THE EFFECTS OF LABOR MARKET CONDITIONS ON WORKING TIME: THE US-EU EXPERIENCE

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CEMFI Working Paper No. 0705

June 2007

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We gratefully acknowledge *Fundación Ramón Areces* for financial support. We thank comments by Marco Cozzi, Makoto Nakajima and Víctor Ríos-Rull and by seminar participants at Amsterdam University, CEMFI, University of Vigo, Bocconi University, Tokyo University, the 2006 ESSIM-CEPR meeting in Tarragona and the DGEM II Workshop in Santiago de Compostela. We are grateful to Laura Hospido for some help with the data.

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Abstract

We consider a labor market search model where, by working londer hours, individuals acquire greater skills and thereby obtain better jobs. We show that job inequality, which leads to within-skill wage differences, gives incentives to work longer hours. By contrast, a higher probability of losing jobs, a longer duration of unemployment, and in general a less tight labor market discourage working time. We show that the different evolution of labor market conditions in the US and in Continental Europe over the last three decades can quantitatively explain the diverging evolution of the number of hours worked per employee across the two sides of the Atlantic. It can also explain why the fraction of prime age male workers working very long hours has increased substantially in the US, after reverting a trend of secular decline.

JEL Codes: G31,J31, E24.
Keywords: Working hours, wage inequality, unemployment, search, human capital.

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1 Introduction

In standard formulations of the competitive labor market model with time separable utility, workers choose how many hours to work by equating the marginal utility of leisure to the marginal value of *current* hourly wage. In practice, by working longer hours, individuals can acquire greater skills, get promoted in the current job, and obtain better jobs, so that working time also yields an intertemporal return. In this paper we show how this return and hence working time decisions are affected by several aggregate features of the labor market.

Our 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.[1] Thus there is wage dispersion and identical workers can earn different income. Workers are risk averse, so wage changes exert both an income and a substitution effect on working time decisions. In the model, hours worked increase current as well as future income because by working longer hours individuals accumulate human capital. Human capital enhances worker productivity and thereby the probability of receiving job offers. This follows, among others, Blanchard and Diamond (1994), Shi (2002), and Shimer (2005a). 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.[2]

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. The effect is stronger the tighter the labor market. In contrast, a higher probability of becoming unemployed and a longer duration of unemployment reduce the rate of use of the stock of human capital accumulated through working time and thereby reduce the incentive to work longer hours.

These links between labor market conditions and working time decisions can help to explain why, since the 70's, the number of hours worked per employee has fallen substantially in Continental Europe (Germany, France, Italy and Spain), while it has remained

[1] Postulating an exogenous wage distribution has some key advantages given that we are interested in comparing (Continental) Europe to the US. Indeed wage determination may differ substantially in Continental Europe and in the US. Moreover the wage distribution has evolved differently over time across the two sides of the Atlantic and there is yet no consensus of why this happened, see Hornstein, Krusell, and Violante (2005) for a survey on possible explanations and the Conclusions for further discussion.

[2] 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.

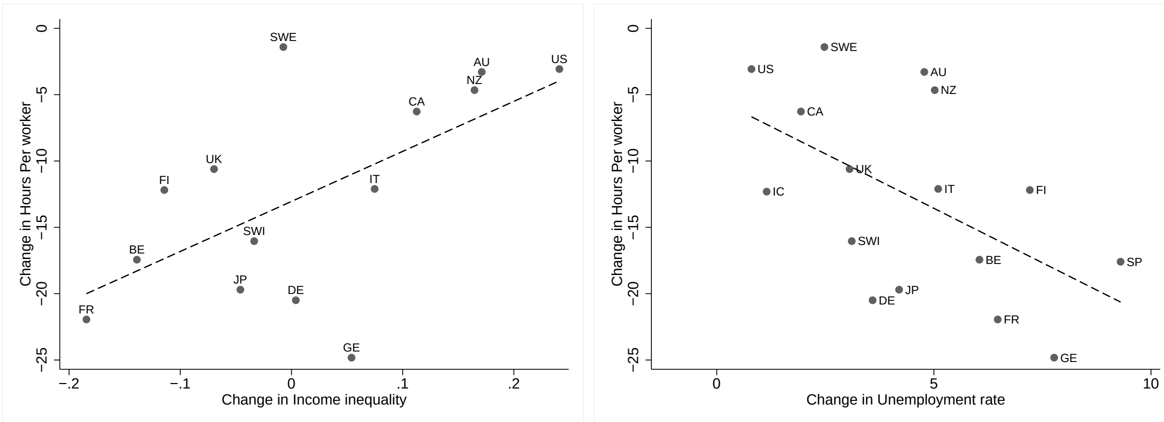
roughly constant in the US after reverting a trend of secular decline.[3] Indeed, over the same period, wage inequality and unemployment have also evolved quite differently across the two sides of the Atlantic. In particular, as reviewed among others by Bean (1994), Gottschalk and Smeeding (1997) and Katz and Autor (1999), it is well known that both the return to skill and within-skill wage inequality have increased substantially in the US but little in Europe, while the unemployment rate has increased considerably in Europe but it has remained roughly constant in the US. Figure 1 provides suggestive evidence that labor market conditions may play a role in accounting for the observed trend differences in hours per worker between the US and Europe. We plot the percentage change in hours worked per employee for selected OECD countries against the changes in earnings inequality (panel a) and in unemployment rate (panel b), respectively. Earnings inequality is measured as the log difference between the ninth and the first decile of the distribution of gross earnings of full-time workers in their main job. Changes are calculated over the 1970-2002 period. The correlation between changes in hours worked and changes in income inequality is around sixty percent. The analogous correlation with unemployment changes is again around minus sixty percent; both are statistically significant at a five percent level of significance. This indicates that hours per worker have fallen more in countries that have experienced a smaller increase in inequality and a sharper rise in unemployment.

Within-skill wage inequality gives incentives to work longer hours because it increases the intertemporal return to hours worked. We use data from the Panel Study of Income Dynamics (PSID), and the German Socio-Economic Panel (GSOEP), to analyze the evolution of the intertemporal return to hours worked in the US and in Germany. This is measured by the effect of past hours on current wages. As in Bell and Freeman (2001), we find that, in either country, hours worked yield a significant intertemporal return. Moreover, the intertemporal return to working time has increased in the US since the 70's, while it has remained roughly constant in Germany (at least since the mid 80's, which is when the GSOEP starts). This is in line with the different evolution of wage inequality observed in the two countries.

Differences in the intertemporal return to hours worked can contribute to explain differences in the evolution of hours per worker in the US and the EU. To quantify the contribution of labor market conditions, we consider an extended model that we calibrate to match a variety of statistics on labor flows and wage dynamics at the micro level. We

[3] See for example OECD (2004, chap. 1) and Table 3 below. The divergence in hours per worker between the US and Europe started in the 70's. In the 50's the Americans were working even less hours than the Europeans, see for example Bell and Freeman (1995).

Figure 1: Hours worked and labor market conditions



(a) Income Inequality and Hours per Worker (b) Unemployment Rate and Hours per Worker

Notes: Changes over the 1970-2002 period. Source OECD, see "http://www.oecd.org". Changes in Hours per Worker are percentage changes in the average annual hours worked per employee in the 1970-2002 period. Changes in the unemployment rate are level variations over the same period. Changes in income inequality are calculated as variations in the log difference of the ninth and the first decile of the distribution of gross earnings in the main job of full-time workers; the sample period used differs because of data availability. We always select the available data closest to 2002 and to 1970, respectively.

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 then analyze the effects of reducing job offer probabilities so as to reproduce the raise in European unemployment over the last thirty years. We find that labor market conditions (in terms of inequality and unemployment) can account for the US-EU differences in hours per worker emerged over the last 30 years.

The idea that labor market conditions play a role in explaining working time differences is novel. Prescott (2004) attributes the relative fall in hours worked in Europe to the sharp increase in taxes experienced by several European countries. This tends to reduce the *net* return to hours worked and discourages working time. We provide evidence that the *gross* return to working longer hours has evolved differently across the two sides of the Atlantic. This suggests that taxes can not be the only reason why working time has evolved differently.[4] Blanchard (2004) argues that Europeans work less than Americans because they have a stronger preference toward leisure. In our model this happens not because Europeans are intrinsically different from Americans, but because they lack career

[4]The Prescott's analysis has recently been questioned either because it hinges on a high elasticity of labor supply (Blanchard 2004) or because it fails to be consistent with some panel data estimates (Nickell 2003) or because it yields counterfactual implications when the effects of taxes and unemployment benefits are analyzed jointly (Ljungqvist and Sargent 2007).

prospects due to the sluggish labor market. Alesina, Glaeser, and Sacerdote (2005) argue that trade unions introduced work sharing arrangements. They restricted the number of hours per worker so as to sustain a higher employment level. Our analysis suggests that the observed different evolution of wage inequality and unemployment in the US and the EU, could simply be part of a trade unions' attempt to make work sharing politically sustainable. Working time restrictions, imposed by law or collective bargaining agreements, become incentive compatible because Europeans do not prefer to work longer hours given the existing labor market conditions.[5]

Our theory can also explain why the fraction of prime age male workers working very long hours (say above fifty hours per week) has increased substantially in the US over the last thirty years, after reverting a trend of secular decline, see Costa (2000) and Kuhn and Lozano (2005). Typically theories that focus just on Europe to explain the widening of the gap in working time have a hard time in accounting for this fact. Moreover Kuhn and Lozano (2005) find that the increase in the fraction of workers working very long hours has been more pronounced in occupations, industries and groups of workers (such as highly educated and high wage earners) that also experienced higher increases in within skill wage inequality, which provides further evidence in favor of our theory.

Our analysis is related to Bell and Freeman (1995, 2001), who have also argued that higher wage inequality gives greater incentives to work longer hours. Looking at the NLSY for the US and at the GSOEP for Germany, Bell and Freeman (2001) show that occupations with larger wage inequality are also occupations in which individuals work longer hours. Here we provide a model and specify an explicit channel whereby wage inequality affects the return to working longer hours. We investigate how several features of the labor market affect working time decisions aside from wage inequality and we quantify their role in accounting for the diverging evolution of working time in the US and the EU.

The idea that hours worked increase worker's human capital is not entirely novel. The idea has been formally 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 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

[5] OECD (1998, chap. 5) reports that the difference between actual and desired working time is generally small for European workers and it has even decreased over the last decades. Bell and Freeman (2001) also document that the fraction of workers that would prefer to work longer hours for given hourly wages is even higher in the US than in Germany.

market with search frictions, several 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.

The plan of the paper is as follows. The next section introduces a simple model that highlights how labor market variables affect working time decisions and presents some preliminary evidence. Section 3 extends the model while Section 4 discusses its parametrization. Section 5 quantifies the role of labor market conditions in accounting for the US-EU experience. Section 6 considers some robustness exercises. Section 7 concludes. The Appendix provides details on data and model computation.

2 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 3.

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

Next period, workers are unemployed with probability ρ. In practice ρ is the joint probability that a worker becomes unemployed *and* that he does not find a new job in the period. Thus ρ is increasing in the job separation probability and decreasing in the job finding probability. An unemployed worker obtains income (and leisure) worth b in utility terms. If the job is not destroyed, the worker can receive a job offer from a firm that pays a wage ω'. Job offers are received with probability $p_e(H')$, which is increasing in the worker's human capital H'. The job offer probability p_e 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 (2005a), 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.[6]

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 ω_1 and q at $\omega_2 > \omega_1$. Preferences over consumption and leisure are given by

$$u(c, \lambda h) = \ln c - \lambda h$$

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

$$V_2(H', \omega') = \max_{h'} \Big\{ \ln\left(\omega' H'^{\alpha} h'^{\theta}\right) - \lambda h' \Big\}, \tag{1}$$

which yields $h' = \frac{\theta}{\lambda}$. In the first period, a worker with human capital H, who currently receives wage ω, chooses hours by solving the following Bellman equation:

$$\begin{aligned} V_1(H, \omega) &= \max_h \Big\{ u\left(\omega H^{\alpha} h^{\theta}, h\right) + \beta\rho b + \beta(1-\rho) V_2(H', \omega) \\ &+ \beta(1-\rho) p_e(H') \int_{\mathbb{R}} \max\{V_2(H', s) - V_2(H', \omega), 0\} \, dF(s) \Big\} \end{aligned}$$

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

$$V_1(H, \omega) = \max_h \Big\{ \ln\left(\omega H^{\alpha} h^{\theta}\right) - \lambda h + \beta\rho\, b + \beta(1-\rho)\left[V_2(H', \omega) + p_e(H')\, q\,(\ln\omega_2 - \ln\omega)\right] \Big\}$$

which, after using (1), yields the following first order condition:

$$\lambda = \frac{\theta}{h} + \beta(1-\rho)\left[\frac{\alpha}{h} + \frac{dp_e}{dH'}\, a\, q(\ln\omega_2 - \ln\omega)\right]. \tag{2}$$

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

[6] 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).

current income, equal to θ/h, and the expected marginal increase in future income—which corresponds to the second term in the right hand side of equation (2). This *intertemporal return* to hours worked is affected by the rate of utilization of human capital $(1-\rho)$, the productivity elasticity to human capital α, 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 h we log-linearize the function describing the job offer probability:

$$p_e(H') \simeq p_0 + p_1 \left(\ln H' - \ln \overline{H}\right) \tag{3}$$

where $\overline{H}$ is an appropriately defined constant while p_1 is the semi elasticity of the job offer probability to human capital. In general p_1 is higher in a tighter labor market, since search efficiency units are marginally more effective when labor market tightness rises. This allows to solve for h so as to obtain that

$$h = \frac{\theta + \beta(1-\rho)\left[\alpha + p_1\, q\,(\ln\omega_2 - \ln\omega)\right]}{\lambda}. \tag{4}$$

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 ω. 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) is instead decreasing in ω, because the chances of obtaining a better job decrease as the current wage rate increases. This discourages working time. The intertemporal return to hours worked is also decreasing in the unemployment probability ρ, because a higher ρ reduces the rate of use of the stock of human capital H', while it is increasing in the productivity elasticity to human capital α. 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 labor market gets tighter—i.e. when the unemployment probability ρ falls or p_1 increases.

2. the productivity elasticity to human capital α rises.

3. within-skill wage inequality, modeled as a mean preserving spread in the wage offer distribution F, increases.

2.1 Some preliminary evidence

A key testable implication of the model is that current hours of work raise future income. Another is that their effects on future income should have increased in the US while they should have changed little in Europe. This is because, as argued in the Introduction, both the return to skill and within-skill wage inequality have increased sharply in the US while they have hardly changed in Europe. We present some evidence supporting these predictions based on estimating an equation relating hourly wages to past hours on micro data. The equation comes directly from the two-period model just discussed.

Consider the second period logged hourly wage, equal to the difference between log income and log hours:

$$\ln w' = \left[\ln \omega' + \alpha \ln H' + (\theta - 1) \ln h'\right]. \tag{5}$$

The log of the wage rate $\ln \omega'$ evolves as

$$\ln \omega' = \ln \omega + p_e\left(H'\right) q \left(\ln \omega_2 - \ln \omega\right) + \epsilon$$

where ϵ denotes a zero mean expectational error. Now use equation (3) to approximate $p_e\left(H'\right)$ and then linearize the resulting expression with respect to $\ln H'$ and $\ln \omega$ around $\ln \overline{H}$ and the average logged wage rate $\ln \overline{\omega}$. After using the fact that $H' = ah$ we obtain:

$$\ln \omega' \simeq cte + p_1 q \left(\ln \omega_2 - \ln \overline{\omega}\right) \ln h + \left(1 - p_0 q\right) \ln \omega + \epsilon \tag{6}$$

where cte is an appropriately defined constant. By using the expression for logged hourly wage at time zero analogous to (5) we obtain an expression for $\ln \omega$ that can be substituted into (6). The resulting expression for $\ln \omega'$ is then substituted into (5) so as to yield

$$\ln w' = cte + (1 - p_0 q) \ln w - (1 - \theta) \ln h' + \left[\alpha + p_1 q \left(\ln \omega_2 - \ln \overline{\omega}\right) + (1 - \theta)(1 - p_0 q)\right] \ln h + \varepsilon \tag{7}$$

where again cte denotes an appropriately defined constant and $\varepsilon \equiv \epsilon + \alpha\left(1 - p_0 q\right) \ln H$. This relation suggests estimating the following equation:

$$\ln w_{i,t} = \psi_0 + \varphi_1 \ln w_{i,t-1} + \varphi_2 \ln h_{i,t} + \varphi_3 \ln h_{i,t-1} + \varepsilon_{i,t} \tag{8}$$

Hours of work increase future income if $\varphi_1 \varphi_2 + \varphi_3 > 0$, which requires a sufficiently positive φ_3. The equation is similar to the regression ran by Bell and Freeman (2001) to identify the effects of past hours on current wages. In their specification, however, they do not control for current hours, which may introduce a bias if θ is different from one. We estimate the equation by OLS and by allowing for a fixed effect. This is because the error term in (7) could contain an unobserved individual fixed effect term, which may be correlated with $\ln y$ and $\ln h$. Fixed effects estimates are based on the two-step Arellano and Bond (1991) estimator (difference GMM estimator). Standard errors are corrected for finite sample bias as in Windmeijer (2005). As in Bell and Freeman (2001), hours and wages are measured as five year averages to remove business cycle effects. In the regressions 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.

We estimate equation (8) for both the US and Germany. The US data come from the Michigan Panel Study of Income Dynamics (PSID), which covers the period 1967-2002. Data are annual up to 1997 and bi-annual thereafter. We restrict our samples to prime age male (between 25 and 55 years old) who are head of households. 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. Hourly wages are computed as annual labor earnings divided by annual hours worked. 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. Labor income measures are expressed in 1992 dollars by using the output deflator. Education is measured as years of schooling and experience as current age minus years of schooling. The German data come from the German Socioeconomic Panel (GSOEP). The data refer to the period 1984-2002. Again we restrict our sample to prime age male (between 25 and 55 years old) who are head of households and who reside in the former Federal Republic of Germany. Appendix A contains further details about the two data sets.

Table 1 presents the results. Panel (a) contains the results for the US whereas panel (b) deals with Germany. The columns labeled as [1] are OLS regressions. We find that φ_3 is positive and statistically significant. This is true for both the US and Germany and independently of whether we consider yearly or weekly hours. The coefficient φ_2 is slightly greater in absolute value in Germany than in the US, while φ_3 is similar in the two economies.[7] The columns labeled as [2] report estimates based on the two-step Arellano-

[7] This may be because in Germany many jobs current income is influenced by collective agreements, and it is set independently of the number of hours worked in the period. So workers can raise their labor income only by either obtaining better jobs or getting promoted in the current one. Thus hourly wages in the current job decrease faster in Germany than in the US when current hours increase.

Bond estimator. The instruments are lagged values of past five years averages. Now the estimated serial correlation of wages as measured by φ_1 falls significantly relative to the OLS estimates. But the estimated φ_3 is again positive, statistically significant and of a very similar magnitude. In all cases, the intertemporal returns implied by these estimates are positive and fairly large (between 15 and 60 percent in the US and between 7 and 18 percent in Germany).

Table 1: The intertemporal return

(a) PSID

	Annual [1]	Annual [2]	Usual weekly [1]	Usual weekly [2]
φ_1	0.81	0.48	0.81	0.43
	(192.4)	(3.57)	(189.2)	(2.7)
φ_2	-0.43	-0.56	-0.35	-0.56
	(-41.4)	(-10.5)	(-34.2)	(-10.1)
φ_3	0.51	0.42	0.49	0.75
	(45.7)	(5.3)	(35.06)	(4.2)
$\varphi_1\varphi_2 + \varphi_3$	0.16	0.15	0.21	0.62
n	31,636	28,105	31,633	28,101

(b) GSOEP

	Annual [1]	Annual [2]	Usual weekly [1]	Usual weekly [2]
φ_1	0.65	0.15	0.67	0.09
	(73.76)	(2.0)	(73.8)	(1.4)
φ_2	-0.63	-1.05	-0.64	-1.03
	(-24.7)	(-11.0)	(-24.2)	(-10.2)
φ_3	0.56	0.23	0.61	0.24
	(23.1)	(2.9)	(22.9)	(2.1)
$\varphi_1\varphi_2 + \varphi_3$	0.15	0.07	0.18	0.15
n	6,371	5,515	6,120	5,261

Notes: Panel (a) deals with PSID, Panel (b) with GSOEP. The first two columns in each panel use total annual hours in all jobs whereas the second two columns use usual weekly hours worked in main job. In column [1] OLS estimates, in column [2] fixed effects estimates. Fixed effects estimates are based on the two steps Arellano and Bond (1991) estimator (difference GMM estimator). Standard errors are corrected for finite sample bias as in Windmeijer (2005). t-statistics in parentheses. The dependent variable is the logged real hourly wage. Hours and wages are measured as five years averages. Instruments are lagged values of past five years averages. All regressions include year and education dummies and potential experience (in levels and squared).

Equation (7) also predicts that an increase in either the productivity elasticity to human capital, α, or in with-skill wage inequality, $(\ln \omega_2 - \ln \bar{\omega})$, makes φ_3 increase. So φ_3 is expected to have increased in the US and to have hardly changed in Europe. To check this, we estimate again equation (8) but allowing for a time-changing coefficient φ_3. We allow the coefficient to change every five or ten years, depending on the specification. Since several authors have argued that in the US the return to education and experience have increased over time, we have also interacted education and experience with time dummies. This allows the return to experience and education to change over time. The results are presented in Table 2. Panel (a) deals with the PSID and panel (b) with the GSOEP. In column [1] we report the OLS estimates, in column [2] the fixed effects estimates. For the US, we find that φ_3 has increased over time. A formal statistical test shows that the intertemporal returns to hours worked are larger in the 90's than in the 80's and in the 70's.[8] In Germany, instead the intertemporal return falls in the 90's relative to the 80's, although the difference is not statistically significative. Overall this evidence complements the findings of Bell and Freeman (2001) and Kuhn and Lozano (2005), who found a positive correlation between hours of work and income inequality. Our theory provides a causal interpretation for their findings.

Table 2: Evolution of the intertemporal return

(a) PSID

	Annual		Usual weekly	
	[1]	[2]	[1]	[2]
$\varphi_{3,70-75}$	0.43	0.41	0.44	0.58
	(15.7)	(4.9)	(12.8)	(4.6)
$\varphi_{3,76-80}$	0.47	0.41	0.47	0.58
	(21.0)	(5.3)	(16.5)	(4.7)
$\varphi_{3,81-85}$	0.46	0.40	0.42	0.56
	(22.1)	(5.1)	(14.8)	(4.5)
$\varphi_{3,86-90}$	0.51	0.41	0.49	0.56
	(28.0)	(5.4)	(20.1)	(4.4)
$\varphi_{3,91-95}$	0.58	0.50	0.61	0.67
	(29.1)	(5.8)	(24.3)	(4.7)
$\varphi_{3,96-00}$	0.60	0.51	0.59	0.64
	(13.3)	(5.5)	(10.1)	(4.6)
$\varphi_{3,70-80}$	0.46	0.42	0.45	0.75
	(25.1)	(5.3)	(20.1)	(4.3)
$\varphi_{3,81-90}$	0.49	0.40	0.45	0.74
	(33.7)	(5.3)	(23.6)	(4.2)
$\varphi_{3,91-00}$	0.59	0.50	0.61	0.86
	(31.4)	(5.6)	(25.9)	(4.6)
Test:				
$\varphi_{3,70-80} = \varphi_{3,81-90}$	.17	.39	.50	.50
$\varphi_{3,70-80} = \varphi_{3,91-00}$	.00	.07	.00	.09
$\varphi_{3,81-90} = \varphi_{3,91-00}$	.00	.00	.00	.03

(b) GSOEP

	Annual		Usual weekly	
	[1]	[2]	[1]	[2]
$\varphi_{3,84-88}$	0.53	0.27	0.57	0.30
	(13.0)	(3.1)	(14.0)	(2.5)
$\varphi_{3,89-93}$	0.60	0.27	0.71	0.30
	(19.1)	(2.8)	(19.6)	(2.0)
$\varphi_{3,94-98}$	0.57	0.22	0.56	0.26
	(15.3)	(2.9)	(14.3)	(2.0)
$\varphi_{3,84-91}$	0.58	0.25	0.63	0.28
	(19.3)	(2.9)	(20.0)	(1.97)
$\varphi_{3,92-02}$	0.56	0.19	0.58	0.22
	(17.8)	(2.3)	(17.1)	(1.8)
Test:				
$\varphi_{3,85-92} = \varphi_{3,93-02}$	.63	.09	.17	0.10

Notes: Panel (a) deals with PSID, Panel (b) with GSOEP. The first two columns in each panel use total annual hours in all jobs whereas the second two columns use usual weekly hours worked in main job. In column [1] OLS estimates, in column [2] fixed effects estimates. Fixed effects estimates are based on the two steps Arellano and Bond (1991) estimator (difference GMM estimator). Standard errors are corrected for finite sample bias as in Windmeijer (2005). t-statistics in parentheses. The dependent variable is the logged real hourly wage. Hours and wages are measured as five years averages. Instruments are lagged values of past five years averages. All regressions include year and education dummies and potential experience (in levels and squared) and allow for a time varying return to education and experience.

3 The general model

To quantitatively study how much the change in labor market conditions can explain of the different evolution of hours per worker in the US and Europe, we now extend the model

[8]Notice that the result is not driven by the change in the sampling frequency of the PSID: the estimated φ_3's using data on the 85-95 period and the 90-00 period are indeed very similar, see the upper panel of Table 1.

in several directions. First, we allow individuals to experience recurrent unemployment spells. Second, we allow for an endogenous unemployment exit probability; third for a downward trend in hours worked; and finally we specify 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' reservation wages and human capital. The third is introduced to match the secular downward trend in hours per worker observed in the data, see for example McGrattan and Rogerson (2004). The last extension is introduced to match key features of the data.

3.1 Model description

Workers are infinitely lived. An employed worker is characterized by her stock of human capital $H \in \mathbb{R}_+$ and by the job wage rate $\omega \in \mathbb{R}_+$. When employed, the worker decides how many hours to work. Hours of work generate a flow of income $\omega H^\alpha (a_t h)^\theta$ in the current period and increase the stock of human capital in the next period according to $H' = (1-\delta) H + a_t h$, where a_t characterizes labor augmenting technological progress (which increases the effectiveness of any source of efficiency units of labor used in production) while $\delta \in [0,1]$ represents the depreciation rate of human capital.

As previously discussed, human capital affects the probability of receiving job offers. We assume that the job offer probability for an unemployed worker ($i = u$) and an employed worker ($i = e$) is given by

$$p_i\left(H, G\right) = \bar{p}_i \, S(H, G), \;\; i = u, e \tag{9}$$

Here $\bar{p}_i$ measures how labor market tightness affects the job contact rate that may differ depending on the employment state of the worker. The function $S\left(H, G\right)$ instead 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—so that he becomes less likely to be offered a job when competing against other applicants.

Job offers are drawn from a given distribution F, which is log normal with variance ν, $\log \omega \sim N\left(-\frac{\nu}{2}, \nu\right)$. This implies that the wage offer distribution has mean one and that changes in ν generate mean-preserving spreads of F. An employed worker loses her job with probability p_s. Since we will focus on steady state allocations, we omit the distribution G from the state space of the worker's problem. Her problem when employed can then be expressed in terms of the following Bellman equation:

$$\begin{aligned} W_t(H,\omega) &= \max_h \Big\{ u\left(\omega H^\alpha (a_t h)^\theta, \lambda_t h\right) + \beta p_s V_{t+1}\left(H', \bar{b}_0\right) + \beta (1-p_s) W_{t+1}(H',\omega) \\ &+ \beta (1-p_s) p_e (H', G) \int_{\mathbb{R}} \max\left[W_{t+1}(H',s) - W_{t+1}(H',\omega), 0\right] dF(s) \Big\} \end{aligned} \quad (10)$$

subject to: $H' = (1-\delta)H + a_t h$. Here λ_t measures the effort cost of working at time t, which may change over time. The parameter $\beta \in (0,1)$ is the intertemporal discount factor and $V_{t+1}\left(H', \bar{b}_0\right)$ is the value of becoming unemployed at time $t+1$, which depends on time (because of the possible time changing values of a_t and λ_t), on the next period worker's human capital, H', and on the utility flow of a worker who has just become unemployed $\bar{b}_0$. Notice that a worker accepts only job offers that yield an increase in utility. This accounts for the integral term in the second row.

An unemployed worker who has experienced τ periods in unemployment obtains income (and leisure) worth b_τ in utility terms. We assume this income to fall over time so that $b_\tau = \bar{b}_0 - \bar{b}_1 \tau$. This can capture the fact that precautionary savings and other sources of income get progressively exhausted as a worker remains unemployed.[9] The problem of an unemployed worker is then characterized by the following Bellman equation:

$$\begin{aligned} V_t(H,b) &= \max_{\omega_r} \Big\{ b + \beta \Big[1 - p_u(H',G)(1-F(\omega_r))\Big] V_{t+1}(H',b') \\ &+ \beta p_u(H',G) \int_{\omega_r}^{\infty} W_{t+1}(H',s)\, dF(s) \Big\} \end{aligned} \quad (11)$$

subject to $H' = (1-\delta)H$ and $b' = b - \bar{b}_1$. Notice that an unemployed worker accepts only wage offers above the (endogenously determined) critical threshold ω_r.

3.2 Functional forms

At every point in time, preferences for consumption and leisure are given by

$$u(c, \lambda_t h) = \ln c - \frac{(\lambda_t h)^{1+\eta}}{1+\eta}, \ \ \eta \geq 0,$$

where η determines the sensitivity of the marginal disutility of working to hours worked. To make the environment stationary we assume that λ_t and a_t grow at the constant rate

[9]Notice that under log preferences $\bar{b}_1$ is simply the rate of decay of unemployment income.

μ, so that $\lambda_t = (1+\mu)^t \lambda$ and $a_t = (1+\mu)^t a$ for any t. We assume μ to be positive in order to match the observed secular downward trend in hours worked for male workers.[10]

Search efficiency units are given by the following logistic function that parsimoniously characterizes some key features of the ranking process of job applicants:

$$S(H, G) = \frac{4}{1 + e^{-\gamma[H - \psi(G)]}}, \ \ \gamma \geq 0.$$

The function is identified by a human capital sensitivity parameter γ and by a shift parameter $\psi(G)$, which is a function of the equilibrium distribution of human capital G. A value of γ equal to zero implies that human capital has no effect on search activities. Formally γ measures the maximal value of the derivative of search efficiency units to capital (which is maximized at $H = \psi(G)$).[11] The parameter $\psi(G)$ characterizes workers' competition for jobs and it tends to increase when the human capital distribution of workers G shifts to the right. Notice that 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 2) 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 start considering a specification where $\psi(G) = \bar{H} \equiv \int HdG$, which implies 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. In Section 6 we will consider some alternative specifications for the function ψ.

[10]We model the secular trend in hours by relying on labor augmenting technological progress rather than by assuming ongoing neutral technological progress and preferences where the income effect dominates the substitution effect. This model choice is partly due to the partial equilibrium nature of the model. In our model, when the income effect dominates the substitution effect, any parameter change (including an increase in the variance of the wage offer distribution) leads to changes in average wages, which tends to affect hours worked. This partial equilibrium effect, however, would tend to dissipate in a general equilibrium version of the model were firms demand workers and capital and wages and the rental price of capital are set endogenously.

[11]Notice that the function does not impose any bounds to the value of the semi-elasticity of search efficiency to human capital, (i.e. to the value of p_1 in Section 2). Instead imposing a generic concave function with positive intercept would implicitly limit the value of the semi-elasticity at given levels of the stock of human capital and of job offer probability.

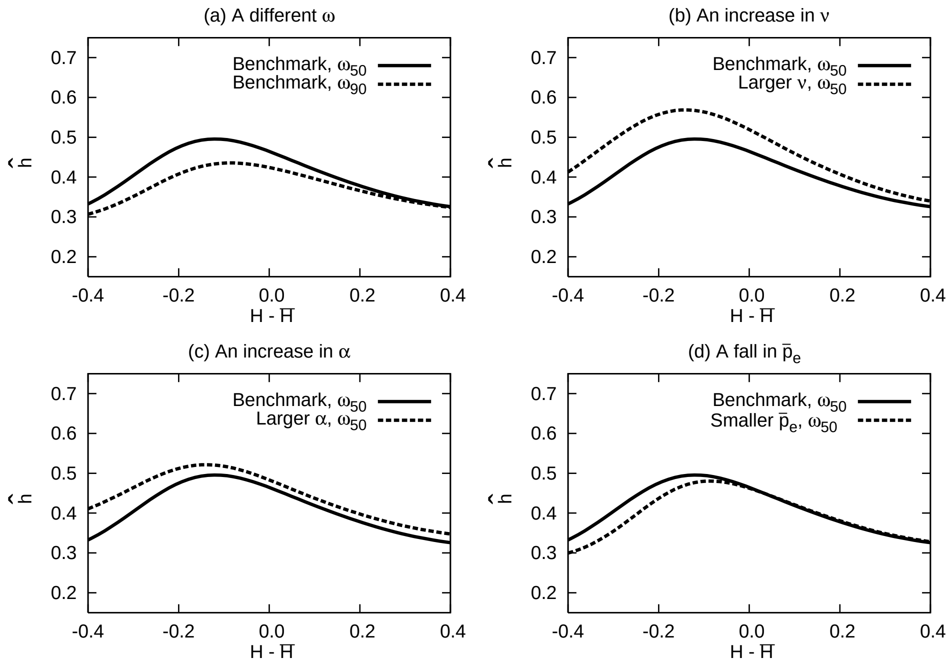
3.3 Model solution

To make the environment stationary, we re-express the worker's problem in terms of *detrended* hours $\widehat{h}_t \equiv h_t(1+\mu)^t$. The solution can then be described by a pair of stationary decision rules, one for detrended hours $\widehat{h}\,(H,\omega)$, and the other for the reservation wage of an unemployed worker $\omega_r\,(H,b)$, see Appendix B for details. The steady state of the economy is characterized by a constant unemployment rate and by unique time-invariant distributions of human capital and wage rate for employed workers, and of human capital and unemployment utility for unemployed workers.

Figure 2 characterizes the policy function for detrended hours worked, $\widehat{h}$. The solid line in Panel (a) (and in the other three panels) represents $\widehat{h}$ as a function of relative human capital, $H - \bar{H}$, at ω equal to one, which corresponds to the median of the wage offer distribution. The decision rule is hump-shaped because the semielasticity of the job offer probability to human capital (i.e p_1 in Section 2) declines as human capital tends to move away from its average in the population. The policy function reaches its maximum at a human capital value smaller than the average 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. If we think that individuals are born with a relatively low human capital level that they progressively increase as they participate in the labor market, this shape is consistent with the age profile of hours worked found in the data, which tends to peak for middle age workers, see for example McGrattan and Rogerson (2004).

The dotted line in Panel (a) represents the policy function at a higher ω—which corresponds to the ninetieth percentile of the wage offer distribution. Workers with higher ω work fewer hours because they have less incentives to accumulate human capital in order to obtain better jobs. The difference in hours worked is less pronounced at extreme human capital values, since, in either tail of the human capital distribution, the semielasticity of the job offer probability to human capital tends to converge to zero. Figure 2 also shows the effects on hours worked of increasing the dispersion of job offers, ν, (Panel b), of increasing the productivity elasticity to human capital, α, (Panel c) and of reducing labor market tightness so that the job offer probability for an employed worker falls, $\bar{p}_e$, (Panel d). The effects of reducing $\bar{p}_u$ would be similar to those of $\bar{p}_e$ and are omitted to save space. An increase in either ν or α shifts the policy function upwards and increases the incentives to work longer hours whereas a reduction in $\bar{p}_e$ shifts the policy function downwards and discourages individuals from working longer hours. The effects are relatively more pronounced at human capital levels below the average in the population. This is because,

Figure 2: Policy function and comparative statics



Notes: Solid line corresponds to the policy function of (detrended) hours worked, $\widehat{h}$, as a function of relative human capital $H - \bar{H}$ at ω equal to one, which corresponds to the median of the wage offer distribution. The parameter values are as given in Table 5 where $\psi = \bar{H}$. The dotted line in the four panels represents the policy function at a higher ω corresponding to the ninetieth percentile of the wage offer distribution (Panel a), at a higher $\nu = 0.55$ (Panel b), at an higher $\alpha = 0.35$ (Panel c) and at a lower $\bar{p}_e = 0.65$ (Panel d), respectively.

at higher human capital levels, marginally increasing hours has smaller percentage effects on human capital which makes the intertemporal return to hours worked less sensitive to any parameters' change.

4 The quantitative exercise

We first describe the evolution of aggregate hours worked in the US and Europe over the last thirty years. We show that hours per worker (the so called intensive margin) plays a very important role in explaining the aggregate trend in hours. We then discuss how we quantify the role played by labor market conditions in accounting for the diverging evolution of the intensive margin across the two sides of the Atlantic.

4.1 The evolution of hours worked

In the model aggregate hours per worker is given by

$$E(h_t) = (1+\mu)^{-t} \int_{\mathbb{R}_+^2} \widehat{h}(H,\omega)\, d\Gamma(H,\omega),$$

where $\widehat{h}$ denotes detrended hours worked and $\Gamma(H,\omega)$ is the probability measure of employed workers with human capital H and wage rate ω in steady state. Hours per worker is just one of the components determining aggregate hours, which can generally be decomposed as follows:

$$\frac{\text{hour}}{\text{pop}} = \frac{\text{hour}}{\text{emp}} \times \frac{\text{emp}}{\text{part}} \times \frac{\text{part}}{\text{wa}} \times \frac{\text{wa}}{\text{pop}}$$

where the first fraction denotes hours per worker, the second denotes one minus the unemployment rate, the third the participation rate, while the fourth is the fraction of working age population over the total population. The percentage changes of the various components underlying the dynamics of hours per capita over the period 1970-2001 for the US and some other countries are summarized in Table 3. We present results both for the whole population and for the population of male workers. The table evidences

Table 3: Evolution of aggregate hours worked, (1970-2001)

	All workers					**Men only**				
	$\frac{\text{hour}}{\text{pop}}$	$\frac{\text{hour}}{\text{emp}}$	$\frac{\text{emp}}{\text{part}}$	$\frac{\text{part}}{\text{wa}}$	$\frac{\text{wa}}{\text{pop}}$	$\frac{\text{hour}}{\text{pop}}$	$\frac{\text{hour}}{\text{emp}}$	$\frac{\text{emp}}{\text{part}}$	$\frac{\text{part}}{\text{wa}}$	$\frac{\text{wa}}{\text{pop}}$
Absolute Percentage Changes										
US	15	-5	0	13	7	3	.5	-.5	-5	8
France	-22	-23	-6	3	4	-24	-10	-5	-13	4
Germany	-24	-26	-7	4	6	-24	-11	-7	-14	8
Spain	-6	-14	-9	10	10	-23	-12	-7	-16	12
UK	-8	-12	-3	4	4	-10	-2	-2	-10	4
Percentage changes relative to the US										
US	0	0	0	0	0	0	0	0	0	0
France	-37	-17	-6	-10	-3	-27	-10.5	-4.5	-8	-4
Germany	-39	-21	-7	-9	-1	-27	-11.5	-4.5	-11	0
Spain	-21	-9	-9	-3	3	-26	-12.5	-6.5	-11	4
UK	-23	-7	-3	-9	-3	-13	-2.5	-6.5	-5	-4

Notes: Source OECD and ILO. For *All workers* '$\frac{\text{hour}}{\text{emp}}$' the is average actual annual hours worked per person in employment, while for *men only* it is the average number of hours paid per week and it is from ILO. In both sample 'emp' is total employment, 'part' is total labor force, 'wa' is population aged 15 to 64 years, and 'pop' is total population. The sample period for *men only* is 1993-2002 for France, 1973-1995 for Germany (that refers to former Federal Republic), 1978-2001 for Spain, 1986-2001 for the UK, and 1970-2001 for the US.

how the intensive margin accounts for around 50 per cent of the trend differences in hours per capita between the US and France, Germany, and Spain. This is true both when considering the population of all workers and the male population, although the fall in hours per worker is somewhat more pronounced in the overall population than when considering only male workers.

We now use the model to quantify how much labor market conditions can explain of the different evolution of hours per worker in the US and Europe. As in Prescott (2004) and Ljungqvist and Sargent (2007) we take the US as the benchmark economy against which to measure the effects of aggregate changes on hours worked. The idea is to evaluate how US workers would have behaved if they had been subject to the same changes in labor market conditions as the Europeans had. 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. 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 the intensive margin in 2000, taking into account changes in policy functions and in the probability distribution of employed workers Γ. We think of the US as an economy that, over the 1970-2000 period, has experienced an increase in within skill wage inequality and in the return to skill, which we model through an increase in the variance of job offers, F, and in the productivity elasticity to human capital α. We think of Europe as an economy where a fall in labor market tightness has reduced the worker probability of receiving job offers so that $\bar{p}_e$ and $\bar{p}_u$ have both fallen. Wage inequality in Europe has instead changed little.

4.2 The baseline economy

The model is described by 15 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). We choose a model period to correspond to one month. Calibrating the model at a quarterly or at an even lower frequency would fail to properly characterize key labor market transitions. For instance, according to Shimer (2005b) and Fallick and Fleischman (2001), the average duration of unemployment is between 2 and 3 months. 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 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.

Table 4: Model and data statistics for the 70's

Statistic	Data	Model				
		Bench.	Fxd het	Lwr γ	Mode	Gtr η
Average separation rate	0.013	0.013	0.013	0.013	0.013	0.013
Avge. prob. leaving unemployment	0.333	0.334	0.337	0.333	0.332	0.341
Average prob. of a job-to-job transition	0.028	0.028	0.028	0.028	0.028	0.028
Elasticity of job-to-job transition to past hours	0.030	0.030	0.030	-0.135	0.030	0.030
Avge. acceptance rate of offers by unemployed	0.750	0.749	0.758	0.755	0.755	0.724
Fraction of long term unemployed ($\tau > 22$ m)	0.034	0.035	0.059	0.029	0.035	0.093
Standard deviation of reemployment wages	0.500	0.503	0.498	0.500	0.494	0.500
Elasticity wage losses wrt. duration	0.080	0.083	0.046	0.071	0.084	0.007
Wage growth on change of current hours	-0.700	-0.684	-0.687	-0.699	-0.684	-0.689
Wage growth on change of human capital	0.040	0.042	0.039	0.045	0.041	0.037
Trend in hours per worker in the job (1950-70)	0.033	0.033	0.033	0.033	0.033	0.033
Average hours per worker in the job	0.400	0.399	0.400	0.400	0.407	0.399
Five-year autocorrelation of hourly wages	0.600	0.180	0.601	0.193	0.178	0.193

Notes: The column labeled "Bench." refers to the benchmark specification described in Section 4. The other columns refer to the extensions discussed in Section 6.

Labor market transitions. In the model there are three transition probabilities characterized by four parameters, p_s, $\bar{p}_u$, $\bar{p}_e$, and γ. To identify the first three parameters we look at average labor market flows. Fallick and Fleischman (2001) calculate, for male workers, the job separation rate (i.e. the rate at which employed workers move into unemployment), the job finding rate for the unemployed and the job to job rate for the employed. At the monthly level the job separation rate is around 1.3% and the job finding probability for an unemployed worker is around 1/3, which is in line with the value reported by Shimer (2005b) when considering an analogous worker population. They also report that every month 2.8% of male workers experience a job-to-job transition. We interpret the event of accepting a new job offer when employed as a job to job transition.

To identify γ—which determines how human capital affects the job offers probability—we use panel data to estimate a relationship between past hours worked and the probability of a job-to-job transition. 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:

$$\text{job-to-job} = \text{cte.} + \varphi_4 \ln h \tag{12}$$

Intuitively a positive φ_4 means that past hours worked increases the probability of a job to job transition. Table 6 presents the results from estimating the equation on PSID data.

Table 5: Parameter values in the 70's

Parameter		Value				
		Bench.	Fxd het	Lwr γ	Mode	Gtr η
p_s,	separation probability	0.013	0.013	0.013	0.013	0.013
$\bar{p}_u$,	tightness parameter, unemployed	0.280	0.288	0.261	0.296	0.303
$\bar{p}_e$,	tightness parameter, employed	0.212	0.202	0.217	0.221	0.203
γ,	job offers sensitivity to human capital	10.103	12.762	7.5	9.537	14.540
$\bar{b}_0$,	initial unemployment utility	-1.071	-1.043	-1.299	-1.051	-0.897
$\bar{b}_1$,	rate of decay of unemployment utility	0.015	0.018	0.003	0.018	0.020
ν,	variance of job offer distribution	0.348	0.162	0.370	0.334	0.334
δ,	depreciation of human capital	0.013	0.013	0.013	0.013	0.013
θ,	elasticity of income to hours	0.300	0.300	0.300	0.300	0.300
α,	elasticity of income to human capital	0.040	0.040	0.040	0.040	0.040
a,	learning-by-doing rate	0.034	0.034	0.034	0.034	0.034
μ,	trend in hours worked ($\times 10^{-4}$)	1.485	1.485	1.485	1.485	1.485
β,	discount factor	0.99	0.99	0.99	0.99	0.99
λ,	weight of leisure	2.436	2.326	2.313	2.393	2.543
η,	curvature of disutility of working	2	2	2	2	3
σ_v^2,	variance of fixed effect	0	0.116	0	0	0

Notes: The column labeled "Bench." refers to the benchmark specification described in Section 4. The other four columns refer to the extensions discussed in Section 6. The parameter σ_v^2 is described in Section 6.

Since we need yearly observations we use data only up to 1997. To check robustness we also report the results with the GSOEP data. In the regressions 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.[12] When using the PSID, we find a value for φ_4 around 0.03. When we look at the GSOEP, we find that φ_4 lies between 0.06 and 0.07. In both cases the estimate is positive and statistically significant. Our estimate for γ is done by indirect inference. We simulate individual data from the model, we aggregate the 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 PSID data but on model generated data. We choose γ so that the estimated coefficient φ_4 in model generated data is equal to its analogue in the PSID.[13]

[12] To check robustness of results we also ran regressions after controlling for tenure in the job. We found that results change little.

[13] Of course the estimate of φ_4 could be driven by some individual fixed effects present in the data but not in the model (say because some skilled workers work longer hours and also experience more job-to-job transitions). This may bias our estimate of γ. To analyze this concern we considered several robustness exercises. We re-estimated equation (12) either by controlling for hourly wages in the current job or by adding a random fixed effect. The estimate for φ_4 changes little, which suggests that individual unobserved heterogeneity does not drive the estimate of φ_4. As discussed in Section 6, we also tried to add to the model individual fixed effects, so as to make the model structure closer to the data. We find that, under this alternative specification, the quantitative results change little, which is again reassuring on our strategy to identify γ.

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

(a) PSID

	Hours measure	
	Annual	Usual weekly
Log past hours	0.03	0.02
	(4.22)	(2.64)

(b) GSOEP

	Hours measure	
	Annual	Usual weekly
log past hours	0.05	0.07
	(4.37)	(5.46)

Notes: Panel (a) deals with PSID, Panel (b) with GSOEP. OLS regressions. t-statistics in parentheses. All regressions include year and education dummies and potential experience (in levels and squared). Hours are measured as five years averages.

Unemployment utility. To set $\bar{b}_0$, the utility value of unemployment upon job loss, and $\bar{b}_1$, the rate of decay of the value of being unemployed, we target the acceptance rate of job offers for unemployed workers and the share of long term unemployment. The idea is that $\bar{b}_0$ determines how appealing is a job offer relative to unemployment, while $\bar{b}_1$ determines how the acceptance rate changes as a worker remains in unemployment, which is a determinant of long term unemployment. Our target for the acceptance rate is a compromise between the value reported by Blau and Robins (1990)—who use workers data and find an acceptance rate of around 70 per cent—and the one by Barron, Bishop, and Dunkelberg (1985)—who use employer data and find a value of 80 per cent. We obtain a measure of the fraction of long-term unemployed by using the CPS-March file. We define as long term unemployed, workers who have experienced at least 22 months, which is the value at which the CPS censors the unemployment duration variable. For prime age males we find that the fraction of long term unemployed is around 3.4%.

Wage Offer distribution. Following den Berg and Ridder (1998) and Postel-Vinay and Robin (2002), we choose the dispersion in the wage offer distribution, ν, 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 these statistics in the PSID and GSOEP data. In the US, we measure the standard deviation of log wages after unemployment to be around 0.5 in the 70's.[14]

Technology. We have five technology parameters: the contribution of hours to human capital accumulation a, the depreciation rate of human capital δ, the income elasticity to human capital α, the income elasticity to hours θ and the rate of skill augmenting

[14] In practice the observed dispersion in re-employment wages is also partly due to worker specific fixed effects. In Section 6 we analyze how results get modified when allowing workers to differ because of a fixed effect in productivity that affects wage inequality. We find that results are little affected.

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

(a) PSID

	Controls included	
	Year	More
$SD_{3,70-80}$	0.52	0.49
$SD_{3,81-90}$	0.62	0.58
$SD_{3,91-02}$	0.77	0.70
n	55,000	54,681

(b) GSOEP

	Controls included	
	Year	More
–	–	–
$SD_{3,84-91}$	0.43	0.43
$SD_{3,92-02}$	0.43	0.42
n	6,321	6,321

Notes: Panel (a) deals with PSID, Panel (b) with GSOEP. Standard Deviation of logged real hourly wage of workers who experienced an unemployment spell in the year. In column 2 we also control for years and education dummies, tenure (in levels and squared) and potential experience (in levels and squared).

technological progress μ. Under log preferences, we can normalize a such that the average human capital in the economy equals one. To identify δ we rely on information about the loss of human capital during unemployment. We target the relationship between wage losses upon reemployment and the duration of the previous unemployment spell. With a positive δ, a longer duration of unemployment implies lower human capital, which causes lower reemployment wages because the efficiency units of labor and the reservation wage rate ω_r are both smaller. Addison and Portugal (1989) reports an elasticity of reemployment wages losses to unemployment duration between 6% and 10%. We find similar figures when we run a regression of re-employment wages on unemployment duration in our PSID sample. We use our simulated data to regress logged reemployment wage losses (defined as the logged difference between the hourly wage in the last job before entering unemployment and the re-employment wage) on the log duration of the unemployment spell:

$$\log \text{wage losses} = \text{cte.} + \varphi_5 \log \text{duration}$$

and we estimate δ by indirect estimate to match a value of φ_5 equal to 0.08.[15]

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

$$\Delta \ln w_{i,t} = \alpha \Delta \ln H_{i,t} - (1-\theta)\, \Delta \ln h_{i,t}. \tag{13}$$

After constructing a measure for the stock of human capital, this equation allows to

[15]Interestingly the resulting estimate of δ is very similar to the depreciation rate of human capital estimated by Imai and Keane (2004), using a different identification strategy.

identify α and θ. We set a value for the depreciation rate of human capital and we use the human capital accumulation equation to construct a synthetic measure of the individual stock of human capital. Then we regress,

$$\Delta \ln w_{i,t} = \text{cte.} + \varphi_6 \Delta \ln H_{i,t} + \varphi_7 \Delta \ln h_{i,t} + \varepsilon \tag{14}$$

on the sample of workers who remain in the same job for two consecutive years. Given equation (13), we then set $\alpha = \varphi_6$ and $\theta = \varphi_7 + 1$ as an approximation.[16] Since again we need yearly observations, we run the regression with data only up to 1997. Table 8 reports the estimates with PSID data when the synthetic stock of human capital is constructed using different values for the corresponding monthly depreciation rate of human capital. The results suggest a value of α around 0.04 and one for θ around 0.3 in the 70's.

The parameter μ is set to replicate the downward trend in hours worked per male worker over the period 1950-1970. McGrattan and Rogerson (2004) use US Census data and report that the average weekly hours worked per prime age male worker has fallen from around 45 hours to 43.5 hours over the 1950-1970 period. This implies a fall of around 3.3 percentage points over a twenty period, which suggests setting $\mu = 0.01485\%$ at the monthly frequency.

Preferences. There are three preference parameters: the discount factor, β, the relative weight of leisure in the utility function, λ, and the elasticity of the marginal disutility of hours, η. To economize on computing time, we set β to 0.99. The value of λ 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).[17] Finally we set η 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 6.4

[16] The mapping between the model parameters and the estimated coefficients would be exact if we could perfectly measure the stock of human capital and if the data were at the monthly frequency as in the model. Alternatively we could estimate α and θ by indirect inference. We could simulate data from the model, aggregate the data at the annual frequency, construct an analogous synthetic measures of human capital in the simulated data, then run the same regression as in the actual data and finally search for the pair of α and θ that make the estimated coefficients using model generated data equal to those obtained in the PSID data. We avoid presenting the result with this strategy just for simplicity. The estimated α and θ under this alternative strategy would be very similar to those in the baseline specification; in particular, we find that when we run the regression (14) with model simulated data the coefficient φ_6 is 4.2 per cent while φ_7 is minus 68.4 per cent, see row 9 and 10 in Table 4.

[17] Notice that the number for weekly hours is slightly higher than the value reported by McGrattan and Rogerson (2004).

Table 8: Determination of α and θ, PSID

Depreciation rate:	$\delta = .01$	$\delta = .013$	$\delta = .016$	$\delta = .02$
$\Delta \ln H$	.051	.054	.055	0.058
	(4.6)	(4.9)	(5.5)	(5.3)
$\Delta \ln h$	-.68	-.68	-.68	-.68
	(-94.7)	(-94.7)	(-94.7)	(-94.7)
Time evolution				
$\Delta \ln H_{70-80}$	.039	.040	.041	.042
	(1.9)	(2.0)	(1.9)	(1.9)
$\Delta \ln H_{81-90}$	.044	.046	.048	.05
	(2.9)	(3.0)	(3.2)	(3.2)
$\Delta \ln H_{91-00}$	.071	.075	.080	.081
	(4.1)	(4.2)	(4.1)	(4.4)
n	16,019	16,019	16,019	16,019
Test:				
$\varphi_{1,70-80} = \varphi_{1,81-90}$	.81	.82	.82	.80
$\varphi_{3,81-90} = \varphi_{3,91-00}$	.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.

for further discussion on this issue. Moreover with our choice for η, the model generates a correlation between annual hourly wages and annual hours of work (both in logs) of minus 12 per cent. This is very similar to the value found in the data in the 70's.[18] So in principle one could also argue that η is set to match the cross sectional correlation between annual hours and annual hourly wages of the 70's.

4.3 The US in the 00's

In the US the unemployment rate has changed little (see Table 3) while wage inequality has increased substantially. Table 7 documents an increase in the standard deviation of re-employment wages from around 0.50 in the 70's to around 0.70 in the 00's. Moreover,

[18]For example, in our sample the analogous correlation is around minus 15 per cent while Heathcote, Storesletten, and Violante (2004), on a PSID sample slightly different from ours, report a value between minus 15 and 11 percent over the 70's.

when we estimate equation (14) allowing for a time-changing effect of human capital on productivity, we find evidence of an increase in α from 0.04 to 0.075, see column 2 in Table 8—which corresponds to the relevant depreciation rate. This gives a second target to characterize the US in 2000.[19] We find that with the new value of α, ν has to increase up to 0.67 in order to match the observed increase of 0.20 points in the standard deviation of re-employment wages, see Table 9. The increase in the dispersion of job offers slightly decreases the average acceptance rate in the economy, and so as a result the employment rate in the US00 economy is 0.3 percent lower than in the US70 economy. This slight fall in the employment rate is consistent with the 1 percent fall in the employment rate of male workers documented in Table 3.

Table 9: Changes in parameters

Parameter	US70	US00	EU00
α	0.040	0.075	0.040
ν	0.348	0.669	0.348
$\bar{p}_e$	0.212	0.212	0.102
$\bar{p}_u$	0.279	0.279	0.135

Notes: Parameters whose value changes in either the US00 or the EU00 economy. The other parameter values are as in Table 5.

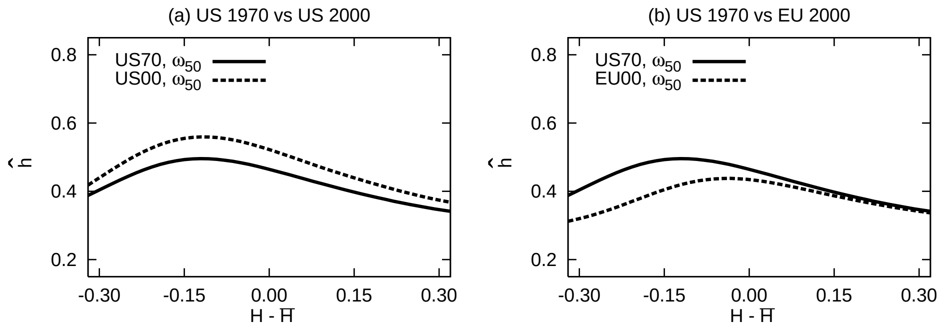
4.4 Europe in the 00's

In Europe the unemployment rate has increased substantially (see Table 3) while wage inequality has changed little.[20] It is also well known that the rise in the EU unemployment rate is mainly due to a fall in the exit rate from unemployment, while the job separation rate has remained roughly constant, see for example OECD (1997, chap. 5) and Bean (1994). To model the increase in unemployment in the EU, we assume that labor market tightness determines the arrival rate of job offers $\bar{p}_e$ and $\bar{p}_u$ and that the relative effectiveness of search on the job and during unemployment has remained unchanged. We then target a fall in labor market tightness that yields a seven per cent fall in the EU employment rate, which is in line with the evidence in Table 3. Parameter changes are reported in Table 9. The resulting EU00 economy exhibits a slight fall in the dispersion

[19] 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 α.

[20] Indeed, the evidence from the GSOEP confirms that inequality has changed little in Europe. For example Table 7 shows no evidence of a change in the dispersion of reemployment wages. Moreover, when we estimated equation (14) on German data and we allowed for a time varying effects of human capital on productivity, we did not find any evidence of a change in α.

Figure 3: Changes in policy function



Notes: The figure characterizes the policy function of (detrended) hours worked, $\widehat{h}$, as a function of relative human capital $H - \bar{H}$ at ω equal to one, which corresponds to the median of the wage offer distribution. The solid line corresponds to the US70 economy, the dotted line in panel (a) and (b) to the US00 and the EU00 economy, respectively.

of hourly wages upon reemployment, which decreases to 0.46.[21]

5 Results

To discuss our quantitative results, we first focus on how average hours per worker change in the US00 and in the EU00 economy. Then we turn to the analysis of other features of the cross-sectional distribution of hours per worker. We conclude by showing that the model reproduces nicely the evolution of the intertemporal return observed in the data.

5.1 Average effects

Figure 3 shows how the policy function for detrended hours changes in the US and Europe in the 00's relative to the 70's. The policy function shifts upward in the US and downward in Europe. The fall in hours in Europe is particularly pronounced for workers with lower than average human capital. This is because, as discussed in Section 3, changes in the job offer probability have bigger effects at relatively lower human capital levels. Figure 4 characterizes the density function of log hourly wages, detrended hours and human capital in the baseline economy of the 70's (as a solid line) and in the relevant economy of the 00's (as a dotted line). The column on the left deals with the US, that on the right with Europe. Density functions are calculated using a Gaussian Kernel where the bandwidth is chosen using the optimal rule proposed by Silverman (1986). Wage inequality increases

[21]This number may be consistent with the findings of Table 7, which documents that since the mid 80's the dispersion of start-up wages in Germany has been roughly constant at the value of 0.43.

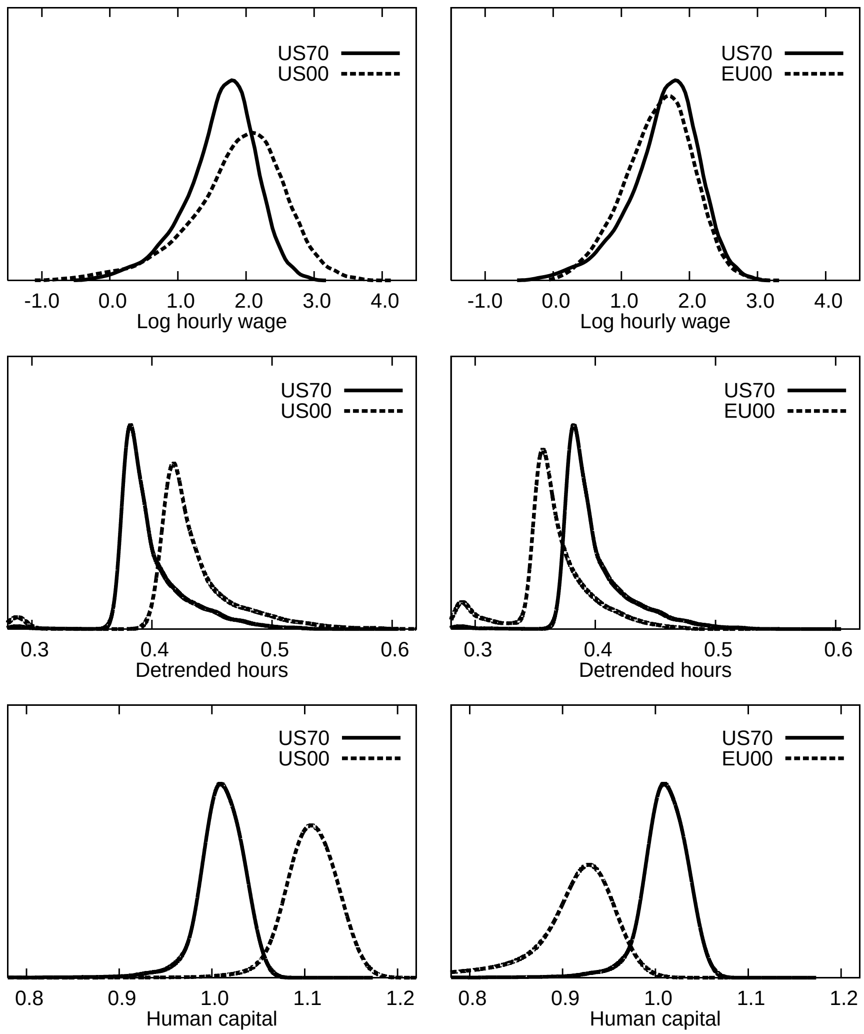
substantially in the US while it changes little in Europe. The distribution of detrended hours (and thereby of human capital) shifts to the right in the US and to the left in Europe. As a result the average number of (detrended) hours worked per worker increases by 8.5 percent in the US while it falls by 8.7 percent in Europe, see Table 10. This implies that the US-EU differential in hours per worker increases by 17.2 per cent in the 00's relative to the 70's. This figure is in line with the empirical evidence if we consider the population of all workers as a benchmark, while it tends to over predict actual changes when focusing on male workers (for instance, the differential between the US and Germany increases by 21 percent in the population of all workers and by 11.5 percent in the men only population, see Table 3). Our calibration for the trend in hours per worker μ implies that over a thirty years period hours falls by around 5.25 per cent. As a result, the model predicts an increase in the level of hours per worker by 3.25 per cent in the US and a fall by 14 per cent in Europe. This is in line with the empirical findings reported in Table 3 when considering the population of male workers, although, again, the model tends to slightly over predict the magnitude of the changes.

Table 10: Changes in detrended hours worked per worker

Economy	Average hours $\times 10^{-2}$	Diff to (1) (%)	US-EU diff (%)
(1) US in 1970	40.0	-	-
Benchmark model, $S(H,G)$			
(2) US in 2000	43.3	8.5	-
(3) EU in 2000	36.5	-8.7	17.2
Fixed G, $S(H,G_{70})$			
(4) US in 2000	41.8	4.6	-
(5) EU in 2000	37.3	-6.7	11.3

We now analyze how each parameter change contributes to the results. First we analyze the contribution of changes in the productivity elasticity to human capital, α, relative to changes in within skill wage inequality, ν, in driving the results for the US. To do so we change only α or only ν (as in Table 9) and we compare the obtained results to those arising in the US00 economy. Row 3 in Table 11 shows that the increase in α induces an increase in detrended hours per worker of just 1.3 per cent. This amounts to just 15 percent of the overall increase in detrended hours in the US00 economy. The increase in ν instead yields an increase of 7.6 per cent in hours per worker, which accounts for almost 90 percent of the overall increase in hours per worker in the US economy (see

Figure 4: Distributions: US 1970 vs US 2000 and vs EU 2000



Notes: Solid line corresponds to the density function in the US 70's economy of the logged hourly wage (first row), monthly hours worked for employed workers (second row) and human capital (third row). The dotted line in panel (a) and (b) corresponds to the density function in the US 2000 and EU 2000 economy, respectively. Density functions are calculated using a Gaussian Kernel where the bandwidth is chosen using the optimal rule proposed by Silverman (1986).

row 4). This suggests that within skill wage inequality plays a major role in explaining the diverging evolution of hours per worker in the US relative to the EU. When we perform a similar exercise for the EU to disentangle the relative contribution of changes in $\bar{p}_e$ and $\bar{p}_u$, we find that the change in the arrival rate of job offers while employed, $\bar{p}_e$, accounts for around 70 per cent of the EU fall in detrended hours per worker (see row 6). Since a fall in $\bar{p}_e$ discourages workers from working longer hours mainly because it makes more difficult to obtain high-wage jobs, this result again evidences the importance of within-skill wage inequality for working hours decisions.

Table 11: Decomposition of the differential

Economy	Average hours $\times 10^{-2}$	Diff to (1) (%)	Relative change (%)
(1) US70	40.0	-	-
(2) US00	43.3	8.5	-4.4
(3) $\Delta\alpha$	40.4	1.3	15.0
(4) $\Delta\nu$	43.0	7.7	89.9
(5) EU00	36.5	-8.7	19.1
(6) $\Delta\bar{p}_e$	37.5	-6.1	69.9
(7) $\Delta\bar{p}_u$	39.6	-0.9	10.4

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 perform our numerical exercises for the US00 and the EU00 economies assuming 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. Parameter changes are again obtained to match the statistics discussed in Section 4.3 and 4.4. We find that, in the absence of equilibrium effects, detrended hours increase by 4.6 per cent in the US, while they fall by 6.7 per cent in Europe, see rows 4 and 5 in Table 10. This implies an increase of 11.3 percent in the US-EU differential which amounts to about 2/3 of the overall increase generated by the model. Thus, accounting for the effects of a changing distribution of workers' human capital on job competition amplifies 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.

5.2 The distribution of hours worked

So far we have analyzed changes in average hours per worker. This focus however masks interesting effects on the shape of the distribution of hours per worker in the economy, which provide further testable implication for the model. For example Kuhn and Lozano (2005) use data from the Current Population Survey for the US and document that, over the last three decades, the fraction of prime age male employees working more than 50 hours per week has increased sharply, between five and eight percentage points, depending on the data used and the sample of workers considered. This change has reversed a secular trend of decline in the fraction of men working long hours. In our model the fraction of US workers working more than 50 hours per week—that corresponds to a value for detrended hours of $0.4 \cdot 50/44.8$ in the 70's and to $0.4 \cdot 50 \cdot 1.053/44.8$ in the 00's—goes from 7 per cent to 15 percent, which implies an increase similar to the one observed in the data.[22]

Another notable feature in the distribution of hours per worker is the emergence in the 00's of a substantial mass of *discouraged* European workers, who work slightly less than 30 hours per week. This group of workers correspond to the smaller peak in the distribution of hours that emerge in the 00's in Europe, see the dotted line in the panel in the second row and second column of Figure 4.[23] These are workers who have experienced a long unemployment spell, and who enter employment with a human capital level that is significantly lower than the average in the population. These workers feel discouraged from working longer hours because marginal increases in human capital improve little their productivity ranking among workers in the economy, which implies that human capital has small effects on the job offer probability at the margin. Interestingly OECD (1998, chap. 5) and OECD (2004, chap. 1) also report that, over the 1985-2002 period, Continental European countries have experienced a sharp increase in the fraction of male workers working very few hours (say working less than 30 or 20 hours per week).

[22] If we do not allow for some measurement error in the simulated data, the model appears to generate too few workers working more than 50 hours per week relative to the data. Kuhn and Lozano (2005) focus the analysis on male workers aged between 25 and 64 years and report a value of around 15 per cent for the fraction in the 70's. When we use the CPS March file and we consider the sample of full time (more than 30 hours per week) male workers aged between 25 and 55 years old we find that in the 70's the fraction of workers working more than 50 hours is around 23 per cent. This is also the value generated by the model when we consider the possibility of adding measurement error to the data on hours generated by the model, which, according to French (2002), has a variance of 0.0167. With measurement error the fraction of workers working long hours then increase up to 29 percent in the US00 economy.

[23] Notice that, due to an increase in the dispersion of the distribution of human capital, a small group of discouraged workers also emerge in the US00 economy; see the dotted line in the first column and second row panel of Figure 4.

5.3 The intertemporal return

To evaluate the model performance, we now analyze the model's ability to reproduce the sign, magnitude, and time evolution of the estimated coefficients of equation (8). This equation was used to provide some preliminary evidence on the evolution of the intertemporal return to hours worked in the US and Europe. We simulate data for 10.000 individuals for 10 years from the US70, the US00 and the EU00 economy. We then pool together the data from the US70 and from either the US00 or the EU00 economy, we construct five year averages of individual yearly wages and hours worked exactly as in the PSID (and the GSOEP) and we run equation (8) on model simulated data. 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 φ_3 in equation 8) to change in the 00's relative to the 70's, exactly as in Table 2. We also consider the effects of introducing measurement error in the model generated data, which several authors have argued to be substantial in PSID data. We base our correction for measurement error on the findings by French (2002) who uses the PSID Validation Study to argue that the variance of the measurement error in wages to be .0207 and that in hours to be .0167. 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 or the GSOEP data.

When we consider the US70 and US00 economies without and with measurement error, and we ran the regression analogous to (8) after allowing for a time-changing intertemporal return we find that

$$\begin{aligned}
\mathrm{US_{NM}}: \quad & \ln w_{i,t} = cte + 0.44 \ln w_{i,t-1} - 0.98 \ln h_{i,t} + 0.65 \ln h_{i,t-1}|_{70\text{'s}} + 0.95 \ln h_{i,t-1}|_{00\text{'s}} \\
\mathrm{US_{YM}}: \quad & \ln w_{i,t} = cte + 0.42 \ln w_{i,t-1} - 0.60 \ln h_{i,t} + 0.29 \ln h_{i,t-1}|_{70\text{'s}} + 0.52 \ln h_{i,t-1}|_{00\text{'s}}
\end{aligned}$$

where the subindex "NM" and "YM" stand for the result from the model simulated data without or with measurement error, respectively. The last two coefficients in each equation characterize the value of the coefficient φ_3 in equation (8) in the 70's and in the 00's, respectively. When instead we consider the US70 and the EU00 economy we obtain that

$$\begin{aligned}
\mathrm{EU_{NM}}: \quad & \ln w_{i,t} = cte + 0.42 \ln w_{i,t-1} - 0.31 \ln h_{i,t} + 0.33 \ln h_{i,t-1}|_{70\text{'s}} + 0.29 \ln h_{i,t-1}|_{00\text{'s}} \\
\mathrm{EU_{YM}}: \quad & \ln w_{i,t} = cte + 0.40 \ln w_{i,t-1} - 0.25 \ln h_{i,t} + 0.21 \ln h_{i,t-1}|_{70\text{'s}} + 0.20 \ln h_{i,t-1}|_{00\text{'s}}
\end{aligned}$$

where again the subindex identifies whether simulated data also contain measurement error. Overall the model reproduces nicely key features of the estimation of equation

(8), as reported in Table 2. The match is more accurate when we allow for some measurement error in the simulated data and we focus on the empirical results based on the Arellano-Bond estimator that was used to correct for the possible presence in the data of individual fixed effects, not present in the model. In particular the model matches quite accurately the magnitude and time evolution of the coefficient φ_3, that characterizes the intertemporal return, which increases in the US while it falls slightly in Europe. Also the coefficient φ_2 that measures how current hours are related to current hourly wages is in line with the data.[24] Only the coefficient φ_1 that measures the serial correlation of wages is lower in the model than in the data. The difference however completely disappears when purging the data from the presence of individual fixed effects.

6 Robustness exercises

We analyze how the quantitative results change (i) when introducing worker specific fixed heterogeneity in the model, (ii) when changing the value of the parameter γ that characterizes the sensitivity of the job offer probability to human capital, (iii) when considering an alternative specification for the function ψ that characterizes the effects of workers competition for jobs, and (iv) when changing the elasticity of the marginal disutility of working η. Overall these exercises confirm that labor market conditions (in terms of wage inequality and unemployment) can quantitatively explain the observed differences in hours per worker between the US and the EU. In all extensions the parameters of the economy in the 70's are estimated again to minimize the difference with the targets in Table 4, while the identification of the parameter changes in the 00's follows the same strategy as in Sections 4.3 and 4.4. The only exception is the depreciation of human capital δ, which we leave as in the benchmark economy.[25] The resulting parameter values for the economies in the 70's and in the 00's appear in Table 5 and 12, respectively.

[24] 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 0.15 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 0.10 in the US00 economy, which appears to be in line with the PSID data.

[25] We are comfortable with this strategy since our estimate for δ is very similar to the analogous estimate by Imai and Keane (2004). Searching for the value of δ that minimizes the distance with the targets in Table 4 would instead involve substantial computational costs, especially because changing δ would also demand for a new estimate of α and θ, see Table 8.

Table 12: Changes in parameters, extensions

	Fixed heterogeneity			Lower γ			Mode			Greater η		
	US70	US00	EU00	US70	US00	EU00	US70	US00	EU00	US70	US00	EU00
α	0.040	0.075	0.040	0.040	0.075	0.040	0.040	0.075	0.040	0.040	0.075	0.040
ν	0.162	0.317	0.162	0.370	0.708	0.370	0.334	0.629	0.334	0.334	0.654	0.334
$\bar{p}_e$	0.202	0.202	0.092	0.217	0.217	0.114	0.221	0.221	0.164	0.203	0.203	0.094
$\bar{p}_u$	0.288	0.288	0.132	0.261	0.261	0.137	0.230	0.230	0.219	0.303	0.303	0.141
σ_υ^2	0.117	0.228	0.117	0	0	0	0	0	0	0	0	0

Notes: Parameters whose value changes in either the US00 or the EU00 economy. The other parameter values are as in Table 5.

6.1 Worker specific fixed heterogeneity

Using as a target wage inequality and neglecting worker specific fixed heterogeneity can lead to a too high estimate of the variance of the wage offer distribution as well as of its increase in the US. This may affect the quantitative results of the model. To analyze this issue, we now extend the model by assuming that a worker produces income $\upsilon\omega H^\alpha h^\alpha$ when employed, and obtains utility $\log \upsilon + b$ when unemployed, where υ is a worker's fixed effect in production. We assume that fixed effects are symmetrically distributed around their mean with variance σ_υ^2. As in Conesa and Krueger (2006), we assume for simplicity that the distribution of fixed effects is characterized by two mass points. Following Moffitt and Gottschalk (2002), we target the autocorrelation of annual hourly wages at a five-year time horizon and we estimate the value of σ_υ^2 in the US70 economy by indirect inference. The idea is that workers specific fixed effects play a predominant role in determining the autocorrelation of wages at a sufficiently long time horizon. In our PSID sample the five-year autocorrelation of hourly wages is around 0.6 during the 70's, which is in line with the finding by Moffitt and Gottschalk (2002). In characterizing the US economy in the 00's, we take into account that part of the observed increase in within-skill wage inequality may be due to fixed heterogeneity. To identify the increase in the variance of fixed effects we target the five-year autocorrelation of wages in the 00's, which we find unchanged relative to the the 70's.[26] Moreover, as in the baseline specification, we characterize the US00 economy by changing α as implied by Table 8 and by targeting the increase in the dispersion of reemployment wages. The EU00 economy is instead characterized using the same targets as in the benchmark case.

The value of (detrended) average hours per worker in the US70, US00 and EU00 economy appears in Table 13. The US-EU differential in hours increases by 17.2 percent,

[26]This is in line with the findings by Moffitt and Gottschalk (2002). A constant autocorrelation implies that the variance of the wage offer distribution and of the workers fixed effects have increased roughly in the same proportion.

exactly as in the baseline specification, see Table 10. The quantitative effects remain unchanged because the percentage increase in the dispersion of the wage offer distribution is almost as in the baseline economy. As it is apparent from equation (4) for the two period model, relative rather than absolute changes in the dispersion of the wage offer distribution determine the magnitude of the percentage changes in hours per worker.

Table 13: Changes in detrended hours per worker, extensions

Economy	Average hours $\times 10^{-2}$	Diff to (1) (%)	US-EU diff (%)
Fixed heterogeneity			
(1) US in 1970	40.0	-	-
(2) US in 2000	43.2	9.1	-
(3) EU in 2000	36.3	-8.1	17.2
Lower γ			
(1) US in 1970	40.0	-	-
(2) US in 2000	44.0	10.0	-
(3) EU in 2000	38.0	-5.0	15.0
Mode			
(1) US in 1970	40.7	-	-
(2) US in 2000	44.0	8.0	-
(3) EU in 2000	37.7	-7.5	15.4
Greater η			
(1) US in 1970	39.9	-	-
(2) US in 2000	42.4	6.3	-
(3) EU in 2000	36.4	-8.7	15.0

6.2 Changing γ

In our baseline specification we have estimated γ—which characterizes the sensitivity of the job offer probability to human capital—by indirect inference by matching the effects of past hours on the probability of a job to job transition. To analyze the robustness of our results we now reduce the value of γ down to 7.5. The calibration strategy is as in the benchmark specification, with the difference that now γ is set exogenously. We find that the differential of hours per worker between the US and Europe increases by 15 percent, which is slightly lower than the 17 percent increase obtained the benchmark calibration. The most significative change is that with a lower γ we have a somewhat larger increase of hours per worker in the US and a smaller fall in hours in the Europe (see Table 13).

6.3 Changing ψ

We now consider an alternative specification for the function ψ that characterizes the effects of workers competition for jobs. We assume that $\psi(G)$ is equal to the mode rather than to the average of the distribution of human capital in the economy. This is a reasonable alternative specification for the function that characterizes the effects of the human capital distribution on the job offer probability since the human capital distribution is arguably more concentrated around its mode that around its mean. So ranking models should predict that the marginal effect of human capital on the job offer probability is maximized at the mode rather than at the average of the distribution of human capital. When considering this alternative specification we find that the results change little, see Table 13. This is because in the model the difference between the mode and the average is small.

6.4 Changing η

In a competitive labor market without human capital accumulation, the elasticity of the marginal disutility of working η is equal to the inverse of the Frisch elasticity of labor supply. In our baseline specification we have chosen a value of η equal to two, that would imply a Frisch elasticity of 0.5. This choice generates a correlation between annual hourly wages and annual hours that is roughly consistent with the data and it is in line with some recent microeconomic estimates of the labor supply elasticity for prime age males, as 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 η); see for instance Blundell and MaCurdy (1999) and the references therein.[27] So we now analyze the effects of reducing the Frisch elasticity (increasing η) by setting $\eta = 3$, which would imply a Frisch elasticity equal to 1/3. As expected, we find that the response of hours in the US is smaller than in the benchmark economy: with a higher η detrended hours increase by 6.3 percent rather than by 8.5 percent as in the benchmark economy, see Table 13. After taking into account the trend in hours, this implies a total increase in US hours per worker in the 00's relative to the 70's of about 1 percent, which is closer to the value in the data. The effects for Europe are

[27]Notice however that it may be misleading to apply standard microeconomic estimates to our model. As argued by Imai and Keane (2004), standard estimates of the elasticity of the marginal disutility of hours are upward biased because they do not take into account the effects of working time on human capital accumulation. And there are reasons to believe that the bias should be even more pronounced when search frictions are also present. This is because, as discussed in Section 3.3, workers work longer hours when employed in jobs with lower wage rates, which tends to induce a negative correlation between hourly wages and hours worked.

instead roughly unchanged. This is partly because with a higher η, the policy function for hours becomes flatter, which implies that γ has to increase relative to its value in the benchmark economy to match the regression coefficient of job-to-job transitions on past hours, see Table 5. Overall, the model with higher η generates an increase in the US-EU differential in hours per worker which is just smaller than the increase obtained in the benchmark economy.

7 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 several features of the labor market can influence the decision on working time. In particular within-skill wage inequality gives incentives to work longer hours, while a longer duration of unemployment, and in general a less tight labor market discourage working time. We used the model to quantify the contribution of within-skill wage inequality and unemployment in explaining the diverging evolution of hours per worker in the US and the EU. 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. We find that differences in labor market conditions can account for the US-EU differences in hours per worker emerged over the last 30 years. Our model also predicts an increase both in the fraction of US workers working very long hours and in the fraction of European workers working few hours. Both implications find empirical support in the data. Theories that focus just on Europe to explain the widening in the US-EU differential in hours per worker, may find hard to explain why the fraction of US workers working long hours has increased sharply over the last thirty years, after reverting a trend of secular decline. Our quantitative results imply that within-skill wage inequality plays a major 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. When we used the PSID data to see whether past hours are related to the job separation probability we did not find any significant evidence for an effect of past hours on job separation. Moreover the separation rate has changed little over time both in the US and in Europe despite the observed changes in hours worked. Given the focus on the US-EU experience, we therefore avoided modeling this effect of human capital. Of course, the effect could yet be important to understand working time behavior in some specific segments of the labor market. We believe this to be an interesting issue to be investigated in future research.

We have also modeled wage inequality and the job offer probability as exogenous. This again is a simplifying assumption that we think is justified on the grounds that there is yet no consensus on why labor market conditions have evolved differently in the US and Europe. The list of suspects is vast and include differences in the evolution of taxes, of labor market institutions, of business-creation costs, of financial market imperfections and of trade liberalization as well as explanations based on the interaction of some constant-over-time differences in institutions with some common shocks to either the pace of technological progress, the level of labor market turbulence or the degree of opening to trade, see Bean (1994) and Hornstein, Krusell, and Violante (2005) for some review of this debate. Of course finding exhaustive explanations for why aggregate hours worked and wage inequality have evolved differently across the two sides of the Atlantic is a priority. In this paper we have just stressed that aggregate labor market conditions 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, as recently suggested by Kamburov and Manovskii (2005), 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

A.1 PSID

We select all male household heads who are in the age group 25-55. 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. Panel A in Table 14 contains some descriptive statistics for the main sample.

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.
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, iv) he has a tenure less than 12 months at time $t+1$, and v) tenure at $t+1$ is smaller than tenure at t plus six. This last requirement is intended to correct for measurement error in the tenure measure.
Employment to unemployment. An individual experiences a transition from employment to unemployment during the year that goes from t to $t+1$ if i) he is employed at t, ii) he experiences more than two weeks in unemployment over the year.

A.2 GSOEP

We select all male household heads who are in the age group 25-55. We focus on individuals who live in West Germany. Data start in 1985 and ends in 2002. Panel B of Table 14 contains some descriptive statistics. Following is a description of the variables used in the analysis.

Labor income. Total annual labor earnings in the previous year. Labor earnings include wage and salary from all employment. It is the sum of income from primary job, secondary job, self-employment, 13th month pay, 14th month pay, Christmas bonus pay, holiday bonus pay, miscellaneous bonus pay, and profit sharing income. It is obtained from Cross National-Equivalent Files.

Yearly hours. Total annual hours worked for money, either as a full-time, part-time or short-time work. It is obtained from Cross National-Equivalent Files.

Weekly hours. Original variable is "tatzeit". This is the response to the question: "How many hours per week do your actual working-hours consist of including possible over-time?" The question refers to the respondent's main job.

Tenure. Original variable "erwzeit". Length of time with current firm (in years).

Months unemployed Number of months received unemployment benefits or reliefs.

Years of education Number of Years of Education completed at the time of survey. It is obtained from Cross National-Equivalent Files.

Hourly wage Labor income divided by Yearly Hours. They are expressed in 2001 Marks by using the CPI index.

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 one month in unemployment over the year, iv) he has a tenure less than one year at time $t+1$, and v) tenure at $t+1$ is smaller than tenure at t plus 0.5. This last requirement is intended to correct for measurement error in the tenure measure.

Employment to unemployment An individual experiences a transition from employment to unemployment during the year that goes from t to $t+1$ if i) he is employed at t, ii) he experiences more than one month in unemployment over the year.

B Computational appendix

We first discuss how we solve for the policy functions that characterize the problem of employed and unemployed workers. Then we discuss how we calculate aggregate statistics in the model economy and how we solve for the parameter values that match the targets in Table 4.

B.1 Solving for the decision rules

We make the problems in (10) and (11) stationary by using the variable $\hat{h} = h_t(1+\mu)^t$. Then we solve the problem by value function iteration as follows:

1. We guess an initial pair of value functions $\left\{W^0, V^0\right\}$

2. We solve for the optimal decisions $h^0(\cdot,\cdot)$ and $z_r^0(\cdot,\cdot)$ and we obtain a new pair $\left\{W^1, V^1\right\}$

Table 14: Descriptive statistics, PSID and GSOEP

A) PSID

Year	Mean Wage	SD log-Wage	Weekly hours	Yearly hours	Yrs of schooling	Experience	Tenure
1968	15.2	.53	44.5	2126.6	11.6	22.1	103.7
1969	15.2	.52	45.5	2188.2	11.7	22.0	100.5
1970	15.5	.52	46.2	2224.8	11.9	21.4	99.6
1971	15.6	.51	45.8	2167.9	12.1	21.1	96.5
1972	15.9	.53	45.7	2150.6	12.2	20.7	89.2
1973	15.8	.53	46.0	2192.2	12.4	19.8	86.4
1974	15.9	.51	46.0	2198.5	12.5	19.3	84.3
1975	16.4	.54	46.0	2157.2	12.7	18.9	86.7
1976	15.4	.53	45.8	2115.7	12.7	18.7	91.0
1977	15.9	.54	46.1	2141.9	12.8	18.3	82.1
1978	16.1	.54	46.3	2154.5	12.8	18.0	75.0
1979	16.6	.53	45.8	2146.9	12.9	17.8	74.8
1980	16.3	.53	45.8	2152.3	12.9	17.7	77.4
1981	16.7	.56	45.1	2096.2	13.0	17.6	80.0
1982	16.3	.56	45.1	2086.8	13.0	17.6	79.0
1983	17.1	.59	44.9	2036.6	13.2	17.4	77.8
1984	16.2	.59	44.9	2061.6	13.2	17.4	81.1
1985	16.9	.61	46.0	2149.7	13.5	17.1	81.2
1986	16.3	.61	46.5	2158.9	13.5	17.2	76.9
1987	16.7	.63	46.3	2156.5	13.6	17.3	83.5
1988	18.1	.64	46.5	2185.4	13.5	17.5	81.8
1989	17.7	.64	46.7	2203.7	13.6	17.6	78.9
1990	17.8	.65	46.7	2201.8	13.6	17.9	78.9
1991	17.7	.65	46.7	2212.1	13.5	18.3	80.9
1992	18.2	.66	46.4	2169.3	13.6	18.6	81.6
1993	19.9	.67	45.3	2111.9	13.6	18.9	86.4
1994	19.3	.66	46.2	2193.1	13.6	19.4	81.3
1995	18.6	.64	46.1	2218.4	13.6	19.6	80.4
1996	19.2	.66	46.4	2248.1	13.6	19.8	81.7
1997	19.3	.65	46.1	2213.4	13.6	20.1	85.8
1999	20.5	.66	46.2	2219.3	13.6	20.5	86.9
2001	20.8	.67	46.3	2217.2	13.6	20.6	87.4

B) GSOEP

Year	Mean Wage	SD log-Wage	Weekly hours	Yearly hours	Yrs of schooling	Experience	Tenure
1984	21.4	.47	44.8	2289.0	11.8	21.8	12.6
1985	24.7	.53	44.4	2235.2	11.8	21.9	12.6
1986	24.3	.52	44.8	2258.2	11.9	22.1	12.6
1987	25.9	.52	44.5	2254.2	11.9	22.2	12.8
1988	26.7	.51	44.0	2236.2	11.9	22.6	13.1
1989	25.8	.47	44.7	2285.2	11.9	22.9	13.1
1990	25.5	.42	43.9	2275.9	12.0	23.3	13.1
1991	27.2	.45	44.0	2269.7	12.0	23.5	13.2
1992	29.1	.44	43.9	2273.5	12.1	23.6	12.8
1993	30.6	.44	43.7	2272.8	12.1	23.6	12.8
1994	31.0	.41	43.7	2267.4	12.1	24.0	13.2
1995	33.3	.47	43.8	2256.6	12.2	24.1	12.8
1996	33.4	.45	43.8	2265.3	12.2	24.2	12.1
1997	33.1	.43	44.1	2313.3	12.2	24.7	12.2
1998	36.3	.50	43.7	2262.5	12.2	27.5	13.1
1999	35.3	.50	43.8	2324.5	12.2	25.5	12.0
2000	36.7	.48	43.8	2324.7	12.3	27.1	12.3
2001	37.0	.44	44.1	2348.2	12.4	26.5	12.3
2002	38.8	.47	43.7	2334.3	12.4	27.5	12.6

Notes: The total number of observations in PSID is 65.492. The total number of observations in GSOEP is 14.270. Tenure is measured in months in PSID in years in GSOEP. Experience is measured in years.

3. We compare $\left\{W^1, V^1\right\}$ and $\left\{W^0, V^0\right\}$. If they are close enough, then the algorithm has converged, otherwise we redefine $\left\{W^0, V^0\right\} = \left\{W^1, V^1\right\}$ and we go back to Step 2.

The pair of functions $\left\{W^1, V^1\right\}$ in Step 2 is obtained by using the right-hand side of the stationary version of the Bellman equations in (10) and (11). We reexpress these equations in terms of the variable $z = \frac{\log \omega + \frac{\nu}{2}}{\sqrt{\nu}}$, which has a standard normal distribution whose cumulative distribution function is denoted by Φ. Then, we define the two following relations:

$$\begin{aligned} W^1(H,z) &= \max_{\hat{h}} \Big\{ u\left(\exp\left(z\sqrt{\nu} - \nu/2\right) H^{\alpha} (a\hat{h})^{\theta}, \lambda \hat{h}\right) + \beta p_s V^0\left(H', b_0\right) \\ &+ \beta (1-p_s)\left[1 - p_e\left(H', G\right)(1 - \Phi(z))\right] W^0\left(H', z\right) \\ &+ \beta (1-p_s) p_e\left(H', G\right) \int_z^{\infty} W^0\left(H', s\right) d\Phi(s) \Big\} \end{aligned} \tag{15}$$

where $H' = (1-\delta) H + a\,\hat{h}$, and

$$\begin{aligned} V^1(H,b) &= \max_{z_r} \Big\{ b + \beta\Big[1 - p_u\left((1-\delta)H, G\right)(1 - \Phi(z_r))\Big] V^0\left((1-\delta)H, b - \bar{b}_1\right) \\ &+ \beta p_u\left((1-\delta)H, G\right) \int_{z_r}^{\infty} W^0\left((1-\delta)H, s\right) d\Phi(s) \Big\} \end{aligned} \tag{16}$$

In implementing (15) and (16) we discretize the state space such that $H \in \mathbf{H} \equiv \{H_1, H_2, \ldots, H_{N_H}\}$, $z \in \mathbf{Z} \equiv \{z_1, z_2, \ldots, z_{N_Z}\}$, and $b \in \mathbf{B} \equiv \{\log b_1, \log b_2, \ldots, \log b_{N_b}\}$.[28] Then we approximate the value functions W^0 and V^0 through the discrete functions $\widetilde{W}^0 : \mathbf{H} \times \mathbf{Z} \to \mathbb{R}$ and $\widetilde{V}^0 : \mathbf{H} \times \mathbf{B} \to \mathbb{R}$, respectively. To evaluate $\widetilde{W}^0$ and $\widetilde{V}^0$ at points outside the grids we use linear interpolation. In solving the maximization problem in (15) we assume that $\hat{h}$ belongs to the discrete set $\mathbf{h} \equiv \{h_1, h_2, \ldots, h_{N_h}\}$, where we set $N_h = 1000$, $h_1 = 0.1$ and $h_{N_h} = 0.9$. This gives an approximated decision rule $\tilde{h}^0 : \mathbf{H} \times \mathbf{Z} \to \mathbf{h}$. To determine the approximated decision rule $\tilde{z}_r^0 : \mathbf{H} \times \mathbf{B} \to \mathbb{R}$ we use the first order condition of the maximization problem in (16):

$$\widetilde{V}^0\left((1-\delta)H, b - \bar{b}_1\right) - \widetilde{W}^0\left((1-\delta)H, z_r\right) = 0$$

which we solve at all points in the set $\mathbf{H} \times \mathbf{B}$ by using the Brent's method.

We approximate integrals in (15) and (16) as follows:

$$\int_{z_a}^{z_{N_z}} \widetilde{W}^0(\cdot, z)\, d\Phi(z) \simeq \sum_{i=a}^{N_z - 1} \frac{\widetilde{W}^0(\cdot, z_i) + \widetilde{W}^0(\cdot, z_{i+1})}{2} \left[\widetilde{\Phi}(z_{i+1}) - \widetilde{\Phi}(z_i)\right] \qquad \forall z_a \in \mathbf{Z} \tag{17}$$

[28] We choose $H_1 = 0$ and H_{N_H} equal to the endogenous upper bound of human capital given the maximum work effort; $z_1 = -4.0$ and $z_{N_Z} = 4.0$ so as to lose only 0.006% of probability mass of a standard normal distribution; $b_{N_b} = \exp(\bar{b}_0)$ and b_1 small but not zero. Finally, we set $N_H = 64$, $N_Z = 45$ and $N_b = 16$.

where the approximation to the CDF of a standard normal $\widetilde{\Phi}(z_i)$ is defined recursively by

$$\widetilde{\Phi}(z_i) = \widetilde{\Phi}(z_{i-1}) + \int_{z_{i-1}}^{z_i} \phi(z)\, dz \tag{18}$$

for any $z_i \in \{z_2, z_3, \dots, z_{N_z}\}$ with $\widetilde{\Phi}(z_1) = 0$. Here ϕ denotes the density function of a standard normal. The integral in (18) is approximated by using a Newton-Coates quadrature. To evaluate integrals for $z_a \notin \mathbf{Z}$ we linearly interpolate adjacent solutions.[29]

Given the number of extensions and the calibration method, we end up solving the model economy for many different combinations of parameters. This uncovers a problem with the probability function $p_u(H, G)$. When γ is large enough the probability goes to zero very fast as H falls. If $p_u(H, G)$ reached zero for a positive H, there would be a non-zero probability that an unemployed worker gets trapped forever into unemployment, which would then become an absorbing state. Our probability function $p_u(H, G)$ never reaches zero but gets very close to it for low values of H when γ is large. To avoid possible problems during the simulation stage we then impose a lower bound equal to ten percent to the function $p_u(H, G)$.

B.2 Finding the aggregate distribution

In order to find the stationary distribution X of human capital and wage rate for employed workers and human capital and unemployment utility for unemployed workers we construct a sample of 10,000 individuals that we simulate for 850 periods. Then, for each individual, we drop the first 600 observations and we use the remaining observations (that correspond to 20 years of monthly data) to obtain a finite sample counterpart of X. This allows to calculate both cross-sectional and time series statistics.

B.3 Matching targets

As described in Section 4, we have 15 parameters that characterize the US70 economy. Of these parameters, 3 are either normalizations or taken from previous estimates (a, β and η) while 4 (p_s, α, θ and μ) have a direct counterpart in the data. The remaining 8 parameters are chosen to minimize the distance between statistics from original data and model simulated data. The distance function is the sum of the squared relative error between the simulated and the data statistics. We use a standard simplex algorithm to minimize the loss function. We proceed analogously when calculating parameter changes that characterize the US00 or the EU00 economy.

[29] We choose this approach to calculate (17) rather than a standard Gaussian quadrature method first because with a Gaussian method the accuracy of the solution tends to differ substantially for different $z_a \in \mathbf{Z}$ and second because a Gaussian method is more expensive in computer time, since for every possible z_a it requires to evaluate the integrand at several points outside $\mathbf{Z}$.

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