

# Intertemporal Labor Supply with Search Frictions\*

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## Abstract

Since the 70's, the number of hours worked on the job by US prime age male workers and wage inequality have both increased. We argue that the two facts are related. We use a labor market search model with on the job search where by working longer hours individuals acquire greater skills. Since job candidates are ranked by productivity, greater skills not only increase worker's productivity in the current job but also help the worker to obtain better jobs. When job offers become more dispersed, wage inequality increases and workers work longer hours to obtain better jobs. As a result average hours per worker in the economy increase. This mechanism accounts for around two-thirds of the increase in hours observed in the data. Part of the increase is inefficient because workers obtain better jobs at the expense of other workers competing for the same jobs.

*JEL classification:* J22, J31, E21

*Keywords:* working hours, wage inequality, search, human capital

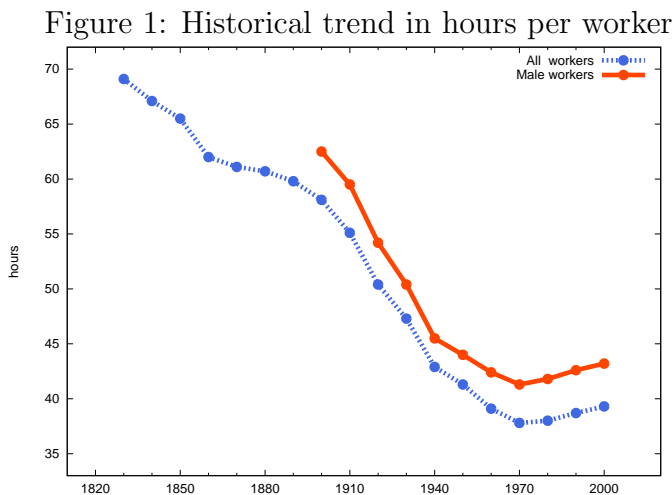
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## 1 Introduction

The average number of hours worked on the job by US workers have increased substantially between 1970 and 2000. This contrasts sharply with the steady secular decline observed over time. Figure 1 documents the long run evolution of the average number of hours worked per US employee in the full population (dotted line) and in the male only population (solid line). The trend reversal since the 70's is apparent and important: now a prime age male worker in the US works longer hours on the job than back in the 50's. Wage inequality, measured either as returns to skill or within-skill dispersion, has also started to increase in the 70's after remaining stable for some decades (see for example Katz and Autor, 1999 and Eckstein and Nagypal, 2004).



Notes: Historical trend in hours usually worked per week by an employed person. The figure is from Vandembroucke (2009), see his paper for details.

In this paper we argue that the increase in wage inequality explains the trend reversal in hours per worker. The timing of changes is consistent with this interpretation. Some micro evidence also suggests that individuals work longer hours when wage inequality is higher: Bell and Freeman (2001) show that individuals work longer hours when employed in occupations with higher wage inequality, both in the US and in Germany. More importantly, we use decennial US Census data to document that hours per worker have increased more in occupations, industries and groups of workers (such as highly educated and high wage earners) that have also experienced higher increases in wage inequality. Similar evidence is provided by Kuhn and Lozano (2005). Roughly we find that an increase of ten percentage points in the variance of logged hourly wage leads to a percentage increase in hours worked on the job of around 2.5 percentage points.

We propose a simple theory where an increase in wage inequality leads to an increase in the average number of hours worked on the job. The theory builds on the idea that by working longer hours, individuals acquire greater skills and obtain better jobs, so working time yields an *intertemporal* return. The model is an extension of the standard search model of unemployment originally due to McCall (1970), where we allow for on-the-job search, a working hours decision, and human capital accumulation. Workers (either employed or unemployed) can receive job offers from a given wage distribution. Thus there is wage dispersion and identical workers earn different income. Workers are risk averse and accumulate assets, so wage changes exert both an income and a substitution effect on working time decisions. Hours worked increase current as well as future labor income because by working longer hours individuals accumulate human capital. Human capital enhances worker productivity and thereby the probability of receiving job offers. This builds on, among others, Blanchard and Diamond (1994), Shi (2002), and Shimer (2005): the idea is that, due to a coordination problem, workers may apply for the same job and applicants are ranked according to their productivity, so more skilled workers are more likely to be offered a job.<sup>1</sup> We show that a rise in the dispersion of job offers, which translates into higher within-skill wage inequality, raises the gains from obtaining better jobs and gives workers greater incentives to work longer hours. This raises average hours worked on the job in the economy.

To quantify the contribution of wage inequality to the trend reversal in hours per worker in the US, we calibrate the model to match a variety of statistics on labor flows and wage dynamics at the micro level. We focus on prime age male workers because these workers are likely to actively engage in the labor market. We analyze the effects of increasing the return to skill and within-skill wage inequality so as to match the rise in wage inequality experienced by the US since the 70's. We find that wage inequality can account for around 2/3 of the trend reversal in hours per male worker emerged over the last thirty years. In general our quantitative model predicts that an increase of twenty percentage points in the variance of logged hourly wage (which is roughly the increase observed in the data) leads to a 5 percentage points increase in average hours worked, which is consistent with the micro level empirical evidence previously discussed.

The model also predicts that the intertemporal return to working time has increased in the US since the 70's. Following Bell and Freeman (2001), we measure the intertemporal return by looking at the (conditional) correlation of current wages with past hours. Using data from the Panel Study of Income Dynamics (PSID), we show that the in-

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<sup>1</sup>Indeed, it is well known that unemployment rates are lower for more skilled workers. Blau and Robins (1990) provide direct evidence that more skilled workers receive more job offers.

tertemporal return to working time has indeed increased in the US since the 70's, in a way quantitatively consistent with the model.

In the model, workers work longer hours to accumulate human capital that help them in obtaining better jobs. But workers do not internalize that their higher human capital reduces other workers' possibility to obtain the same jobs, which generates an externality. We find that in the 70's Americans worked around 4 hours per week more than what is socially optimal. Since the externality is stronger when inequality is greater, we also find that the inefficiency has increased over time. This provides a novel interpretation for the claim that Americans are overworked and it might justify restricting working time decisions.

The ranking mechanism is key for generating a positive relation between residual wage inequality and hours worked. In the absence of a positive link between a worker's productivity and the job offer probability, the model predicts that hours fall in response to an increase in the dispersion of wage offers. This is consistent with Heathcote, Storesletten, and Violante (2008) who show that, when agents have sufficiently high insurance possibilities, hours fall in response to an increase in wage uncertainty.

The link between wage inequality and hours worked can help explaining why, since the 70's, hours per worker in the US have increased by approximately 20 percent relative to continental European countries, see OECD (2004, chap. 1). Over the same period, the return to skill and within-skill wage inequality have increased substantially in the US but little in Europe (see Gottschalk and Smeeding, 1997 and Katz and Autor and 1999). The focus on the US to explain the diverging evolution in hours across the two sides of the Atlantic is novel. In general the trend reversal of hours per worker in the US is a major puzzle for theories, such as Prescott (2004), that rely on changes in specific European institutions to explain the divergence in hours between the US and Europe.<sup>2</sup>

The idea that hours worked increase worker's human capital has already been put forward, in the context of a competitive labor market model, by Shaw (1989) and Imai and Keane (2004). Olivetti (2006) has also used the idea to explain the recent rise in US female labor force participation. In all these models the intertemporal return to working time is just determined by the elasticity of productivity to the human capital accumulated through working hours. We show that, in a labor market with search frictions, several

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<sup>2</sup>One could argue that in the last 30 years Europe has been characterized by an increase in unemployment risk. In that case, our model has generally ambiguous implications for the dynamics of hours per worker in Europe. On the one hand, an increase in unemployment risk reduces the rate of use of the stock of human capital accumulated through working time, which reduces working hours. On the other hand, higher unemployment risk increases the value of accumulating precautionary savings when employed, which increases working hours.

other salient features of the labor market affects this return. In particular, we find that within-skill wage inequality accounts for a major part of the observed intertemporal return in working time and for its evolution over time.

Section 2 contains the evidence with US Census data. Section 3 presents a simple model that highlights some links between inequality and hours. The model is extended in Section 4 and parameterized in Section 5. Section 6 quantifies the role of wage inequality in explaining the US experience in hours per worker and looks at further testable implications. Section 7 discusses robustness checks. Section 8 concludes. The Appendix provides details on data. A Technical Appendix is available as online material.

## 2 Some evidence on the link between inequality and hours per worker

We use cross sectional data from the US to show that changes in wage inequality and in hours are positively related. The data come from the decennial Census as provided by the Integrated Public Use Microdata Series (IPUMS) at the University of Minnesota ([www.ipums.org](http://www.ipums.org)). We use the 1 percent sample and, to focus on workers likely to actively engage in the labor market, we restrict the analysis to full time male workers aged between 25 and 64 years old. Regressions and descriptive statistics are calculated using Census provided individual weights. Further details on the data are in Appendix A.1.

Since most of the increase in wage inequality has occurred after 1970—see for example Eckstein and Nagypal (2004) and Heathcote, Perri, and Violante (2010)—we focus on decennial censuses 1980 through 2000, which include the question “During the weeks worked in 19xx, how many hours did this person usually work each week?”. This is the basis for constructing the variable *Hours usually worked per week*. Table 1 describes the evolution of hours per worker for different educational groups and different wage levels. Since hours worked per week exhibits a pronounced mass point at 40 hours of work, we start focusing on the fraction of workers usually working long hours (more than 49 hours per week). This fraction has increased for all skill groups. The increase has been more pronounced for more educated workers: the fraction of workers with long hours has increased by 5 percentage points for workers with less than high school, while the increase for workers with a college degree has been more than twice as much. The increase has also been more pronounced for workers at the top of the wage distribution. Since the increase in wage inequality has been more pronounced for high skilled workers, this is *prime facie* evidence for the existence of a potential link between wage inequality and hours. Similar results are obtained when considering average hours worked per week.

To analyze more formally the link between wage inequality and hours worked we

Table 1: Fraction of men usually working long hours

<b>Census year:</b>	<b>1980</b>	<b>1990</b>	<b>2000</b>
All	.23	.28	.32
By education:			
Less than High School	.18	.20	.23
High School	.21	.24	.27
Some College	.23	.28	.32
College	.28	.36	.40
By wage quintiles:			
1st	.15	.17	.17
2nd	.17	.21	.24
3rd	.17	.24	.29
4th	.19	.26	.34
5th	.31	.42	.49

Notes: Fraction of male workers usually working long hours (more than 49 hours per week). Source of data is US Census 1% sample. Sample is male workers of age 25-64 working full time. A low quintile is associated with a low wage.

identify segments of the labor market where workers search for jobs, firms search for workers, and with limited mobility across segments. One can think of each segment as an island in the standard Lucas and Prescott (1974) economy or as a submarket in the more recent papers by Shimer (2007), Alvarez and Shimer (2008), and Mortensen (2007). We are interested in checking whether segments that have experienced larger increases in inequality are also segments where workers have increased more their hours worked on the job. Since the definition of labor market segment is somewhat arbitrary, we experiment with several alternatives depending on whether the relevant segments of the labor market are defined by 1) the two-digit occupational categories in the Census, 2) the combination of an occupational category and an educational level, 3) the two-digit industry categories in the Census, or 4) the combination of an industry category and an educational level. Occupation and industry categories are based on the 1990 Census Bureau classification scheme. We consider four educational levels: 1) Less than high School; 2) High School; 3) Some College; 4) College.

We then estimate segment by segment regressions (one for each year and labor market segment) of log hourly wages on a set of race dummies, educational levels dummies, and a quartic on age. To reduce measurement error, wages are calculated only for workers who usually work more than 30 hours per week and they are employed for more than 30 weeks in the year and whose hourly wage is greater than half of the minimum wage in the corresponding year. For each specific segment and for each year we use the wage regressions residuals to calculate four different measures of inequality: the variance, and the 90–10, the 90–50, and the 50–10 percentile differences. We then estimate the following

multivariate regression models:

$$n_{jt} - n_{jt-1} = \varphi_I \cdot (INE_{jt} - INE_{jt-1}) + \beta_x \cdot X_{jt} \quad (1)$$

where  $j$  denotes the labor market segment,  $n_{jt}$  is a measure of hours worked (either average hours or fraction of workers with long hours),  $INE_{jt}$  measures wage inequality, and  $X_{jt}$  is a set of controls which include a constant, the changes in the average value of the variables entering the individual wage regressions in levels plus the change in the average log wage in labor market segment  $j$ . Changes are calculated over the period 1980-2000, so that  $t - 1 = 1980$  while  $t = 2000$ . The estimation method is Weighted Least Square using Census provided weights. We are interested in the sign and magnitude of the coefficient  $\varphi_I$ . A positive value for  $\varphi_I$  means that hours worked have increased more in labor market segments which have experienced greater increases in inequality. Table 2 reports the results from running regression (1) when considering alternative specifications. For each specification we report the coefficient  $\varphi_I$  and in parenthesis its standard error. In square brackets we also report the  $R^2$  of the corresponding regression. Each column corresponds to a different definition of labor market segment, each row to a different measure of inequality  $INE$ . Panel A deals with the incidence of long usual hours, panel B with average hours usually worked. In all specifications the coefficient  $\varphi_I$  is positive and generally strongly significant. Only when inequality is measured by the difference between the median and the bottom decile, statistical significance is less clear-cut. This could be due to the somewhat smaller cross sectional variation in the changes of the inequality measure. The  $R^2$  is between five and ten percentage points higher when measuring inequality changes by the variance of residuals. With this inequality measure, the simple multivariate regressions in (1) explains between 40 and 57 percent of the cross sectional variability of changes in hours. The estimates in Panel B indicate that an increase of ten percentage points in the variance of log wages leads to a percentage increase in average hours worked on the job of around 2.5 percent. Overall the evidence in Table 2 is consistent with the claim that workers work longer hours when wage inequality increases.

### 3 A two-period stylized model

In this section we study how labor market conditions affect the intertemporal return to hours worked and the choice of hours. We do so in a purposely very stylized model that highlights some basic forces. The model will also suggest some natural ways to identify key parameters of the general model for the quantitative analysis presented in Section 4.

Table 2: Regression analysis of changes in hours on changes in residual wage inequality

Market segments by:	Occup	Occup x Educ	Industry	Ind x Educ
<b>A) Change in the fraction of long hours</b>				
Change in variance	.58** (.21) [.57]	.51** (.11) [.49]	.55** (.15) [.46]	.57** (.11) [.44]
Change in 90-10 perc.	.20** (.07) [.54]	.15** (.05) [.42]	.26** (.07) [.50]	.16** (.03) [.37]
Change in 90-50 perc.	.25* (.11) [.54]	.20** (.07) [.43]	.29** (.12) [.43]	.16** (.05) [.32]
Change in 50-10 perc.	.34 (.23) [.45]	.20* (.10) [.36]	.46** (.10) [.49]	.28** (.07) [.36]
<b>B) Change in average hours</b>				
Change in variance	9.8** (4.5) [.48]	8.6** (2.4) [.40]	10.9** (2.7) [.53]	10.2** (2.0) [.44]
Change in 90-10 perc.	3.4** (1.2) [.47]	2.5** (1.0) [.35]	4.9** (1.1) [.55]	3.0** (.6) [.38]
Change in 90-50 perc.	4.4* (2.0) [.47]	3.4** (1.2) [.35]	6.0** (2.3) [.48]	3.0** (.8) [.33]
Change in 50-10 perc.	5.7 (4.5) [.37]	3.2 (2.0) [.29]	8.0** (1.8) [.51]	5.0** (1.3) [.37]
<i>N.</i>	79	277	86	233

Notes: Estimates of the  $\varphi_I$  coefficient in regression (1). Standard Error in parenthesis.  $R^2$  in square brackets. “\*\*\*”: significant at 1%; “\*\*”: significant at 5%. Panel A deals with the incidence of long hours, Panel B with average hours worked. Rows correspond to different inequality measures, columns to different labor market segments. Changes are calculated over the 1980-2000 period. Sample is full time male workers of age 25-64. Estimation method is Weighted Least Square. Data from US Census 1% sample, see Appendix A.1 for further details.

The economy lasts for two periods. In the first period workers are employed with human capital  $h \in \mathbb{R}_+$ . By working  $n$  hours they produce an amount of efficiency units of labor  $h^\alpha n^\theta$ . The job remunerates efficiency units of work at rate  $\omega$ . We refer to  $\omega$  as the *wage* rate of the job. So the worker’s income is  $\omega h^\alpha n^\theta$ . Next period’s stock of human capital  $h'$  is related to the number of hours worked in the current period:  $h' = a n$ . Here



for simplicity we are assuming that human capital fully depreciates in a period.

Next period, workers are unemployed with probability  $\pi$ . In practice  $\pi$  is the joint probability that a worker becomes unemployed *and* that he does not find a new job in the period. Thus  $\pi$  is increasing in the job separation probability and decreasing in the job finding probability. An unemployed worker obtains income (and leisure) worth  $\bar{u}$  in utility terms. If the job is not destroyed, the worker can receive a job offer from a firm that pays a wage  $\omega'$ . Job offers are received with probability  $p(h')$ , which is increasing in the worker's human capital  $h'$ . The job offer probability  $p$  should be interpreted as the product of a parameter related to labor market *tightness* and a term that characterizes the effects of human capital on search activity. There are several reasons why human capital may help in getting job offers. One is that more skilled workers may be more efficient at job searching activities. Another is that, due to a coordination problem as in Blanchard and Diamond (1994), Shi (2002), and Shimer (2005), workers may apply for the same job and applicants are ranked according to their productivity, so more skilled workers are more likely to be offered a job. The latter is our favorite interpretation.<sup>3</sup>

Job offers are a random draw from a given wage distribution  $F(\omega)$ . The distribution  $F$  captures within-skill wage inequality. In equilibrium workers will accept offers whenever  $\omega' > \omega$ . For simplicity we assume that the wage offer distribution is discrete with mass  $1 - q$  at  $\omega_1$  and  $q$  at  $\omega_2 > \omega_1$ . Preferences over consumption and leisure are given by

$$v(c, n) = \ln c - \lambda n$$

where  $\lambda > 0$  measures the effort cost of working. This choice of preferences implies that the income and the substitution effects cancel out exactly, so that permanent wage changes have no effects on hours worked. For simplicity we assume that workers do not save and can not borrow. Therefore, consumption is simply equal to labor income.

We solve the model backwards. In the second period an employed worker solves

$$V_2(h', \omega') = \max_{n'} \left\{ \ln(\omega' h'^{\alpha} n'^{\theta}) - \lambda n' \right\}, \quad (2)$$

which yields  $n' = \frac{\theta}{\lambda}$ . In the first period, a worker with human capital  $h$ , who currently

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<sup>3</sup>Blau and Robins (1990) provide direct evidence that more skilled workers receive more job offers. Here we model ranking and the effects of skill on job offers probabilities in reduced form. Montgomery (1991) and Peters (1991) provide an explicit probabilistic model, known as the *urn-ball process*, that leads to a coordination problem in job applications and to ranking of applicants. Reduced-form functions have been used before by Acemoglu (2001), Acemoglu and Shimer (2001), Michelacci and Suarez (2006), and Mortensen and Wright (2002).

receives wage  $\omega \in \{\omega_1, \omega_2\}$ , chooses hours by solving the following Bellman equation:

$$V_1(h, \omega) = \max_n \left\{ v(\omega h^\alpha n^\theta, n) + \beta \pi \bar{u} + \beta(1 - \pi) V_2(h', \omega) \right. \\ \left. + \beta(1 - \pi) p(h') \int_{\mathbb{R}} \max\{V_2(h', s) - V_2(h', \omega), 0\} dF(s) \right\}$$

subject to  $h' = an$ . Using our simple wage offer distribution we can rewrite  $V_1(h, \omega)$  as

$$V_1(h, \omega) = \max_n \left\{ \ln(\omega h^\alpha n^\theta) - \lambda n + \beta \pi \bar{u} + \beta(1 - \pi) \left[ V_2(h', \omega) + p(h') q(\ln \omega_2 - \ln \omega) \right] \right\}$$

which, after using (2), yields the following first order condition:

$$\lambda = \frac{\theta}{n} + \beta(1 - \pi) \left[ \frac{\alpha}{n} + \frac{dp}{dh'} a q(\ln \omega_2 - \ln \omega) \right]. \quad (3)$$

This says that hours worked are chosen by equating the marginal disutility of working to its marginal return. The marginal return is the sum of the value of the marginal increase in current income, equal to  $\theta/n$ , and the expected marginal increase in future income—which corresponds to the second term in the right hand side of equation (3). This *intertemporal return* to hours worked is affected by the rate of utilization of human capital  $(1 - \pi)$ , the productivity elasticity to human capital  $\alpha$ , and by the expected increase in income due to job offers. It is to this second channel that inequality in jobs is related.

To obtain an explicit expression for  $n$  we log-linearize the function describing the job offer probability:

$$p(h') \simeq p_0 + p_1 (\ln h' - \ln \bar{h}) \quad (4)$$

where  $\bar{h}$  is an appropriately defined constant while  $p_1$  is the semi elasticity of the job offer probability to human capital. This allows to solve for  $n$  so as to obtain that

$$n = \frac{\theta + \beta(1 - \pi) [\alpha + p_1 q(\ln \omega_2 - \ln \omega)]}{\lambda}. \quad (5)$$

Notice that the intra-temporal return to hours worked (the first term in the numerator of the right-hand side of the equation) is independent of  $\omega$ . This is because with log preferences the income and the substitution effect cancel out. The intertemporal return to hours worked (the second term in the numerator) increases with the semi-elasticity of the job offer probability with respect to human capital  $p_1$  and with the dispersion of job offers  $(\ln \omega_2 - \ln \omega)$ . A higher  $p_1$  implies that hours worked are marginally more valuable in obtaining better jobs, while a greater dispersion makes these jobs more valuable. The

two effects interact with each other and encourage working time. The intertemporal return to hours worked is also decreasing in the unemployment probability  $\pi$ , because a higher  $\pi$  reduces the rate of use of the stock of human capital  $h'$ , while it is increasing in the productivity elasticity to human capital  $\alpha$ . This last would be the only determinant of the intertemporal return in a competitive labor market model, as in Shaw (1989) and Imai and Keane (2004). Thus hours worked increase when:

1. the productivity elasticity to human capital  $\alpha$  rises.
2. within-skill wage inequality, modeled as a mean preserving spread in the wage offer distribution  $F$ , increases. This effect is stronger when  $p_1$  is larger.

## 4 The general model

We now quantitatively study how much the change in wage inequality (due to the increase in the productivity elasticity to human capital and the dispersion of wage offers) can explain of the evolution of hours per worker in the US. To do so we extend the model in several directions. First, individuals now experience recurrent unemployment spells; second, there is an endogenous unemployment exit probability; third, individuals accumulate assets; fourth, there is a downward trend in hours worked; and finally we allow for more general functional forms for preferences and technology. The first extension is introduced to separately analyze the effects of the job separation rate and the job finding rate on working time decisions. The second implies that unemployment exit rates are affected by workers' human capital. The third extension is important since precautionary savings motives play an important role in hours decisions, see for example Pijoan-Mas (2006). The fourth is introduced to match the secular downward trend in hours per worker observed in the data, see for example McGrattan and Rogerson (2004) and Figure 1. The last extension is introduced to match key features of the data.

### 4.1 Model description

Workers are infinitely lived. Time is continuous as in Lise (2009). An employed worker is characterized by the amount of assets owned  $b_t \in \mathbb{R}_+$ , by the stock of human capital  $h_t \in \mathbb{R}_+$  and by the wage rate of the job where he is employed  $\omega_t \in \mathbb{R}_+$ . When employed, the worker decides how many hours to work and how much to consume. Hours of work generate a flow of income  $\omega_t h_t^\alpha n_t^\theta$  in the current period and increase the stock of human

capital according to the law of motion

$$\dot{h}_t = an_t - \delta h_t,$$

where  $\delta > 0$  represents the depreciation rate of human capital and  $a$  is a given constant. The law of motion of assets is given by,

$$\dot{b}_t = rb_t + \omega_t h_t^\alpha n_t^\theta - c_t$$

where  $r$  is the real interest rate. We also assume that at any point in time  $b_t \geq 0$ , which will correspond to the natural borrowing limit of the economy. Workers are risk averse with instantaneous utility  $v(c_t, \kappa_t n_t)$ . Here  $\kappa_t$  measures the utility cost of working at time  $t$ , which we assume grows over time at rate  $\mu < \delta$ , so that  $\kappa_t = e^{\mu t}$ .<sup>4</sup>

As previously discussed, human capital affects the probability of receiving job offers, which arrive according to a Poisson process with arrival rate

$$p(h, G) = \bar{p} S(h, G), \tag{6}$$

where  $\bar{p}$  measures how labor market tightness affects the job contact rate while the function  $S(h, G)$  characterizes how human capital helps in getting job offers. The function is increasing in worker's human capital  $h$ . It is also decreasing in the cumulative distribution function of workers' human capital in the economy,  $G$ , that is when  $G$  shifts to the right (i.e. it becomes stochastically greater), the job offer probability falls. This is because a worker with given human capital has to compete with relatively more skilled workers for the same jobs, which makes him less likely to be offered a job. We also assume that the function is homogenous of degree zero, which formalizes the idea that a worker's job offer probability is affected by the relative position of the worker in the distribution of human capital. This also guarantees the existence of a steady state equilibrium.

Job offers are drawn from a given distribution  $F$ .<sup>5</sup> Employed workers become unem-

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<sup>4</sup>This modeling is based on the idea by Mincer (1962) and Becker (1965) that workers obtain utility from leisure goods, which are produced combining time at home and some market goods, whose (relative) price falls over time. As a result the utility cost of working in the market rather than at home increases. This mechanism is empirically supported by Gonzales-Chapela (2007). An alternative modeling of the secular trend in hours would be through technological progress and preferences where the income effect dominates the substitution effect. Our modeling choice is partly driven by the partial equilibrium nature of the model.

<sup>5</sup>In principle we could endogenize the wage offer distribution along the lines of Burdett and Mortensen (1998). The Burdett-Mortensen model has been recently extended by Burdett and Coles (2003) to allow for wage tenure contracts and non linear preferences (but still imposing that current income is equal to consumption). As shown by Shi (2009) wage offer distributions can also be obtained in a linear preferences

ployed according to a Poisson process with instantaneous arrival rate  $p_s$ . Let  $\hat{G}$  denote the distribution of  $\hat{h} \equiv \kappa h$ , that will turn out to be time invariant in steady state. The individual state variables of an employed worker and an unemployed worker are given by  $\mathbf{s}_e \equiv (h, b, \omega)$  and  $\mathbf{s}_u \equiv (h, b)$ , respectively. The aggregate state variables are  $\kappa$  and  $\hat{G}$ , but since we focus on steady states we will omit  $\hat{G}$ . In a steady state, the value function of the employed workers is the solution to the following Bellman equation:

$$\begin{aligned} \rho W(\mathbf{s}_e, \kappa) &= \max_{c, n} \left\{ v(c, \kappa n) + p_s [U(\mathbf{s}_u, \kappa) - W(\mathbf{s}_e, \kappa)] \right. \\ &+ p(\kappa h, \hat{G}) \int_{\omega}^{\infty} [W(h, b, i, \kappa) - W(\mathbf{s}_e, \kappa)] dF(i) \\ &\left. + \frac{\partial W}{\partial h} (an - \delta h) + \frac{\partial W}{\partial b} (rb + \omega h^\alpha n^\theta - c) + \frac{\partial W}{\partial \kappa} \mu \kappa \right\} \end{aligned} \quad (7)$$

where we used the assumption that the job offer probability is homogenous of degree zero. The interpretation of the equation is standard. It can be read as an asset type equation that equates permanent income (the term in the left hand side) to realized income (the term in the right hand side). The first term in the RHS is the instantaneous utility from consumption and leisure, the second term represents the expected capital gains (losses) due to unemployment risk, while the third the capital gains due to job offers received on the job. Notice that job offers are accepted only if they are better than the current one, which follows from the fact that  $\frac{\partial W}{\partial \omega}$  is positive. Finally the three terms in the last row are the capital gains due to the accumulation of assets, the accumulation of human capital, and the changes in the utility cost of working, respectively. The first order conditions of the problem with respect to  $c$  and  $n$  are

$$v_1 = \frac{\partial W}{\partial b}, \quad (8)$$

$$-\kappa v_2 = \frac{\partial W}{\partial b} \theta \omega h^\alpha n^{\theta-1} + a \frac{\partial W}{\partial h}. \quad (9)$$

The first equation says that workers equate the marginal utility of consumption to the marginal value of wealth; the second that workers equate the marginal disutility of working to the marginal value of working, which is equal to the sum of the marginal value of the additional current income obtained by working longer hours and the value of increasing human capital. The solution leads to a pair of decision rules for hours and consumption

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model that belongs to the directed search tradition pioneered by Moen (1997). But we are not aware of models that generate endogenously wage distributions in a world where workers differ in human capital, they accumulate savings and where hours worked are an endogenous choice.

given by  $n = g^n(\mathbf{s}_e, \kappa)$  and  $c = g^{c_e}(\mathbf{s}_e, \kappa)$ , respectively.

The problem of an unemployed worker is characterized by the Bellman equation:

$$\begin{aligned} \rho U(\mathbf{s}_u, \kappa) &= \max_{c, \omega_r} \left\{ v(c, 0) + p(\kappa h, \hat{G}) \int_{\omega_r}^{\infty} [W(h, b, i, \kappa) - U(\mathbf{s}_u, \kappa)] dF(i) \right. \\ &\quad \left. + \frac{\partial U}{\partial h}(-\delta h) + \frac{\partial U}{\partial b}(rb - c) + \frac{\partial U}{\partial \kappa} \mu \kappa \right\} \end{aligned} \quad (10)$$

Since  $\frac{\partial W}{\partial \omega}$  is positive it is easy to check that the reservation wage  $\omega_r$  satisfies the condition

$$W(h, b, \omega_r, \kappa) \geq U(\mathbf{s}_u, \kappa) \quad (11)$$

with equality if  $\omega_r$  is strictly positive. The first order condition for consumption reads as

$$v_1 = \frac{\partial U}{\partial b} \quad (12)$$

which is analogous to (9). This together with (11) characterize the decision rules  $\omega_r = g^{\omega_r}(\mathbf{s}_u, \kappa)$  and  $c = g^{c_u}(\mathbf{s}_u, \kappa)$ .

## 4.2 Functional forms

We choose the wage offer distribution  $F$  to be log normal, so that  $\log \omega \sim N(-\frac{\nu}{2}, \nu)$ . This implies that  $F$  has unit mean and that  $\nu$  generates mean-preserving spreads.

The instantaneous utility function is

$$v(c, \kappa n) = \ln c - \lambda \frac{(\kappa n)^{1+\eta}}{1+\eta}, \quad \eta > 0, \lambda > 0$$

where  $\eta$  determines the sensitivity of the marginal disutility of working to hours worked and  $\lambda$  measures the relative weight of leisure.

The ranking process is described through the following logistic function:

$$S(h, G) = \frac{2}{1 + e^{-\gamma[\frac{h}{\psi(G)} - 1]}}, \quad \gamma \geq 0,$$

This function is characterized by a human capital sensitivity parameter  $\gamma$ , and by a shift parameter  $\psi(G)$ , which is function of the equilibrium distribution of human capital  $G$ . Formally  $\gamma$  measures the maximal value of the derivative of  $S$  to human capital, which is reached at  $h = \psi(G)$ . The quantity  $\psi(G)$  characterizes workers' competition for jobs and it increases when the human capital distribution of workers  $G$  shifts to the right. The

logistic function imposes the property that human capital generates marginally more job offers at an average human capital value than at an extreme value (belonging to either tail of the human capital distribution). For example the semielasticity of search efficiency to human capital (i.e. the analogue of  $p_1$  in Section 3) goes to zero when human capital goes to either zero or infinity. This property captures the idea that marginally increasing human capital yields more job offers, only when it gives the worker a productivity edge over a significant mass of workers, which is a general feature of any ranking model. We will assume that  $\psi(G) = H \equiv \int h dG$ , which means that the marginal effect of human capital on the job offer probability is maximized at the average human capital in the population. This is a reasonable assumption if the distribution of human capital is concentrated around its mean, as it will be in our model specification.<sup>6</sup>

### 4.3 The steady state

The model contains a time trend in the utility cost  $\kappa_t$  of working time, so hours of work, human capital, labor income, consumption and assets fall over time. In the Technical Appendix, we show that in steady state the quantities  $\hat{n}_t = n_t \kappa_t$ ,  $\hat{h}_t = h_t \kappa_t$ ,  $\hat{c}_t = c_t (\kappa_t)^{\alpha+\theta}$ , and  $\hat{b}_t = b_t (\kappa_t)^{\alpha+\theta}$  are stationary and we rewrite the Bellman equation in terms of detrended variables so that  $\kappa$  drops from the aggregate state space while the vectors of individual state variables for the employed and unemployed workers become  $\hat{\mathbf{s}}_e = (\hat{b}, \hat{h}, \omega)$  and  $\hat{\mathbf{s}}_u = (\hat{b}, \hat{h})$ , respectively. The solution to these Bellman equations yields decisions rules for (detrended) hours  $\hat{n} = \hat{g}^n(\hat{\mathbf{s}}_e)$ , for (detrended) consumption while employed  $\hat{c} = \hat{g}^{c_e}(\hat{\mathbf{s}}_e)$ , and for (detrended) consumption while unemployed  $\hat{c} = \hat{g}^{c_u}(\hat{\mathbf{s}}_u)$ , whereas the reservation wage of an unemployed worker is always equal to zero.

The steady state of the economy is characterized by a constant unemployment rate  $u$  and by two time-invariant probability measures  $\hat{\Gamma}_e$  and  $\hat{\Gamma}_u$  defined over the  $\sigma$ -algebras generated by the individual state space of the employed workers  $\hat{\mathbf{s}}_e$  and of the unemployed workers  $\hat{\mathbf{s}}_u$ , respectively.<sup>7</sup> Notice that with this notation we can express average hours per worker at time  $t$  as  $E(n_t) = e^{-\mu t} \int_{\mathbb{R}_+^3} \hat{g}^n(\hat{\mathbf{s}}_e) d\hat{\Gamma}_e$

<sup>6</sup>In principle one could assume that  $\psi(G)$  is equal to the mode of the distribution of human capital. In practice the two assumptions would yield very similar results. Under our parametrization, the distribution of human capital is quite symmetric: the mean to median ratio is 0.993 in our benchmark economy for the 70's, and it changes very little over time—it rises slightly to 0.996 in the 00's. We prefer using the mean rather than the mode just for computational reasons.

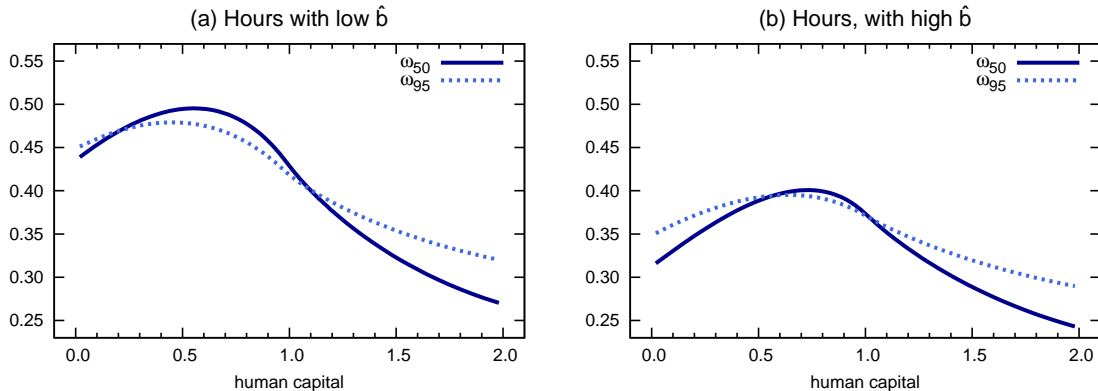
<sup>7</sup>The distribution of detrended human capital  $\hat{G}$  comes from integrating these measures.

#### 4.4 The hours decision

The optimal choice of hours retains the key features of the two-period model described in Section 3. But now, the hours decision interacts with the saving decision, whose main features are as in Lise (2009). Figure 2 characterizes the effects of the three individual state variables  $\hat{h}$ ,  $\hat{b}$  and  $\omega$  on the policy function for hours,  $\hat{n} = \hat{g}^n(\hat{\mathbf{s}}_e)$ . We plot hours against human capital  $\hat{h}$  for different asset levels  $\hat{b}$ 's and wage rates  $\omega$ 's. Panel (a) focuses on a low value of wealth (corresponding to the 20th percentile of the wealth distribution in the benchmark economy, see Table 5), and Panel (b) focuses on a high value of wealth (corresponding to the 95th percentile). In each panel the solid line corresponds to the policy function for a wage rate  $\omega_{50}$  equal to the median of the wage offer distribution, while the dotted line corresponds to a wage rate  $\omega_{95}$  equal to the 95th percentile of the wage offer distribution.

In all cases, the hours decision rule is hump-shaped in the level of human capital. This is because the semi-elasticity of the job offer probability to human capital (i.e.  $p_1$  in Section 3) declines as human capital tends to move away from its average value in the population, which reduces the intertemporal return to working time and thereby hours worked. The policy function reaches its maximum at a human capital value smaller than the average even if the semi-elasticity is maximized at the average. This is because, with less than full capital depreciation, a marginal increase in hours yields smaller percentage increases in human capital at higher human capital levels—which reduces the marginal return to hours worked when human capital increases.

Figure 2: Decision rule for hours



Notes: The decision rules are computed with the parameter values in column *Bench* of Table 5;  $\omega_{50}$  and  $\omega_{95}$  correspond to the 50th and 95th percentiles of the wage offer distribution  $F$ ; low  $\hat{b}$  and high  $\hat{b}$  correspond to the 20th and the 95th percentile of the wealth distribution.

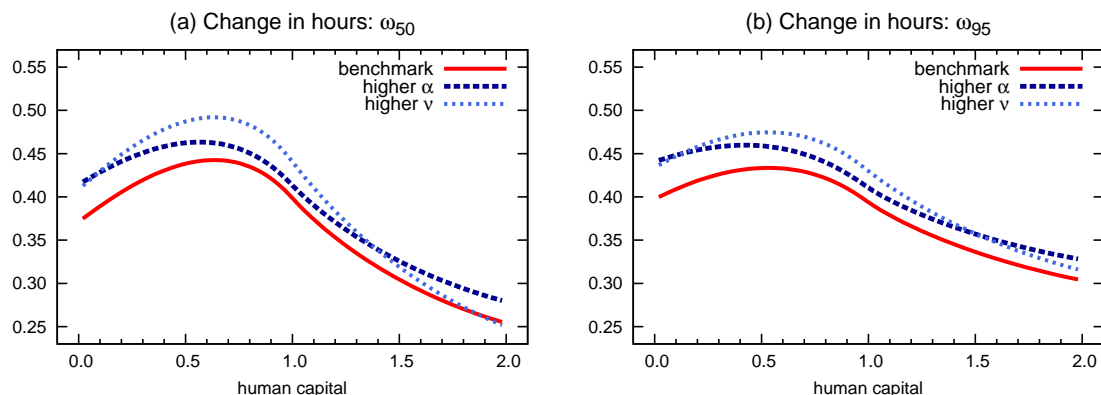


The decision rule for hours is non-monotonic in the wage rate  $\omega$ . This is because a change in  $\omega$  has two opposite effects on hours. On the one hand, as in a standard incomplete markets economy without human capital and search frictions, workers substitute work and leisure intertemporally. So a temporary increase in the wage rate gives workers an incentive to work harder and accumulate savings. On the other hand, as in our two period model, when the current wage rate  $\omega$  is lower a new job offer yields greater expected wage increases, which implies a greater return from accumulating human capital to obtain job offers. This force tends to make hours decreasing in  $\omega$ , while the intertemporal substitution effect makes working hours increasing in  $\omega$ . The semi-elasticity of the job offer probability to human capital determines which of the two effects dominate: at high and low levels of human capital the semielasticity is low and the intertemporal substitution effect dominates, so hours are increasing in  $\omega$ . At medium levels of human capital instead, hours are decreasing in  $\omega$  since the semielasticity is high and thereby the return from accumulating human capital is large.

Finally, hours fall monotonically with wealth. This is because of a standard income effect which makes the marginal value of labor income lower when wealth is higher.

In Figure 3 we characterize the effects on hours of an increase in the dispersion of wage offers  $\nu$  and of an increase in the returns to human capital  $\alpha$ . The policy functions of hours are plotted against human capital. In each panel, the solid line corresponds to the benchmark economy, the dashed line to a greater  $\alpha$ , and the dotted line to a higher  $\nu$ . Panels (a) and (b) differ in the choice of  $\omega$ . As in the two period model of Section 3, an

Figure 3: Decision rule for hours: changes in  $\nu$  and  $\alpha$



Notes: The decision rules for *benchmark* are computed with the parameter values in column *Bench* of Table 5; *higher  $\nu$*  and *higher  $\alpha$*  multiply the corresponding parameter by 2.5;  $\omega_{50}$ ,  $\omega_{95}$  are as in Figure 2. In all cases asset levels are equal to the median.

increase in  $\nu$  or  $\alpha$  raises the incentives to work longer hours. The effects of the increase in  $\alpha$  are quite homogenous at different points of the state space. The effect of the increase in  $\nu$  are instead smaller for very high or very low levels of human capital. This is as in the two-period model, where the effects of an increase in the dispersion of job offers is increasing in the semi-elasticity of the offer probability, which is small at either tail of the distribution of human capital in the population.

## 5 The quantitative exercise

We now use the model to quantify how much wage inequality can explain of the trend reversal in hours per worker in the US. We focus the analysis on prime age male workers because they are most likely to be actively engaged in the labor market, which is a decision neglected by the model. In Table 3 we report the average weekly hours per employed person as reported by McGrattan and Rogerson (2004). The first row focuses on the total male population, the second on prime age males. Average hours per male worker fell by 5.8% between 1950 and 1970 and then they increased by 4.2% in the subsequent thirty years. This corresponds to the numbers in Figure 1 in the Introduction. Changes are

Table 3: Hours per worker, from 1950 to 2000

	Average hours						Perc. change	
	1950	1960	1970	1980	1990	2000	50-70	70-00
Male workers, all	44.0	42.5	41.5	41.9	42.7	43.2	-5.7%	+4.2%
Male workers, aged 25-55	44.9	44.2	43.6	43.9	44.7	45.4	-2.8%	+4.0%

Notes: “Average hours” refers to weekly hours per employed persons. Data come from McGrattan and Rogerson (2004).

slightly more muted for prime age males: hours fell by 2.8% over the 1950–1970 period and they increased by 4.0% in the 1970–2000 period. If we take the downward trend between 1950 and 1970 as given, and we assume that it has continued until 2000, weekly hours for prime age workers should have fallen to 41.9 in 2000. Instead, we observe that in 2000 hours were 45.4, which means that between 1970 and 2000 hours per prime age male worker have increased by 8.5% relative to trend.

We calibrate the model to moment conditions in the 70’s (which will correspond to  $t = 0$ ) and we then analyze how changes in labor market conditions affect average hours per worker in 2000, taking into account changes in the policy function  $\hat{g}^n$  and in the probability distribution of employed workers  $\hat{\Gamma}_e$ . We think of the US as an economy that, over the 1970–2000 period, has experienced an increase in wage inequality due to within skill wage inequality and in the return to skill, which we model through an increase in

Table 4: Model and data statistics

Statistic	Data	Model						
		70's					00's	
		Bench	$\gamma = 0$	Gtr $\gamma$	FH	Yng	Gtr $\eta$	Bench
Monthly separation prob (%)	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3
Monthly unemployment-to-job prob (%)	33	33	33	33	33	33	33	33
Elasticity of job-to-job to past hours	.03	.03	-.10	.04	.03	.03	.03	.07
Variance of reemployment wages	.25	.25	.25	.25	.09	.07	.25	.49
Unemp. with more 1 yr duration (%)	4.0	4.0	0.8	4.0	4.0	4.0	4.0	4.5
Wage growth on human capital growth	.04	.04	.04	.04	.04	.04	.04	.07
Wage growth on hours growth	-.70	-.70	-.70	-.70	-.70	-.70	-.70	-.68
Average wealth to income ratio	3.0	3.0	3.0	3.0	3.0	3.0	3.0	4.0
Average hours per employed worker	.40	.40	.40	.40	.40	.40	.40	.42
Change in hours per worker (50-70) (%)	-2.8	-2.8	-2.8	-2.8	-2.8	-2.8	-2.8	-2.8
Unemployment rate (%)	4.0	3.8	3.8	3.8	3.8	3.8	3.8	3.8
Monthly job-to-job prob (%)	2.8	3.2	3.1	3.2	3.2	3.2	3.2	3.2
Variance of log hourly wages	.26	.17	.17	.17	.07	.05	.17	.32

Notes: The first 10 rows describe statistics used to calibrate the model economy. The column labeled “Bench” refers to the benchmark specification described in Section 5. The column labeled “ $\gamma = 0$ ” refers to the economy without ranking, described in Section 6.2. The other columns refer to the extensions discussed in Section 7. For the “Yng” economy, the variance of reemployment wages is computed after regressing out human capital.

the variance of job offers,  $\nu$ , and in the productivity elasticity to human capital,  $\alpha$ . We start discussing the calibration of the economy in the 70’s and then turn to the 00’s. To help the reader, the targets used and the model fit for the 70’s are reported in Table 4, the calibrated parameters for the economy in the 70’s are listed in Table 5, while the parameters for the 00’s appear in Table 9.

### 5.1 The baseline economy: US in the 70’s

We adopt the convention that one unit of time corresponds to one year. The model is described by 13 parameters. Except for 3 parameters that are chosen by either using a normalization condition or relying on previous estimates (see below), the model is calibrated to match moment conditions on labor flows and wage dynamics at the micro level. This process can be seen as estimation by indirect inference, see for example Gouriéroux, Monfort, and Renault (1993). Out of these 10 parameters, 2 can be set directly. This leaves a system of 8 equations in 8 unknowns.

**Labor market transitions.** In the model, the parameters  $p_s$  and  $\bar{p}$  affect directly average labor market transitions, while the parameter  $\gamma$  regulates the relation between labor market transitions and past hours worked. To identify the first two parameters we

look at average labor market flows in the data. Fallick and Fleischman (2001) calculate, for male workers, the monthly job separation rate to be equal to 1.3%, the monthly job finding rate for the unemployed to be around 33%, and the monthly job to job rate for the employed to be 2.8%. We set  $p_s$  to reproduce the average separation rate and use  $\bar{p}$  to match the average job finding probability. Since  $\bar{p}$  also determines the average job to job movements, we will use the job to job transition rates as an over-identifying restriction of the model.

Table 5: Parameter values in the 70's

Parameter	Value					
	Bench	$\gamma = 0$	Gtr $\gamma$	FH	Yng	Gtr $\eta$
$p_s$ , separation arrival rate	.16	.16	.16	.16	.016	.16
$\bar{p}$ , tightness parameter	4.4	4.0	4.4	4.4	4.4	4.4
$\gamma$ , job offers sensitivity to human capital	5.6	0	7.0	3.8	3.4	4.6
$\nu$ , variance of job offer distribution	.24	.34	.24	.09	.07	.24
$\delta$ , depreciation rate of human capital	.16	.16	.12	.27	.32	.21
$\alpha$ , elasticity of income to human capital	.12	.11	.14	.10	.10	.10
$\theta$ , elasticity of income to hours	.32	.35	.33	.34	.35	.32
$\rho$ , discount rate (%)	2.9	3.2	2.9	2.5	2.5	2.9
$\lambda$ , weight of leisure	15.1	6.4	17.5	11.1	10.4	34.0
$\mu$ , trend in hours worked $\times 10^2$	.14	.14	.14	.14	.14	.14
$a$ , learning-by-doing rate	.42	.42	.32	.71	.82	.54
$\eta$ , curvature of disutility of working	2.0	2.0	2.0	2.0	2.0	3.0
$r$ , interest rate	.02	.02	.02	.02	.02	.02

Notes: One time unit corresponds to a year. See the notes to Table 4 for details about notation.

The parameter  $\gamma$  regulates the effects of human capital on the job offers probability. To infer its value we use panel data to estimate a relation between the probability of a job-to-job transition and past hours worked. We construct a dummy variable that equals one if the individual experiences a job-to-job transition in the following year. We regress this variable against the log of the average hours worked by the individual over the past five years:

$$\text{job-to-job} = \text{cte.} + \varphi_1 \ln n \quad (13)$$

Intuitively a positive  $\varphi_1$  means that past hours worked increases the probability of a job to job transition. Table 6 (Panel a) presents the results from estimating the equation using data from the Michigan Panel Study of Income Dynamics (PSID). We focus on male households heads and, since we need yearly observations, we use data only up to 1997 (data are biannual thereafter). We consider two measures for hours worked. The first denoted *Yearly hours* is the total annual hours worked for money by the worker in any job. The second denoted *Weekly hours* is the number of hours usually worked per

week in the main job. In the regressions we allow for a high order polynomial in current hourly wages. This is because workers in better paid job are less likely to receive offers which improve their current job.<sup>8</sup> We also control for education and experience. These controls have no counterpart in our simple model, but are regarded as important in the empirical literature.<sup>9</sup> Job changes are identified by using tenure information in the job. A job-to-job transition is defined as a change of job with no intervening unemployment spell, see Appendix A.2 for further details on the construction of the variable.

To check robustness we also report results from estimating equation (13) using data from the National Longitudinal Survey of Youth, started in 1979 (NLSY79). This is a nationally representative sample of 12,686 young men and women who were 14-22 years old when they were first interviewed in 1979. Again we focus the analysis on the male only population. An important advantage of NLSY79 relative to other surveys (including PSID) is that it allows to identify job-to-job transitions without relying on information on tenure, which is well known to be plagued by substantial measurement error. Indeed NLSY79 reports each respondent-specific list of employers for whom a respondent has reported working between two consecutive interviews. Information on a specific employer can be easily linked across survey years through an employer code associated to each worker’s record. This is likely to be much less contaminated by measurement error and it allows to better identify job-to-job transitions, see Appendix A.3 for further details. We report the results in Table 6 (Panel b). When using the PSID, we find a value for  $\varphi_1$  in

Table 6: Hours worked and job-to-job transitions

(a) PSID	Hours measure		(b) NLSY79	Hours measure	
	Annual	Usual weekly		Annual	Usual weekly
Log past hours	.03	.02	log past hours	.05	.04
	(5.0)	(2.8)		(4.3)	(2.5)

Notes: Panel (a) deals with PSID, Panel (b) with NLSY79. OLS regressions. *t*-statistics in parentheses. All regressions include year and education dummies, potential experience (in levels and squared) and a higher polynomial of degree five in current hourly wages. Hours are measured as five years averages.

the range 0.02-0.03. When we look at the NLSY79, we find that  $\varphi_1$  lies between 0.04 and 0.05. This might be due to the greater measurement error present in the PSID data. In both cases the estimate is positive and statistically significant.

<sup>8</sup>In practice controlling for hourly wage in the current job does not affect substantially the estimate of the coefficient  $\varphi_1$  reported in Table 6. But it makes  $\varphi_1$  in the model simulated data more strongly dependent of  $\gamma$  and thereby it speeds up the calibration substantially.

<sup>9</sup>To check robustness of results we also ran regressions after controlling for tenure in the job. We found that results change little.

Our estimate for  $\gamma$  is done by indirect inference. We simulate individual data from the model, we aggregate job to job transitions and hours worked at the annual frequency, we construct five year averages of hours worked and we then run the same regression as in the data but on model generated data. We choose  $\gamma$  so that the estimated coefficient  $\varphi_1$  in model generated data is equal to its analogue in the PSID. In Section 7 we analyze the robustness of results when allowing for a greater value for  $\varphi_1$ , more in line with the empirical evidence from NLSY79.

**Wage Offer distribution.** Following den Berg and Ridder (1998) and Postel-Vinay and Robin (2002), we choose the dispersion in the wage offer distribution,  $\nu$ , to match the dispersion of start-up wages after an unemployment spell. The idea is that the wage offer distribution has greater effects on start-up wages than on overall wages. Table 7 present the evolution of this statistic in the PSID. When we control for observable determinants of wages, we measure the variance of log wages after unemployment to be around 0.25 in the 70's.<sup>10</sup>

Table 7: Dynamics of variance of start-up wages after unemployment

	(a) All workers			(b) Young workers			
	Year	Controls included		Year	Controls included		
		More	Fixed effect		More	Fixed effect	
$Var_{70-80}$	.27	.24	.10	$Var_{70-80}$	.21	.19	.07
$Var_{81-90}$	.38	.37	.15	$Var_{81-90}$	.27	.25	.10
$Var_{91-02}$	.59	.48	.23	$Var_{91-02}$	.44	.38	.15

Notes: Variance of logged real hourly wage of workers who experienced an unemployment spell in the year. Data come from PSID. Panel (a) deals with all male workers population, Panel (b) with young male workers (with less than 10 years of labor market experience). In column 2 we also control for years and education dummies, tenure and potential experience (both in levels and squared). In Column 3 we control for an individual fixed effects whose variance change by decade.

**Technology.** We have five technology parameters: the exogenous interest rate  $r$ , the contribution of hours to human capital accumulation  $a$ , the depreciation rate of human capital  $\delta$ , the income elasticity to human capital  $\alpha$ , and the income elasticity to hours  $\theta$ . We set the interest rate equal to 2 percent. Under log preferences, we can normalize  $a$  such that the average human capital in the economy equals one.<sup>11</sup>

<sup>10</sup>In practice the observed dispersion in re-employment wages is also partly due to worker specific unobserved fixed effects. In Section 7 we analyze how results get modified when changing the wage inequality target.

<sup>11</sup>Our choice of  $\psi(G) = H$  simplifies the calibration of the parameter  $a$ , whose value can be obtained using a recursive analytical relation. In steady state we have  $H = \frac{a}{\delta}N$ , where  $N$  is aggregate hours equal to the product of the employment rate and average hours per worker, which are both calibration

To identify  $\delta$  we look at the distribution of unemployment durations. We have used  $\bar{p}$  to match an average duration of 3 months. With a higher depreciation rate, human capital declines faster and hence there are more unemployed workers with long unemployment durations. So we target the average fraction of unemployed workers with more than one year of unemployment. We use the CPS data for the decade of the 70's and we obtain that this fraction is around 4%.

To determine  $\alpha$  and  $\theta$  we notice that hourly wages are given by  $w = \omega h^\alpha n^{\theta-1}$ . For individuals who do not change job and do not experience unemployment spells we can express the within job wage increase as

$$\Delta \ln w_{i,t} = \alpha \Delta \ln h_{i,t} - (1 - \theta) \Delta \ln n_{i,t}. \quad (14)$$

With direct observation of human capital this equation allows to identify  $\alpha$  and  $\theta$ . But human capital is not directly observable, so we estimate  $\alpha$  and  $\theta$  by indirect inference. We simulate data from the model, aggregate the data at the annual frequency, construct identical synthetic measures of human capital in the simulated data and the data, then run the regression,

$$\Delta \ln w_{i,t} = \text{cte.} + \varphi_2 \Delta \ln h_{i,t} + \varphi_3 \Delta \ln n_{i,t} + \varepsilon \quad (15)$$

on the sample of workers who remain in the same job for two consecutive years and choose  $\alpha$  and  $\theta$  such that the regression in the PSID data and in the simulated data give the same coefficients  $\varphi_2$  and  $\varphi_3$ . Since again we need yearly observations, we run the regression with data only up to 1997. The synthetic measure of human capital in the data and in the model is obtained by summing annual hours worked with a constant yearly depreciation factor equal to  $1 - \delta$ . Table 8 reports the estimates with PSID data when the synthetic stock of human capital is constructed using different values for the corresponding depreciation rate  $\delta$  of human capital. In constructing the synthetic measure in the model we use a value of  $\delta = .156$  and we match the corresponding regression coefficients in the 70's, which are  $\varphi_3 = -0.7$  and  $\varphi_2 = 0.04$  (see column 2 in Table 4).

**Preferences.** There are four preference parameters: the discount rate  $\rho$ , the relative weight of leisure in the utility function  $\lambda$ , the elasticity of the marginal disutility of hours

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targets. Then the normalization condition  $H = 1$  implies that  $a = \frac{\delta}{N}$ , which specifies a unique value for  $a$  after determining  $\delta$ . This analytical solution for  $a$  would be lost if we were to focus on an alternative specification for the function  $\psi$ , and without it we should search for an extra parameter when minimizing the calibration loss function, see the separate companion appendix for further details.

Table 8: Determination of  $\alpha$  and  $\theta$ , PSID

Depreciation rate:	$\delta = .12$	$\delta = .156$	$\delta = .192$	$\delta = .24$
$\Delta \ln h$	.05 (4.6)	.05 (4.9)	.05 (5.5)	.06 (5.3)
$\Delta \ln n$	-.68 (-94.7)	-.68 (-94.7)	-.68 (-94.7)	-.68 (-94.7)
<i>Time evolution</i>				
$\Delta \ln h_{70-80}$	.04 (1.9)	.04 (2.0)	.04 (1.9)	.04 (1.9)
$\Delta \ln h_{81-90}$	.04 (2.9)	.05 (3.0)	.05 (3.2)	.05 (3.2)
$\Delta \ln h_{91-00}$	.07 (4.1)	.07 (4.2)	.08 (4.1)	.08 (4.4)
$n$	16,019	16,019	16,019	16,019
<i>Test:</i>				
$\varphi_{2,70-80} = \varphi_{2,81-90}$	.81	.82	.82	.80
$\varphi_{2,81-90} = \varphi_{2,91-00}$	.18	.19	.17	.10

Notes: OLS estimates.  $t$ -statistics in parentheses. All regressions include year and education dummies and potential experience (in levels and squared). The dependant variable is the within job real wage growth of workers. In the lower panel education and experience are interacted with time dummies to allow their return to change over time.

$\eta$ , and the rate of increase in the utility cost of working  $\mu$ . As it is standard in the literature on consumption and saving with incomplete markets,  $\rho$  is chosen such that the model economy yields a wealth to annual income ratio equal to 3, which is in line with the data.

The value of  $\lambda$  is chosen so that the average fraction of time spent at work when employed is 0.4. This is the value we find in our PSID sample after dividing *Weekly hours* (that in the 70's were around 44.8) by total non-sleeping weekly hours (approximately equal to 16 hours a day times 7 days a week).

We set  $\eta$  equal to 2. In a competitive labor market without human capital accumulation, this would imply a Frisch elasticity of labor supply equal to 0.5, which is reasonably in line with standard microeconomic estimates; see Section 7 for further discussion on this issue. Finally the parameter  $\mu$  is set to replicate the downward trend in hours worked per prime age male worker over the period 1950-1970. Table 3 indicates a fall of around 2.82 percentage points over the 1950-1970 period, which implies  $\mu = 0.0014$ .



**Model fit** As Table 4 shows, the model matches the calibration targets well. The parameter values are reported in Table 5. Some of these parameters have a direct interpretation and have been measured elsewhere. For example the depreciation rate  $\delta$  of human capital is equal to 16.3 percent in annual terms, which is line with the value found by Imai and Keane (2004) using data from the NLSY.<sup>12</sup> The annual subjective discount rate is equal to 2.9 percent and greater than the interest rate, which is needed to have a bounded distribution for assets.

In the bottom panel of Table 4 we also report some statistics that we have not targeted. The unemployment rate in the 70's was around 4 percent, which is in line with the value generated by the model. This is not surprising since we have targeted both the employment to unemployment and the unemployment to employment flow. The model predicts a monthly job-to-job flow of 3.25 percent which is slightly larger than, but reasonably close to, the value of 2.8 percent reported by Fallick and Fleischman (2001). Finally the unconditional dispersion of log hourly wages in the model is 0.17, which is smaller than the value in the data. There are two reasons for this. First, the job-to-job transition rate is slightly higher in the model than in the data (which leads to a higher concentration of workers at high paid jobs) and secondly, and more importantly, our target for the variance in start-up wages after an unemployment spell was obtained after controlling for age and education. So the model can not account for the variation due to age, education and other fixed effects.

Finally, we study the quantitative properties of wage growth. We take a group of workers with human capital and assets two standard deviations below the mean, and with a random job from the wage offer distribution. We may think of these workers as representing a (young) new cohort of workers in their first job. Wages grow partly due to human capital accumulation and partly due to job-to-job movements. The average annual wage growth in the first five years is 11.0 percent, and in the next five is 2.3 percent.

## 5.2 The US in the 00's

To characterize the US economy in the 00's we increase the dispersion of the wage offer distribution  $\nu$  and the return to skill  $\alpha$  to match the increase in wage inequality experienced in the US. In particular, the increase in  $\nu$  is set to reproduce the increase in the

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<sup>12</sup>Heckman, Lochner, and Taber (1998) and Huggett, Ventura, and Yaron (2006) use a Ben-Porath (1967) life-cycle model of human capital accumulation and find a lower depreciation rate of human capital. Their model is not comparable to ours. In the Ben-Porath model a low depreciation rate is needed to guarantee that the earnings of workers close to retirement does not decline too steeply with age.

dispersion of re-employment wages documented in Table 7. The table indicates that the variance of re-employment wages has approximately doubled over the 1970–2000 period. The increase in  $\alpha$  is set to replicate the increase in the returns to experience. When we estimate equation (15) allowing for a time-changing effect of human capital on productivity, we find evidence of an increase in  $\alpha$  from 0.04 to 0.07, see column 2 in Table 8—which corresponds to the relevant depreciation rate.<sup>13</sup> The resulting new values of  $\nu$  and  $\alpha$  are reported in Table 9.

Table 9: Parameter changes in the 00’s

Parameter	Value					
	Bench.	$\gamma = 0$	Gtr $\gamma$	FH	Yng	Gtr $\eta$
$\nu$ , variance of job offer distribution	.48	.62	.48	.22	.15	.48
$\alpha$ , elasticity of income to human capital	.19	.18	.24	.16	.16	.18

Notes: See the notes to Table 4 for details about notation.

## 6 Results

We first discuss the magnitude of the change in hours per worker, then we study the contribution of the ranking mechanism, and finally we report on the evolution of the intertemporal return to hours worked.

### 6.1 The 70’s versus the 00’s

When comparing the model economy in 2000 with the one in 1970, we find that detrended hours worked per worker increase on average by 5.3 percent. This represents 62% of the increase in detrended hours for prime age males in the US, see row (3) in Table 10. To measure the contribution of each parameter change, we solve again for the economy in 2000 but allowing only one parameter change at a time. Row (4) in Table 10 shows that the increase in  $\alpha$  induces an increase in detrended hours per worker of 2.21 percent. This amounts to about 41 percent of the increase in detrended hours predicted by the model and 26 percent of the overall increase in detrended hours in the US between 1970 and 2000. The increase in  $\nu$  instead yields an increase of 3.08 percent in hours per worker, which accounts for 58 percent of the increase in detrended hours predicted by the model (see row 5). This implies that within skill wage inequality accounts for around 2/3 of the model generated increase in hours per worker.

<sup>13</sup>Violante (2002) finds that wages grow faster on the job in the 80’s and in the 90’s than in the 70’s, which again may be due to an increase in  $\alpha$ .

Table 10: Increase in (de-trended) hours: 70's to 00's

Economy	Relative change (%)	Proportion to (2) (%)	Contribution (%)
Data			
(1) Overall increase	4.0		
(2) Increase relative to trend	8.5		
Model: benchmark			
(3) $\Delta\alpha$ and $\Delta\nu$	5.3	62	
(4) $\Delta\alpha$	2.2	26	42
(5) $\Delta\nu$	3.1	36	58
(6) $\Delta\alpha$ and $\Delta\nu$ , fixed distribution	3.0	35	56
Model: $\gamma = 0$			
(7) $\Delta\alpha$ and $\Delta\nu$	2.4	28	
(8) $\Delta\alpha$	4.2	50	174
(9) $\Delta\nu$	-1.9	-22	-79

In the model, parameter changes affect aggregate hours per worker both directly, through their effects on policy functions, and indirectly, through the effects that changes in the equilibrium distribution of human capital exert on workers ability to obtain job offers. To analyze the contribution of this equilibrium effect, we now increase  $\alpha$  and  $\nu$  as in the main exercise, but we assume that the function that characterizes search efficiency in the 70's remains unchanged in the 00's—so that search efficiency units in the 00's are given by  $S(h, G_{70})$ , where  $G_{70}$  denotes the distribution of human capital in the 70's. We find that, in the absence of equilibrium effects, detrended hours increase by 3.0 percent, see row (6) in Table 10. This amounts to 55 percent of the overall increase predicted by the model. Thus, equilibrium effects amplify the effects of parameter changes. This multiplier effect arises because, when aggregate average human capital increases, workers work longer hours to catch up with other workers in order to obtain job offers.

We can also look at the value of other statistics in our model economy in 2000. Some of them are reported in the last column of Table 4. Labor market flows change little: the unemployment to job flow falls slightly (from 33 percent to 32.7 percent on a yearly basis) whereas the job to job flow increases somewhat (from 2.8 to 3.2 percent on a monthly basis). The unemployment rate falls little (from 4 to 3.8 percent), and there is a slight increase in the fraction of unemployed workers with durations longer than a year (from 4 to 4.46 percent). The increase in wage dispersion naturally increases the precautionary savings motive and the wealth to income ratio goes up.

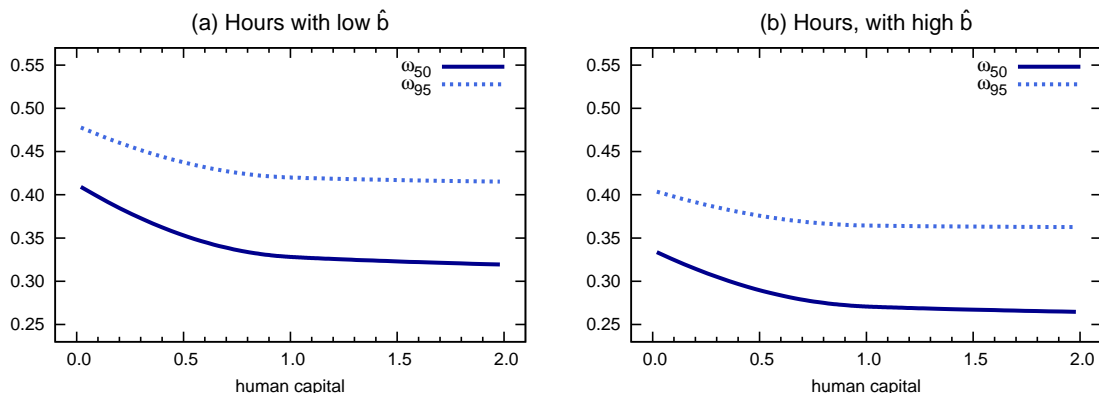
## 6.2 A world without ranking

To analyze the importance of the ranking mechanism, we now study an economy where the job offer probability does not depend on worker's human capital  $\hat{h}$ , so that  $\gamma = 0$ . In this model, labor supply is still an intertemporal decision because the law of motion of human capital is unchanged and higher human capital yields higher income through  $\alpha$ . We calibrate this economy using the same targets as our benchmark economy, but with two exceptions. First, we do not target the elasticity of job-to-job transitions to past hours, which was the target used to identify  $\gamma$ . We now find that the elasticity of job-to-job to past hours is negative and equal to  $-0.10$ , compared to the empirical estimate of  $0.03$ . The negative coefficient is due to the endogenous positive correlation between  $\hat{h}$  and  $\omega$  in the model, which implies that workers with high  $\hat{h}$  (those who worked many hours in the recent past) tend to change job less often because they are already employed in jobs with high  $\omega$ . Second, we keep  $\delta$  as in the benchmark economy and hence leave free the share of unemployed workers with unemployment duration longer than a year. The reason for this is that, in a world without ranking, the depreciation of human capital does not affect the exit rate from unemployment and thereby the distribution of unemployment duration. We find that the model without ranking delivers a very different distribution of unemployment duration, with the fraction of unemployed workers with durations over a year falling to just 0.8 percent (compared to the empirically measured 4 percent). The new model parameters can be found in Table 5, while the value of the calibration targets is reported in Table 4.

In Figure 4 we plot the policy function for de-trended hours at the same points of the state space as in Figure 2. In the model without ranking hours increase monotonically with  $\omega$ . This is because a higher  $\omega$  now only induces the standard intertemporal substitution effect. The policy function is now slightly decreasing in human capital rather than hump-shaped. The hump disappears because the elasticity of job offers to human capital is always equal to zero while the policy function is decreasing in human capital because workers with higher human capital are richer and hence work fewer hours due to a standard income effect. The policy function is less sensitive to human capital when workers have greater assets or work in jobs with higher  $\omega$  since the added income of higher human capital is less important. Finally, hours also fall monotonically with wealth.

To study the effects of inequality on hours in the model without ranking we calibrate the value of  $\alpha$  and  $\nu$  for the US in the 00's (see Table 9) using the same strategy as in the benchmark economy. We find that, as in the benchmark economy, the increase in  $\alpha$  increases hours worked (see Table 10, row 8). But now the increase in the dispersion

Figure 4: Decision rule for hours: no ranking



Notes: The decision rules are computed with the parameter values given in Table 5, column  $\gamma = 0$ .  $\omega_{50}$ ,  $\omega_{95}$ , low  $\hat{b}$  and high  $\hat{b}$  as in Figure 2.

of job offers  $\nu$  induces a fall in hours of almost 2 percent (see Table 10, row 9). This is coherent with the theoretical finding by Heathcote, Storesletten, and Violante (2008), who show that an increase in the variance of transitory wage shocks makes hours fall when agents have access to sufficient insurance opportunities to smooth consumption over time. This happens because the increase in wage dispersion increases the opportunities of intertemporal substitution across periods with high and low wages. These opportunities make the worker richer and hence less willing to work, due to a conventional income effect

### 6.3 The intertemporal return

In the model, the intertemporal return to hours worked increases in response to the increase in wage inequality. To test this model implication, we use PSID data to estimate the following regression model first proposed by Bell and Freeman (2001):

$$\ln w_{i,t} = \text{cons.} + \varphi_4 \ln w_{i,t-1} + \varphi_5 \ln n_{i,t} + \varphi_6 \ln n_{i,t-1} + \varepsilon_{i,t} \quad (16)$$

where  $i$  refers to worker and  $t$  to time,  $w_{i,t}$  and  $n_{i,t}$  denote hourly wages and hours of work, respectively. The coefficient  $\varphi_4$  captures the serial correlation in wages due to the serial correlation in the job type (say due to  $\omega$  in the model). The coefficient  $\varphi_5$  measures the effect of current hours on current wages, which tends to be negative if labor income increases less than linearly with hours ( $\theta < 1$  in the model). The coefficient  $\varphi_6$  measures the effect of past hours on current wages—i.e. the intertemporal return. A positive  $\varphi_6$

indicates that hours worked increase future wages. We estimate the regression by OLS and by allowing for a fixed effect using the two-step Arellano and Bond (1991) estimator. The instruments are lagged values of past five years averages. Standard errors are corrected for finite sample bias as in Windmeijer (2005). Hours and wages are measured as five year averages to remove business cycle effects. We also control for education and experience, interacted with time. The  $\varphi_6$  coefficient is allowed to change every five or ten years, depending of the specification.

The results, using either yearly or weekly hours, are presented in Table 11. Columns [1] focus on OLS estimates, columns [2] on fixed effects estimates. As expected  $\varphi_4$  is positive while  $\varphi_5$  is negative. The coefficient  $\varphi_6$  is positive, statistically significant and increases over time. Overall the intertemporal return to hours worked is larger in the 90's

Table 11: Evolution of the intertemporal return, PSID

	Annual hours		Usual weekly hours	
	[1]	[2]	[1]	[2]
$\varphi_4$	.81 (192)	.48 (3.6)	.81 (189.2)	.43 (2.7)
$\varphi_5$	-.43 (-41.4)	-.56 (-10.5)	-.35 (-34.2)	-.56 (-10.1)
$\varphi_{6,70-75}$	.43 (15.7)	.41 (4.9)	.44 (12.8)	.58 (4.6)
$\varphi_{6,76-80}$	.47 (21.0)	.41 (5.3)	.47 (16.5)	.58 (4.7)
$\varphi_{6,81-85}$	.46 (22.1)	.40 (5.1)	.42 (14.8)	.56 (4.5)
$\varphi_{6,86-90}$	.51 (28.0)	.41 (5.4)	.49 (20.1)	.56 (4.4)
$\varphi_{6,91-95}$	.58 (29.1)	.50 (5.8)	.61 (24.3)	.67 (4.7)
$\varphi_{6,96-00}$	.60 (13.3)	.51 (5.5)	.59 (10.1)	.64 (4.6)
<i>Test:</i>				
$\varphi_{6,70's} = \varphi_{6,80's}$	.17	.39	.50	.50
$\varphi_{6,70's} = \varphi_{6,90's}$	.00	.07	.00	.09
$\varphi_{6,80's} = \varphi_{6,90's}$	.00	.00	.00	.03

Notes: Data come from PSID. First two columns use annual hours, last two usual weekly hours. Columns [1] are OLS estimates, column [2] are fixed effects estimates, using the Arellano and Bond (1991) estimator (difference GMM). Standard errors are corrected for finite sample bias as in Windmeijer (2005).  $t$ -statistics in parentheses. The dependent variable is logged real hourly wage. Hours and wages are five years averages. Instruments are lagged values of past five years averages. All regressions include education dummies and potential experience (in levels and squared) interacted with time dummies. The last rows test for time changes in the value of  $\varphi_6$  in (16).

than in the 80's and in the 70's.<sup>14</sup> Results hold independently of whether we consider yearly or weekly hours. When using the two-step Arellano-Bond estimator, results change little. Just the serial correlation of wages as measured by  $\varphi_4$  falls significantly.

We now evaluate whether the model can reproduce the sign, magnitude, and time evolution of the estimated coefficients in (16). We simulate data for 10.000 individuals for 20 years from the US70 economy, and the US00 economy. We pool together the data from the two economies, we construct five year averages of individual yearly wages and yearly hours worked exactly as in the PSID and we run regression (16) on model simulated data. We also introduce measurement error in the model generated data, which several authors have argued to be substantial in PSID data.<sup>15</sup> To analyze the evolution of the intertemporal return in the model we allow the effect of past hours on current wage (i.e. the analogue of  $\varphi_6$  in equation 16) to change in the 00's relative to the 70's, exactly as in Table 11. Notice that at no point of the calibration we imposed that the model should match the size and magnitude of the regression coefficients estimated with the PSID data. We find that

$$\begin{aligned} \text{OLS : } \quad & \ln w_{i,t} = \text{cons.} + 0.38 \ln w_{i,t-1} - 0.32 \ln n_{i,t} + 0.71 \ln n_{i,t-1}|_{70's} + 0.79 \ln n_{i,t-1}|_{00's} \\ \text{FE : } \quad & \ln w_{i,t} = \text{cons.} + 0.45 \ln w_{i,t-1} - 0.40 \ln n_{i,t} + 0.42 \ln n_{i,t-1}|_{70's} + 0.52 \ln n_{i,t-1}|_{00's} \end{aligned}$$

where the results in the first line are based on OLS, and those in the second on the Arellano-Bond estimator. The last two coefficients in each equation characterize the value of  $\varphi_6$  in (16) in the 70's and in the 00's. The match is quite accurate especially when we focus on the empirical results based on the Arellano-Bond estimator that is intended to correct for the possible presence in the data of individual fixed effects, not present in the model. The model matches well the time evolution of the intertemporal return as measured by  $\varphi_6$ . The magnitude of  $\varphi_5$  that measures how current hourly wages are related to current hours is also in line with the data.<sup>16</sup> Only the coefficient  $\varphi_4$  that measures the serial correlation of wages is remarkably lower in the model than in the data when considering the OLS estimates. The difference between model and data however

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<sup>14</sup>Notice that the result is not driven by the change in the sampling frequency of the PSID: the estimated  $\varphi_6$ 's using data on the 85-95 period and the 90-00 period are indeed very similar, see Table 11.

<sup>15</sup>Our correction for measurement error is based on French (2002) who argue that the variance of the measurement error in wages is .0207 and that in hours is .0167.

<sup>16</sup>This coefficient captures the correlation between current wages and current hours. Heathcote, Storesletten, and Violante (2004) have argued that the correlation between hourly wages and yearly hours have changed over time: it was around minus 0.12 at the beginning of the 70's, it then increased up to 0.02 in the mid 80's and then dropped again to minus 0.11 in 1996. In our model the correlation between annual wages and yearly hours is equal to minus 0.15 in the 70's and minus 0.09 in the US00 economy, which appears to be in line with the PSID data.

completely disappears when purging the data from the presence of individual fixed effects.

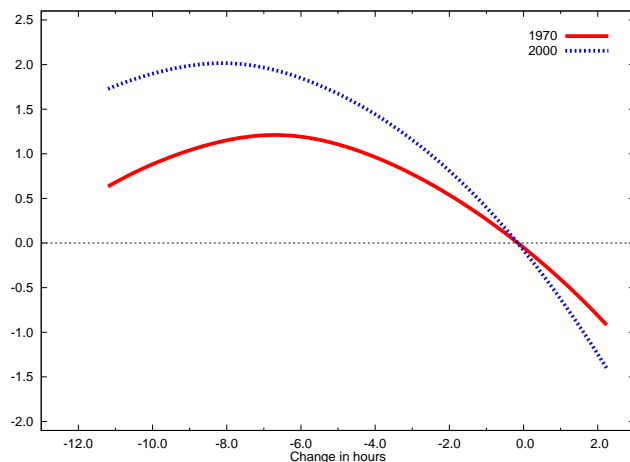
## 6.4 Welfare

When workers decide to work longer hours to accumulate human capital and thereby increase their chances to get offers, they do not internalize that their higher human capital will reduce other workers' probabilities to obtain the same jobs. This generates an externality, which makes the hours decision in the decentralized equilibrium different from the decision that would be taken by a social planner who maximizes the sum of the present discounted utility of all individuals in the economy. To measure the importance of the negative externality, we solve again the individual problem characterized by the Bellman equations (7) and (10), when the social planner commands a change of  $n^p$  in the hours decision of each worker so that the workers choice of hours becomes  $n = g^n(\mathbf{s}_e, \kappa) + n^p$ . The worker remains free to choose consumption and savings optimally according to (9) and (12). We solve this new economy for different values of  $n^p$ , and search for the value of  $n^p$  that maximizes the Benthamite social welfare in steady state. Of course, the steady state distributions  $\hat{\Gamma}_e$  and  $\hat{\Gamma}_u$ , and the steady state unemployment rate  $u$  will change as we change  $n^p$ . For this reason, the steady state level of average hours per worker will differ from the commanded change  $n^p$ .

In Figure 5, we report the steady state value of social welfare for different values of  $n^p$ . Social welfare is measured by the percentage increase of consumption units that each worker should receive in the decentralized equilibrium to achieve the corresponding level of social welfare. The commanded increase in hours is measured in terms of weekly hours. The solid line refers to our benchmark economy in the 70's, the dotted line to the corresponding economy in the 00's. We see that, as the planner commands a reduction in hours, social welfare increases. The maximum is reached at a commanded reduction of 6.5 weekly hours, which yields a steady state hours reduction of 3.7 weekly hours. In percentage terms, hours worked in 1970 were 9 percent too high relative to the value that maximizes steady state welfare. The implied welfare gains are equivalent to a 1.3 percent consumption increase. When we consider the same exercise for the economy in 2000, we see that the welfare gains of reducing hours are larger in 2000 than in 1970 and they are now equivalent to a 2.0 percent increase in consumption. This is because the increase in the dispersion of job offers increases the competition for jobs and exacerbates the negative externality. The optimal commanded reduction in weekly hours also increases in 2000 and it is now equal to 7.7 hours per week, which yields a steady state fall of 4.3 weekly hours. In percentage terms this amounts to a reduction of 11 percent in hours worked.



Figure 5: Steady state welfare gains of reducing hours



Notes: The figure plots the steady state welfare gains, measured in consumption equivalent, by asking each workers to work an additional given amount of hours  $n^p$ . The commanded hours change is expressed in number of weekly hours.

## 7 Robustness

We now analyze the robustness of our quantitative exercise to alternative calibrations.

### 7.1 Higher $\gamma$

The parameter  $\gamma$  is calibrated to match the semi-elasticity of job to job transitions to past hours worked. The value of the semi-elasticity is approximately 0.03 in the PSID and 0.04 in the NLSY, see Table 6. In the benchmark calibration we targeted the lower value obtained in the PSID data which implies  $\gamma = 5.6$ , see column 1 in Table 5. We now analyze how the results change when we set  $\gamma$  equal to 7 which implies a semi-elasticity of job to job movements to past hours of 0.041, which is more consistent with the NLSY estimates. All the remaining parameters are calibrated to match the same targets as in the benchmark specification. Table 4 reports the model fit and Table 5 the new resulting parameter values.

With this new parametrization, the magnitude of the increase in hours in 2000 is very similar: row (3) in Table 12 shows that the overall increase is now by 5.4 percent, compared with the 5.3 percent increase obtained in the benchmark specification. The relative contribution of  $\alpha$  and  $\nu$  to the overall increase is also unchanged. At first the similarity of results may appear surprising, since a higher  $\gamma$  implies a higher semi-elasticity of the job offer probability to human capital, which should amplify the effects of an increase in  $\nu$ , see for example equation (5). But when we increase  $\gamma$ , the depreciation rate of human capital  $\delta$  falls from 16.3 to 12.3 percent. This is because a greater  $\gamma$  implies

Table 12: Increase in (de-trended) hours: 70's to 00's

Economy	Relative change (%)	Proportion to (2) (%)	Contribution (%)
Data			
(1) Overall increase	4.0		
(2) Increase relative to trend	8.5		
Model: Greater $\gamma$			
(3) $\Delta\alpha$ and $\Delta\nu$	5.4	64	
(4) $\Delta\alpha$	2.3	27	43
(5) $\Delta\nu$	3.1	36	56
Model: Fixed heterogeneity			
(6) $\Delta\alpha$ and $\Delta\nu$	5.6	66	
(7) $\Delta\alpha$	2.6	31	46
(8) $\Delta\nu$	3.2	37	56
Model: Young and fixed heterogeneity			
(9) $\Delta\alpha$ and $\Delta\nu$	4.9	57	
(10) $\Delta\alpha$	2.7	32	55
(11) $\Delta\nu$	2.3	27	48
Model: Greater $\eta$			
(12) $\Delta\alpha$ and $\Delta\nu$	3.8	45	
(13) $\Delta\alpha$	1.8	21	47
(14) $\Delta\nu$	2.1	25	55

that human capital is more important in getting offers, which increase the dispersion of unemployment durations for given value of  $\delta$ . For the model to have only 4 percent of unemployed workers with durations longer than a year, we then have to reduce the rate of depreciation of human capital  $\delta$ .

## 7.2 Alternative wage inequality measures

We now consider alternative measurements of the level and of the increase in residual wage inequality. In the benchmark economy we targeted the variance of re-employment wages after controlling just for education and potential experience. However, part of this wage dispersion might be due to some unobserved fixed heterogeneity in workers skills, whose variance might also have changed over time. To address this issue, we follow Hornstein, Krusell, and Violante (2007) and we target the dispersion of residuals in a wage regression where we also control for unobserved fixed effects. Column three in Panel (a) of Table 7 reports the variance of the re-employment wage residuals, which is now equal to 0.10 in the 70's and 0.23 in the 00's. We refer to this new economy as *Fixed Heterogeneity*. Table 4 reports the model fit while Table 5 reports the new implied parameter values. As expected, the calibrated variance of the wage offer distribution  $\nu$  falls to 0.094 (it was 0.243 in the benchmark specification). But now also  $\gamma$  falls substantially while the depreciation

rate of human capital  $\delta$  increases. This is due to the same logic as in the previous section which implies that  $\gamma$  and  $\delta$  tend to move in opposite directions. Overall the quantitative predictions of the model change little: the model now predicts an increase in hours of 5.7 percent relative to trend, just greater than the 5.3 percent increase obtained in the benchmark calibration, see row (6) in Table 12.

Another concern with the measurement of residual wage inequality is that, if workers are subject to permanent wage shocks, the variance of the permanent component tends to increase as workers age, see for example Storesletten, Telmer, and Yaron (2004). Failing to control for this may lead to an over-estimate of the level of frictional wage dispersion when focusing on the overall population. To address this issue we now focus on a subsample of relatively young workers (with less than 10 years of labor market experience). In panel (b) of Table 7 we report the variance of re-employment wages for this group of workers. After controlling for experience and unobserved fixed effects, the variance of reemployment wages becomes equal to 0.07 in 1970 and 0.15 in 2000, see column 3.

We recalibrate our economy to match this alternative wage inequality target. Since workers are infinitely lived, it is not obvious how to characterize young workers in the model. We think of them as workers with similar (identical) levels of labor market experience and we choose as the corresponding model statistic the variance of reemployment wages after regressing out variation in human capital. We refer to this new economy as *Young and Fixed Heterogeneity*. The model fit and the new model parameters are reported in Tables 4 and 5, respectively. We find that the variance of the wage offer distribution  $\nu$  falls to 0.073, which is even smaller than the 0.094 value found when matching the overall population wage inequality measure obtained after controlling for fixed effects. Also the calibrated  $\gamma$  is smaller, while, as expected,  $\delta$  is greater. In Table 9 we report the new calibrated  $\alpha$  and  $\nu$  for the 2000. Compared to the economy that controls for fixed effects on the overall population, the variance of the wage offer distribution increases less—it now goes from 0.073 to 0.152 compared with the previously reported increase from 0.094 to 0.226. In this parametrization hours increase by 4.9 percent, compared to the 5.3 increase obtained in the benchmark economy, see row (9) in Table 12. The increase in the dispersion of the wage offer distribution now accounts for around 50 per cent of the overall effect. This is smaller than in the benchmark economy, but still sizeable.

### 7.3 Higher $\eta$

In the main calibration we have chosen a value of  $\eta = 2$  for the curvature in the disutility of working. This would imply a Frisch elasticity of 0.5 which is in line with some recent

microeconomic estimates of the labor supply elasticity for prime age males, see for example Lee (2001) and Domeij and Flodén (2006). Still, the empirical literature on labor supply of prime age males has traditionally argued in favor of a smaller value for the Frisch elasticity (a higher  $\eta$ ); see for instance Blundell and MaCurdy (1999) and the references therein. We now check how the quantitative results change when we increase  $\eta$  from 2 to 3. We recalibrate the new economy to the same targets as before, see Table 4 and Table 5. The new results are in Table 12. As expected, we find that the increase in hours predicted by the model is now smaller: hours increase just by 3.8 percent compared with the 5.3 percentage increase of the baseline economy. This amounts to about half of the increase observed in the data.

## 8 Conclusions

We constructed a labor market search model where, by working longer hours, workers acquire greater skills and can thereby obtain better jobs. In the model within-skill wage inequality and the return to skill gives workers incentives to work longer hours. We used the model to quantify the contribution of the increase in wage inequality in explaining the trend reversal in hours per worker observed in the US since the 70's. The model is estimated by matching a variety of statistics on labor flows and wage dynamics at the micro level, mainly obtained from the PSID. Our quantitative results show that within-skill wage inequality plays an important role in accounting for this fact.

We purposely simplified the theoretical analysis in some dimensions. For example we have assumed that human capital helps in obtaining job offers, because more skilled workers are more likely to be preferred when competing against other job applicants. Yet one may think that human capital also helps in keeping jobs, so that more skilled workers lose their job less often. The effect could be important and we believe this to be an interesting issue to be investigated in future research. We have also modeled wage inequality as exogenous. This again is a simplifying assumption that we think is justified on the grounds that there is yet no consensus on why wage inequality has increased in the US. In this paper we have just stressed that wage inequality can have an important effect on aggregate hours worked also because of their effect on hours per worker, which is a novel claim with several interesting implications.

Finally, we have characterized the effects of human capital on job offer probabilities by making simplifying assumptions intended to capture key properties of ranking models. For example, we have assumed a specific functional form and we have estimated its parameters by looking at the average elasticity of job to job movements to past hours worked. One

could instead estimate a non-parametric relationship between job to job transitions and human capital so as to recover the shape of the function from data. We have also assumed that only some specific moments of the distribution of human capital in the economy affect job offer probabilities. It might yet be that also other moments matter. To identify these effects one should observe some independent variation in the distribution of human capital across labor markets. For example, one could assume that human capital is occupation-specific and then analyze how the distribution of human capital in various occupations affect job offer probabilities. This would be an interesting extension that would require however to model carefully the flows of workers within and between occupations.

## A Data appendix

We start discussing data from the CENSUS, then from PSID and finally from NLSY79.

### A.1 CENSUS data

The source of our CENSUS data is the Integrated Public Use Microdata Series (IPUMS) created at the University of Minnesota ([www.ipums.org](http://www.ipums.org)). We use 1 percent sample and we restrict the analysis to male workers aged between 25 and 64 years old. Regressions and descriptive statistics are calculated using individual weights.

*Weights.* This is variable PERWT which measures how many persons in the US population are represented by a given person in an IPUMS sample.

*Black.* This is one if the individual is “black/negro”. It is constructed using variable RACE.

*Hispanic.* This is one if the individual is either “Mexican”, “Puerto Rican”, “Cuban” or “Other”. It is constructed using variable RACE.

*Occupation.* It is obtained from variable OCC1990, which is a modified version of the 1990 Census Bureau occupational classification scheme. It offers researchers a consistent long-term classification of occupations. Following the suggestions by IPUMS we further aggregate the original OCC1990 classification categories into the broad occupational categories implicit in the 1990 scheme: Managerial and Professional (000-200); Technical, Sales, and Administrative (201-400); Service (401-470); Farming, Forestry, and Fishing (471-500); Precision Production, Craft, and Repairers (501-700); Operatives and Laborers (701-900). This leaves us with 79 Occupational categories.

*Industry.* It is obtained from variable IND1990, which classifies industries in the years since 1950 using the 1990 Census Bureau industrial classification scheme.

*Educational dummies.* They are constructed using variable EDUC which is a recoded combination of two separate IPUMS variables, HIGRADE and EDUC99. EDUC indicates respondent’s educational attainment, as measured by the highest year of school or degree completed. We use the variable to construct four educational dummies: 1) Less than high School if “No schooling or Grades 1-11”; 2) High School if “Grade 12 and High School diploma or GED”; 3) Some College if “1 to 3 years of college (some college but no degree) or occupational associate degree or academic associate degree”; 4) College if “4+ years of college, bachelor’s degree, master’s degree, professional degree or doctorate degree”.

*Age.* This is the variable AGE which reports the person’s age in years as of the last birthday.

*Hours usually worked per week.* This is variable UHRSWORK which is available just in CENSUS year 1980–2000. UHRSWORK reports the number of hours per week that the respondent

usually worked, if the person worked during the previous calendar year. It is top coded at 99 hours. Statistics are calculated for workers who usually work at least 30 hours per week when employed.

*Hours worked last week.* This is variable HRSWORK1 which reports the total number of hours the respondent was at work during the previous week. It is top coded at 99 hours (98 for 1950). The variable is available just in CENSUS year 1950–1990. Statistics are calculated for workers who work at least 30 hours in the previous week.

*Fraction of workers usually working long hours.* Fraction of workers usually working more than 49 hours per week when employed.

*Fraction of workers working long hours last week.* Fraction of employed workers working more than 49 hours per week last week.

*Labor income.* This is variable INCWAGE which reports each respondent’s total pre–tax wage and salary income—that is, money received as an employee—for the previous calendar year in 1999 dollars (using Consumer Price Index factors). It includes wages, salaries, commissions, cash bonuses, tips, and other money income received from an employer; it excludes payments-in-kind or reimbursements for business expenses.

*Weeks worked.* This is variable WKSWORK1 which reports the number of weeks that the respondent worked during the previous calendar year. This variable is available only starting from 1980.

*Weekly wage.* This is obtained by dividing *Labor income* by *Weeks worked*. Weekly wages are calculated just for workers that work at least 30 weeks in the calendar year.

*Hourly wage.* This is the variable *Weekly wage* divided by *Hours usually worked per week*. Wage statistics are constructed only for those workers who usually work more than 30 hours per week and more than 30 weeks a year, and whose hourly wage is higher than half of the minimum wage in the corresponding year.

## A.2 PSID

We select all male household heads who are in the age group 25-55. We focus on these workers because they are most likely to actively engage in the labor market; this reduces sample selection problems related to labor market participation, which is an issue not explicitly analyzed in the model. We exclude the SEO sample. Data start in 1968 and ends in 2001. The survey is annual up to 1997 and bi-annual thereafter. We include individuals with at least 3 observations in a 5 year period. Below we describe the variables used in the analysis.

*Labor income.* Total annual labor income from all jobs. Self-employed income is split between labor and capital income. In this case only the labor part is added.

*Yearly hours.* Total annual hours worked for money, from family files. It refers to all possible jobs of the worker. It includes overtime.

*Weekly hours.* Hours usually worked per week in main job, top coded at 98 hours per week.

*Tenure.* Months with present employer. Since data for the 1968-1974 period are bracketed, tenure for those years is measured by the mid point of the interval.

*Race.* Race code for individual, from family file. In all regressions, we consider three dummies corresponding to white, black, or others.

*Years of education.* Highest grade completed, 1-17 classification.

*Hourly wage.* Labor income divided by Yearly Hours. They are expressed in 1992 dollars by using the GDP deflator.

*Weeks unemployed.* Number of weeks of unemployment over the last year. In 1968 and 1969 this information is bracketed and with only one interval from 6 weeks onwards.

*Weeks worked.* Number of weeks worked in main job.

*Experience.* Measured as age minus six minus years of education.

*Job-to-job.* An individual experiences a job-to job transition during the year that goes from  $t$  to  $t + 1$  if i) he is employed at  $t$ , ii) he is employed at  $t + 1$ , iii) he has experienced less than two weeks in unemployment over the year, and iv) he has a tenure less than 12 months at time  $t + 1$ .

*Synthetic measure of human capital.* The synthetic measure of human capital in the data and in the model is obtained by summing annual hours worked with a constant yearly depreciation factor equal to  $1 - \delta$ . In constructing the synthetic measure we use a value of  $\delta = 0.156$ . The sum is calculated over a maximum of seven years. For individuals entering the panel when they are already experienced, we impute the hours worked in the missing years by using the corresponding year's average hours worked by a worker with the same educational level. Missing data for workers with a positive number of weeks worked in the year are imputed analogously.

### **A.3 National Longitudinal Survey of Youth**

We focus on a sample of 6,111 individuals designed to be representative of the non-institutionalized civilian segment of the US young population. We consider only the 13 more recent waves, from 1986 to 2002. The sample is restricted to full time workers (working a minimum of 30 hours per week) with reliable data on wages and with positive labor market experience. Following is the description of the main variables.

*Regional Dummies.* There are four dummies constructed from the variable "Region of current residence".

*Schooling.* This is the "Highest grade completed as of May 1 survey year".



*Experience.* Age of worker at interview date, minus years of schooling, minus six.

*Working Hours.* Until 1993 the number of working hours per week is obtained from the variable “Hours per week usually worked at current/most recent job”. Starting in 1994, job 1 always coincides with the CPS job and information about working hours is obtained from the variable “Hours per week worked at job 1”.

*Hourly wage.* Until 1993 the hourly wage in dollar is obtained from the variable “Hourly rate of pay current job”. Starting in 1994 we used the variable “Hourly rate of pay of job 1”. To eliminate obvious data entry errors we drop observations whose hourly wage is greater than \$500 or less than half the minimum wage in the year.

*Employer Tenure.* This is obtained from the five variables “Total Tenure in weeks with employer job 1 (2, 3, 4, 5)”. We then identify whether job 1, 2, 3, 4 or 5 corresponds to the CPS job by using the questions “Internal Check: Is job 1 (2, 3, 4, 5) the same as current job”. After 1993 the CPS job corresponds to job 1.

*Job-to-job.* NLSY reports each respondent-specific list of employers for whom a respondent has reported working between two consecutive interviews. Information on a specific employer can be linked across survey years through a job identifier. The procedure to link a specific employer across survey years is detailed in Appendix 9 of the NLSY user’s guide. We follow the procedure closely. An individual experiences a job-to job transition during the year that goes from  $t$  to  $t + 1$  if i) he is employed at  $t$ ; ii) he is employed at  $t + 1$ ; iii) he has experienced a change in the employer; and iv) he has spent less than two weeks in unemployment over the year.

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