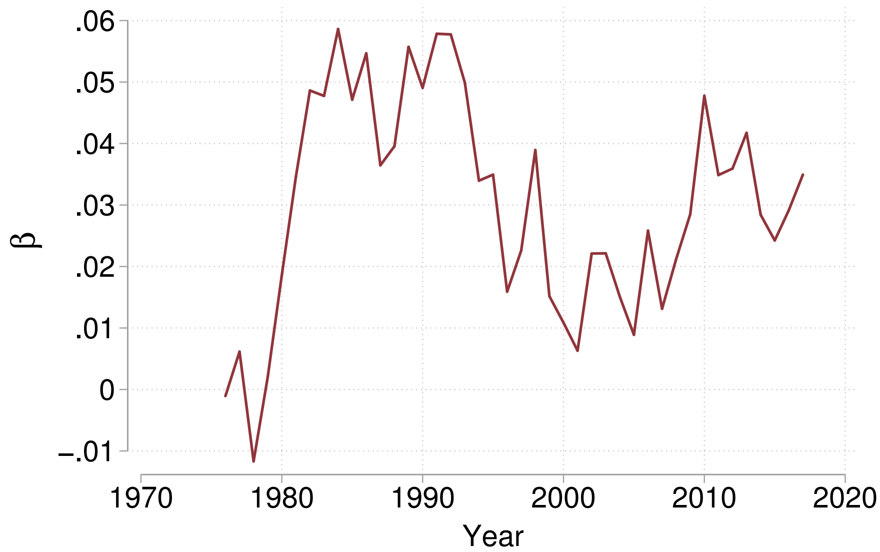

Figure A.12: Cross-sectional hours-wage correlation using ’usual weekly hours worked’ from ASEC, 1976-2018,females only. Source: ASEC, own calculations.

A.2.4 Implications: Supporting Figures

In Figure A.13 I plot the gender gap in wages and its relationship with the elasticity of earnings to hours by occupation. The data is from Goldin (2014), and I refer the reader to the original paper for details on the construction of the variables. The key message, already highlighted in the original paper, is that there is a strong, negative relationship between the elasticity of earnings to hours and the gender gap. In other words, the more earnings respond to hours, the higher is the gender gap at the occupation level. This suggests that how time is valued in production (at the occupation level) might be fundamental to study the determinants of the gender gap.

The second element in the data that supports the hypothesis that the gender gap might be related to technological changes in the value of working time in production is plotted in Figure A.14. It shows the gender gap over time in US, by wage decile in the population. What this figure clearly shows is that while the gender gap has reduced across wage deciles, starting from the 1990’s, the pace at which it has reduced changed significantly for workers at the top (red dashed line) and in the middle percentile (black line). Very similar evidence is reported in Blau and Kahn (2017). Couples with the evidence that earnings are particularly elastic to hours at the top of the wage distribution (which is precisely what is predicted by the model), this suggests that the mechanism I propose in this paper to explain income inequality across males might also be very useful in explaining gender inequality across genders. I pursue the full investigation in a separate project.

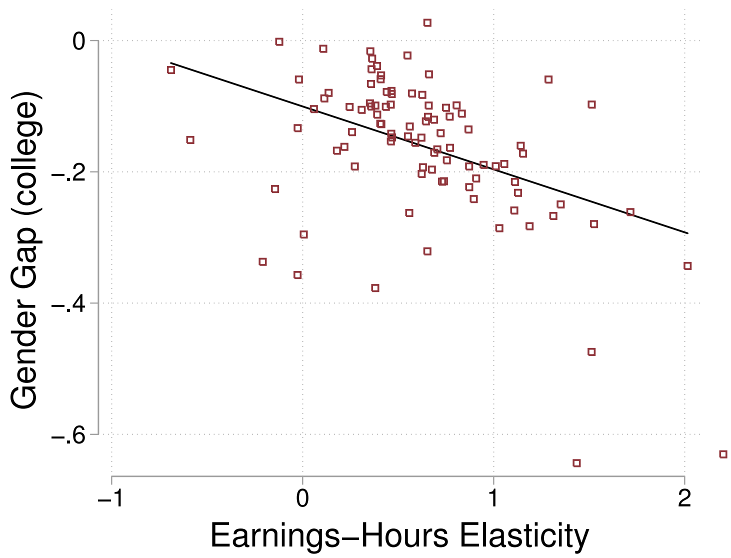

Figure A.13: Gender Wage Gap and Hours Elasticity (US).

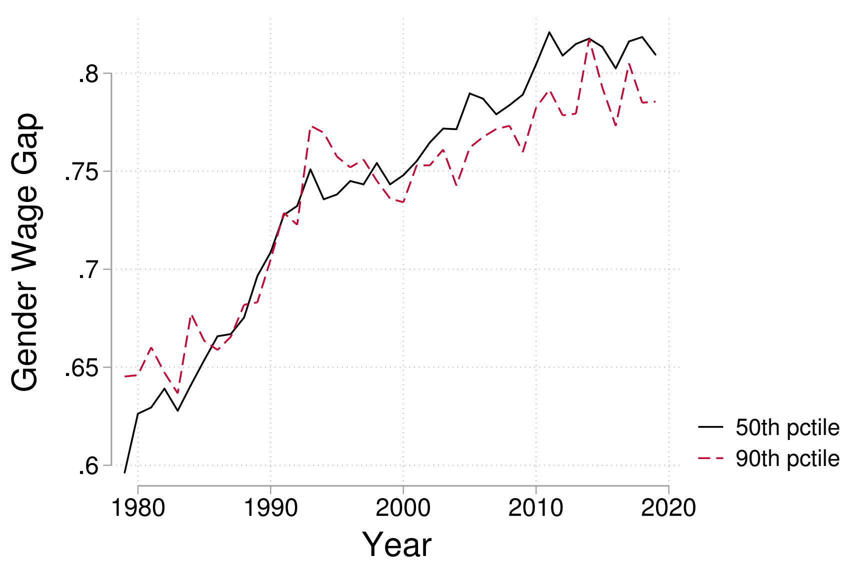

Figure A.14: Gender Wage Gap across Wage Deciles (US).

B Theory Appendix

B.1 Conditions for Assortative Matching

Proof of Proposition 2 We write the terms in (9) explicitly as follows:

$$U_y = u_c \cdot f_y + U_h \cdot \frac{\partial h}{\partial y} = u_c \cdot f_y \tag{B.1}$$

$$U_x = u_c \cdot (f_x + f_h h_x) + u_h h_x + U_h \cdot \frac{\partial h}{\partial y} = u_c \cdot (f_x + f_h h_x) + u_h h_x \tag{B.2}$$

$$U_V = -u_c \tag{B.3}$$

And notice that $U_h = 0$ by the envelope theorem since U is maximized with respect to h.

$$U_{xy} = \left(u_{cc} f_y + u_{cc} f_h h_y\right) f_x + u_c \left(f_{xy} + f_{xh} h_y\right) + \left(u_{cc} f_y + u_{cc} f_h h_y\right) f_h h_x + u_c h_x \left(f_{hy} + f_{hh} h_y\right) + u_{hh} h_x h_y \tag{B.4}$$

$$U_{Vx} = \left(-u_{cc} + u_{cc} f_h h_V\right) f_x + u_c \left(f_{xh} h_V\right) + \left(-u_{cc} + u_{cc} f_h h_V\right) f_h h_x + u_c \left(f_{hh} h_x h_V\right) + u_{hh} h_V h_x \tag{B.5}$$

The sorting condition (7) becomes:

$$\underbrace{u_{cc}\left(f_y + f_h h_y\right)\left(f_x + f_h h_x\right) + u_c\left(h_x(f_{hy} + f_{hh} h_y) + f_{xy} + f_{xh} h_y\right) + u_{hh} h_x h_y}_{U_{xy}} - \underbrace{\left[u_{cc}\left(-1 + f_h h_V\right)\left(f_x + f_h h_x\right) + u_c\left(f_{xh} h_V + f_{hh} h_x h_V\right) + u_{hh} h_V h_x\right]}_{U_{Vx}} \cdot \underbrace{\left(-f_y\right)}_{\frac{U_y}{U_V}} > 0 \tag{B.6}$$

We can simplify this expression further, by getting explicit expressions for h_y and h_V using the implicit function theorem. First, notice that the first order condition of the household with respect to hours h is:

$$u_c(\underbrace{f - V}_{w})w_h + u_h = 0 \tag{B.7}$$

Denote $F(y, V, h(y, V)) = u_c w_h + u_h$. By virtue of the theorem applied to (B.7) we can write:

$$\frac{\partial F}{\partial V} + \frac{\partial F}{\partial h} h_V = 0$$

from which we have that:

$$\underbrace{-u_{cc} w_h}_{\frac{\partial F}{\partial V}} + \underbrace{\left(u_{cc} f_h w_h + u_c w_{hh} + u_{hh}\right)}_{\frac{\partial F}{\partial h}} h_V = 0 \tag{B.8}$$

Rearranging and multiplying by h_x, and noting that f_h and w_h are interchangeable since $w = f - V$:

$$h_x u_{cc} f_h = h_x h_V \left(u_{cc} f_h f_h + u_c f_{hh} + u_{hh}\right) \tag{B.9}$$

Analogously, by noting that $\frac{\partial F}{\partial y} + \frac{\partial F}{\partial h} h_y = 0$ by the implicit function theorem applied to (B.7), we get:

$$\underbrace{f_h u_{cc} w_h}_{\frac{\partial F}{\partial y}} + \underbrace{\left(u_{cc} f_h w_h + u_c w_{hh} + u_{hh}\right)}_{\frac{\partial F}{\partial h}} h_y = 0 \tag{B.10}$$

Hence, similarly to before we can rearrange and multiply by h_x to get:

$$f_h h_x u_{cc} f_h = h_x h_y \left(u_{cc} f_h f_h + u_c f_{hh} + u_{hh}\right) \tag{B.11}$$

Use (B.9) and (B.11) in the sorting condition above (B.6) to get:

$$\begin{aligned} u_{cc}(f_y + f_h h_y) f_x + u_c(f_{xh} h_y) + u_c(f_{xy} + f_{hy} h_x) - \\ \left(u_{cc}(-1 + f_h h_V) f_x + u_c(f_{xh} h_V)\right) \cdot (-f_y) > 0 \end{aligned} \tag{B.12}$$

Notice that (B.8) and (B.10) imply that:

$$\begin{aligned} -1 &= -F_h h_V \frac{1}{u_{cc} w_h} \\ f_y &= -F_h h_y \frac{1}{u_{cc} w_h} \end{aligned}$$

where $F_h = \frac{\partial F}{\partial h}$. Rearranging the latter two equations, we have that:

$$\frac{-1}{h_V} = \frac{f_y}{h_y} \implies -f_y h_V = h_y$$

Using $-f_y h_V = h_y$ in (B.12), we are simply left with:

$$f_{xy} > -f_{hy} h_x \tag{B.13}$$

since u_c is assumed to be positive.

This is the condition expressed in Corollary 1. To fully express this in terms of primitives, we further write h_x explicitly as follows. Using the implicit function theorem, we have that

$$h_x = -\frac{\begin{vmatrix} \frac{\partial U_h}{\partial x} & \frac{\partial U_h}{\partial y} \\ \frac{\partial U_y}{\partial x} & \frac{\partial U_y}{\partial y} \end{vmatrix}}{|H|}$$

The determinant of the Hessian of the problem, appearing in the denominator, is equivalent to B.15. We can write explicitly the terms in the numerator as:

$$\begin{aligned}
U_{xh} &= u_{cc} f_x f_h + u_c f_{xh} \\
U_{yx} &= u_{cc} f_x (f_y - V_y) + u_c f_{xy} = u_c f_{xy} \\
U_{hy} &= u_{cc} f_h (f_y - V_y) + u_c f_{hy} = u_c f_{hy} \\
U_{yy} &= u_{cc} (f_y - V_y)(f_y - V_y) + u_c (f_{yy} - V_{yy}) = u_c (f_{yy} - V_{yy})
\end{aligned}$$

We can plug the resulting expression for h_x in B.13 to get:

$$f_{xy} > -f_{hy} \left[\frac{-u_c (f_{yy} - V_{yy})(u_{cc} f_x f_h + u_c f_{xh}) - u_c f_{hy} u_c f_{yx}}{u_c (f_{yy} - V_{yy})(u_{cc} f_h f_h + u_c f_{hh} + u_{hh}) - u_c f_{hy} u_c f_{yh}} \right]$$

which becomes (simplifying u_c and bringing the denominator to the left hand side):

$$f_{xy} \left[(f_{yy} - V_{yy})(u_{cc} f_h f_h + f_{hh} + u_{hh}) - u_c f_{hy} u_c f_{yh} \right] > -f_{hy} \left[(f_{yy} - V_{yy})(u_{cc} f_x f_h + u_c f_{xh}) - u_c f_{hy} u_c f_{yx} \right]$$

which simplifies to

$$f_{xy} \left[(f_{yy} - V_{yy})(u_{cc} f_h f_h + f_{hh} + u_{hh}) \right] > -f_{hy} \left[(f_{yy} - V_{yy})(u_{cc} f_x f_h + u_c f_{xh}) \right]$$

We can finally divide both the rhs and lhs of the previous equation (note that $f_{yy} - V_{yy} <$

0 so we switch sign):

$$f_{xy}\left[(u_{cc}f_hf_h+f_{hh}+u_{hh})\right]>-f_{hy}\left[(u_{cc}f_xf_h+u_cf_{xh})\right]$$

which is the condition in the main text. ■

Alternative Proof of Proposition 2 We can repeat the derivation before using a similar method. This derivation makes use of the Hessian of the second order condition of the problem to derive the PAM (NAM) condition, similarly to Eeckhout and Kircher (2018). Notice that we start with the same problem:

$$U(x,y,V)=\max_{y,h}\quad u\left(f(x,y,h)-V,h\right) \tag{B.14}$$

This time, we don't make use of U as a matching problem (and the solution method in Eeckhout (2018) and Eeckhout and Sepahsalari (2018)), but rather derive PAM/NAM conditions based on the Hessian of the problems. We take the FOCs, which are:

$$\begin{aligned}U_h=0 &\implies u_cf_h+u_h=0\\ U_y=0 &\implies u_c(f_y-V_y)=0\end{aligned}$$

The second order condition of the problem require that the Hessian $\mathbf{H}$ is negative definite. In this case, the Hessian $\mathbf{H}$ is:

$$\mathbf{H}=\begin{bmatrix}\frac{\partial U_h}{\partial h} & \frac{\partial U_h}{\partial y}\\ \frac{\partial U_y}{\partial h} & \frac{\partial U_y}{\partial y}\end{bmatrix}$$

For $\mathbf{H}$ to be negative definite, we require the determinants of the principal minors to have alternating signs, starting with negative sign. This is equivalent to say that we need $\frac{\partial U_h}{\partial h}<0$ and $|\mathbf{H}|>0$, where $|\mathbf{H}|$ is the determinant of $\mathbf{H}$. We can write each term composing $|\mathbf{H}|$ as follows [58]:

[58] We use the notation U_{hh} to express $\frac{\partial U_h}{\partial h}$, and similarly for other terms.

$$
\begin{aligned}
U_{hh} &= u_{cc} f_h f_h + u_c f_{hh} + u_{hh} \\
U_{hy} &= u_{cc}(f_y - V_y) f_h + u_c f_{hy} \\
U_{yh} &= u_{cc}(f_y - V_y) f_h + u_c f_{yh} \\
U_{yy} &= u_{cc}(f_y - V_y)(f_y - V_y) + u_c(f_{yy} - V_{yy})
\end{aligned}
$$

hence for optimality, we require $U_{hh} = u_{cc} f_h f_h + u_c f_{hh} + u_{hh} < 0$ and $U_{hh}U_{yy} - U_{hy}U_{yh} > 0$. Using the explicit expressions derived just above, we can write the latter inequality as:

$$
\begin{aligned}
U_{hh}U_{yy} - U_{hy}U_{yh} = (u_{cc} f_h f_h + u_c f_{hh} + u_{hh}) \left(f_{yy} - V_{yy} \right) \\
- (u_c f_{hy})(f_{yh}) > 0,
\end{aligned}
\tag{B.15}
$$

where we divded both terms in B.15 by u_c since it is assumed to be positive. We can get more intuition if we write the term $f_{yy} - V_{yy}$ explicitly. To do so, we differentiate the second FOC ($f_y - V_y$) with respect to y, along the equilibrium allocation:

$$
f_{yx}\mu_y + f_{yy} + f_{hy}h_y - V_{yy} = 0
$$

which implies

$$
f_{yy} - V_{yy} = -f_{yx}\mu_y - f_{hy}h_y
$$

Use this into B.15 to have:

$$
\begin{aligned}
&= -u_{cc} f_h f_h f_{yx}\mu_y - u_c f_{hh} f_{yx}\mu_y - u_{hh} f_{yx}\mu_y \\
&- u_{cc} f_h f_h f_{hy} h_y - u_c f_{hh} f_{hy} h_y - u_{hh} f_{hy} h_y - u_c f_{hy} f_{yh} > 0
\end{aligned}
\tag{B.16}
$$

Next, we want to write h_y in the explicitly in the previous expression. To do so, differentiate the first FOC ($U_h = 0$) with respect to worker type, to get:

$$u_{cc}(f_x\mu_y + f_Y + f_h h_y - V_y)f_h + u_c f_{hx}(\mu_y + f_{hy} + f_{hh}h_y) + u_{hh}h_y = 0$$
$$u_{cc}(f_x\mu_y + f_h h_y)f_h + u_c(f_{hx}\mu_y + f_{hy} + f_{hh}h_y) + u_{hh}h_y = 0$$

Rearrange and multiply both sides by $h_y f_{hy}$ to get:

$$f_{hy}(u_{cc}f_x f_h \mu_y + u_c f_{hx}\mu_y + u_c f_{hy}) = (-u_{cc}f_h f_h - u_c f_{hh} - u_{hh})h_y f_{hy} \tag{B.17}$$

Use the terms on the right hand side of (B.17) into (B.16) and rearrange to get:

$$\mu_y(f_{yx}(-u_{cc}f_h f_h - u_c f_{hh} - u_{hh}) + f_{hy}(u_{cc}f_x f_h + u_c f_{hx})) > 0 \tag{B.18}$$

which is the condition expressed in the main text. ■

C Estimation Appendix

C.1 Estimation Results

In the following figure, I plot the model and data moments targeted in the estimation.

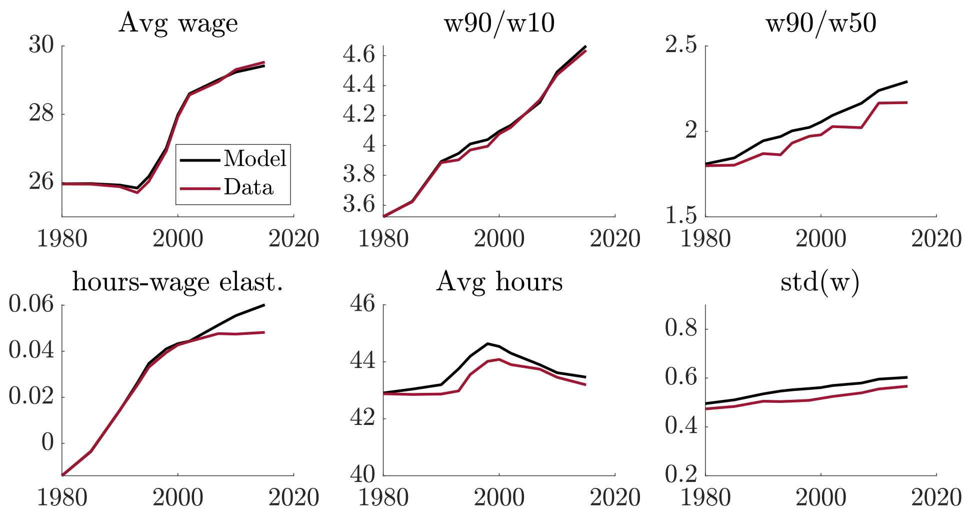

Figure C.1: Model Fit (1980-2015)

The figure below shows the estimated parameter changes for the period of the quantitative application.

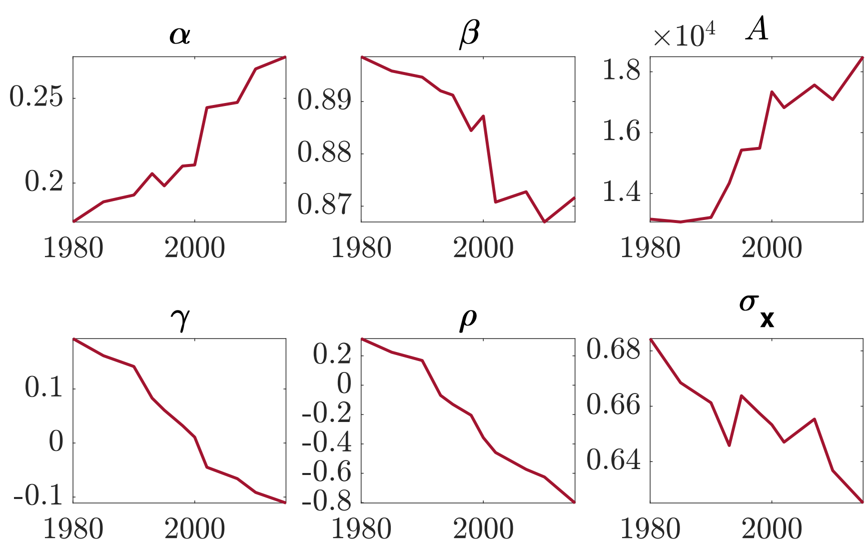

Figure C.2: Estimated parameter changes (1980-2015)

C.2 Additional Counterfactuals

Figure C.3 contains coounterfactuals coming from moving parameters one at a time, i.e. feeding the model with parameters changes (respectively, γ, α, ρ, and β) and leaving all other parameters unchanged.

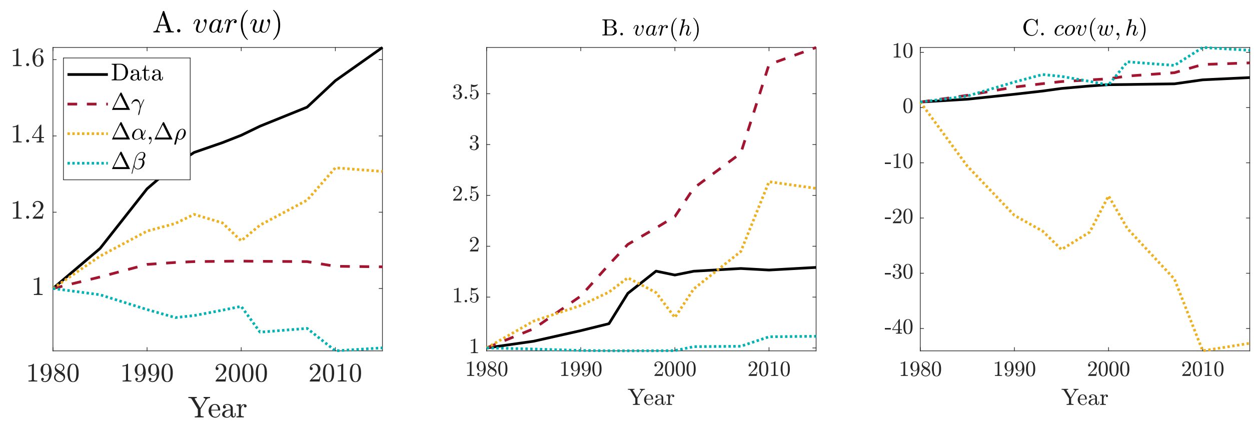

Figure C.3: Alternative Counterfactuals.

C.3 Robustness

Table C.3 reports the estimated parameter values for a lower value of σ (curvature in consumption). Table C.4 reports the estimates following an alternative assumption on the skills and jobs distributions (assuming they follow a Beta distribution).

$$f(x,y,h) = A\left(\beta(\alpha y^{\rho} + (1-\alpha)h^{\rho})^{\frac{\gamma}{\rho}} + (1-\beta)x^{\gamma}\right)^{\frac{1}{\gamma}}$$

Parameter	1980	2015	Meaning
β	0.40	0.90	weight of (y,h) in prod.
α	0.73	0.97	weight of jobs y in prod.
γ	-3.3	-4.5	compl. (x,y/h)
ρ	0.56	0.04	compl. (h,y)
A	4,489	27,597	TFP

Table C.1: Estimated parameters with $f(x,y,h) = A\left(\beta(\alpha y^{\rho} + (1-\alpha)h^{\rho})^{\frac{\gamma}{\rho}} + (1-\beta)x^{\gamma}\right)^{\frac{1}{\gamma}}$.

Parameter	1980	2015	Meaning
β	0.09	0.17	weight of (x,h) in prod.
α	0.80	0.85	weight of skills in prod.
γ	1.01	-0.34	compl. ($\tilde{x}$,y)
ρ	0.17	0.11	compl. (h,x)
A	32,209	27,276	TFP

Table C.2: Estimated parameters with $f(x,y,h) = A\left(\beta(\alpha x^{\rho} + (1-\alpha)h^{\rho})^{\frac{\gamma}{\rho}} + (1-\beta)y^{\gamma}\right)^{\frac{1}{\gamma}}$.

Parameter	1980	2016	Meaning
β	0.99	0.98	weight of (x,y) in prod.
α	0.05	0.13	weight of skills in prod.
γ	0.51	0.09	compl. $(h,(x,y))$
ρ	0.98	-0.57	compl. (x,y)
A	28,5179	26,677	TFP

Table C.3: Estimated parameters with $\sigma = 1.2$ (lower income effects).

Parameter	1980	2016	Meaning
β	0.94	0.91	weight of (x,y) in prod.
α	0.08	0.14	weight of skills in prod.
γ	0.30	-0.07	compl. $(h,(x,y))$
ρ	0.93	-2.48	compl. (x,y)
A	16,5103	16,5703	TFP

Table C.4: Estimated parameters with x, y following a Beta dsitributiong (Lise *et al.* (2016)).