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Technology Adoption, Turbulence and the Dynamics of Unemployment

Georg Duernecker

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Abstract

The divergence of unemployment rates between the United States and Europe coincided with a substantial acceleration in capital-embodied technical change in the late 1970s. Evidence suggests that European economies have lagged behind the United States in the adoption and usage of new technologies. This paper argues that the obsolescence of an economy's technological capital is a key determinant for the way the economy's labor market reacts to an acceleration in capital-embodied technical change. The proposed framework offers a novel explanation for the observed divergence of unemployment rates across economies that are hit by the very same shock (i.e. the acceleration in embodied technical change) but differ in their technology adoption. The results of the paper challenge the popular, but controversial, view that blames generous unemployment insurance for high unemployment in Europe. The analysis shows that the observed institutional heterogeneity is insufficient to explain the diverse evolution of unemployment rates

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†University of Mannheim, L7 3-5, 68161 Mannheim, Germany, email: duernecker@uni-mannheim.de

1 Introduction

After low levels of unemployment in Europe prior to the late 1970s, European unemployment became high relative to that in the United States. Labor markets in Europe began to deteriorate at a time when there was a substantial acceleration in the arrival of new technologies, as measured by capital-embodied technical change. Documented by Gordon's (1990) influential work on the quality-adjusted price of capital, and, more recently, by Cummins and Violante (2002), the rate of change in the relative price of new capital investments in the U.S. has substantially increased in magnitude, from -2% before the mid-1970s to -4.5% in the 1990s, suggesting an acceleration in capital-embodied technical change. There is convincing empirical evidence, provided by Oliner and Sichel (2000), Jorgenson and Stiroh (2000) and van Ark et al. (2002), among others, indicating that certain economies in Europe have lagged behind the United States (and other European economies) in the adoption and usage of new technologies. This delay is reflected by a persistent growth and technology gap of these countries, as measured by labor productivity growth, the share of information and communication technologies (ICT) in investment and its contribution to output growth. This paper argues that the coexistence of a technology gap, resulting from slack technology adoption, and the divergence of unemployment rates across economies is not coincidental. Rather, the degree of obsolescence of an economy's technological capital is a key determinant for how the economy's labor market reacts to an acceleration in capital-embodied technical change.

The quantitative part of the paper uses a calibrated labor market matching model to study the implications of the increase in the rate of embodied technical change after the 1970s for OECD labor markets. The main result is that the observed cross-country differences in technology adoption and usage can account for a large part of the different evolutions of OECD unemployment rates since the 1970s. Countries with sizable technology gaps are predicted to experience a severe deterioration of labor market outcomes, unlike countries with high technology usage in which unemployment rates rise only slightly. In contrast to previous work, the framework proposed here can explain (a) the divergence of unemployment rates between the major European countries and the United States and (b) a large part of the observed variation in unemployment rates across OECD economies. The technological heterogeneity across countries is found to be central for explaining cross-country differences in labor market outcomes. This result challenges the popular, but controversial, hypothesis that blames generous unemployment benefits for high unemployment in Europe.[1] The analysis shows that the observed institutional heterogeneity is insufficient to explain the diverse evolution of OECD unemployment

[1]The controversy comes from the fact that the institutions that are held responsible were also present in the 1960s, yet in the 1960s unemployment was much higher in the United States than in Europe, see e.g. Blanchard and Wolfers (2000).

rates. Moreover, many European welfare-state economies with generous unemployment insurance systems have successfully maintained low rates of unemployment. All of these economies have also had high technology adoption rates.

The analysis in this paper is based on the labor market matching framework proposed by Mortensen and Pissarides (1998). The standard model is augmented with an endogenous technology choice by firms. It assumes that individuals to possess human capital that is specific to the technology they use. A technology frontier characterizes the state-of-the art technology that is available to all firms at a given point in time. Constant productivity growth at the frontier renders all existing technologies gradually obsolete. Hence, at a certain point, it is optimal for a firm to scrap its current technology and adopt a new one or to destroy the job. The skills of the employed worker are vintage-specific. Therefore, the adoption of a new technology by a firm leads to a skill mismatch with the employed worker because the new technology requires different skills. The firm can overcome this mismatch by re-training the worker, which is assumed to be costly. Moreover, the costs of re-training are assumed to increase with the technological distance between the firm's current technology and the new technology that is installed. The same type of skill mismatch occurs when a firm hires a new worker from unemployment, and the skills of the worker are obsolete and do not fit to the firm's technology. We speak of skill obsolescence when the human capital of a worker fits a technology that is less advanced than the firm's current technology. Re-training expenses for a newly employed worker diminish a firm's surplus of creating a new job. Therefore, the obsolescence of the unemployed workers' skills is an important determinant of aggregate labor market outcomes because it determines the firms' expected costs of hiring and training a new employee and thereby affects the equilibrium number of jobs.

The first part of the paper studies the effects of a rise in the rate of embodied technical change on firms' technology choice, workers' skills and aggregate labor market variables. The analysis in this section is conducted within a tractable framework that allows for an analytical characterization of the main mechanisms at work. All of the insights generated in this analysis carry over to the quantitative model and contribute to interpretation of the results of the quantitative analysis. An acceleration in embodied technical change, such as that observed in the mid-1970s, affects aggregate labor market outcomes via three effects: an *obsolescence effect*, a *capitalization effect* and a *cost effect*. In response to faster technical change, firms allow for a larger critical technology gap. That is, firms allow their technologies to become more obsolete before replacing them. The greater technological obsolescence translates to a lower value of a job because the firm foregoes part of the higher productivity growth at the frontier. A lower job value discourages job creation and raises unemployment. This is the essence of the obsolescence effect. The capitalization

effect is commonly found in vintage technology models. Higher growth lowers the firm's discount rate, at which it capitalizes expected future income emerging from the current technology and any future upgrading. Thus, future profits are discounted at a lower rate, leading to an increase in the discounted stream of future profits and a rise in the value of the job which, in turn, promotes job creation and lowers unemployment.
The cost effect is related to the human capital obsolescence of the unemployed. When new technologies arrive at an increased pace, the skills of the unemployed deteriorate more rapidly relative to the frontier knowledge. Furthermore, firms that allow for a larger critical technology gap imply that employed individuals work, on average, with more outdated technologies. When these workers eventually separate from their jobs and enter unemployment, their skills are more obsolete. Both of these factors lead to a deterioration of the average skills of the unemployed, suggesting that in times of faster technical change, it becomes more costly for a firm to hire and re-train a new employee. The increase in costs reduces the firms' incentives to create new jobs and tends to increase unemployment.

The negative cost and obsolescence effects are found to be relatively mild in economies in which firms have a high technology adoption rate and stay close to the technology frontier. By contrast, in economies where technology updating is slack, both of the effects are strong, and therefore the increase in unemployment in these countries is more pronounced.

The second part of the paper performs a quantitative analysis of a cross-section of 23 OECD countries. The labor market model is calibrated to match the observed technology gap (relative to the United States) for each country. The quantitative model is then used to simulate the 1970s increase in the rate of embodied technical change. Based on this simulation, we can assess the extent to which the model can match the observed change in labor market variables and other macroeconomic outcomes for each country. Various robustness checks are considered to test the sensitivity of the model results to some of the underlying assumptions. The proposed framework accounts remarkably well for the observed cross-country patterns of the rate and the duration of unemployment and labor productivity growth. The technological heterogeneity reflected by cross-country differences in technology updating is a key element in explaining the observed cross-country differences in various economic outcomes. By contrast, institutional factors, such as the unemployment insurance system, are quantitatively of much lesser importance.

The European unemployment experience has attracted a great deal of attention in recent years. Economists have offered numerous explanations for the emergence of high European unemployment in the late 1970s, including overly generous welfare systems, slow TFP growth and capital market imperfections[2]. One particularly influential strand

[2]See Nickell (2003) for a recent survey of research on the issue of European unemployment. Blanchard

in the literature emphasizes the interaction of macoeconomic shocks and labor market institutions as the main driving force for high levels of European unemployment. Key references include Ljungqvist and Sargent (1998, 2007), Marimon and Zilibotti (1999) and Hornstein, Krusell and Violante (2007). The framework proposed by Ljungqvist and Sargent (1998) is the first rigorous attempt to study the shock-policy interaction within a calibrated model. A related explanation is offered by Marimon and Zilibotti (1999). The line of argument proposed by these authors is as follows. European unemployment increased due to reduced incentives for workers to exit unemployment. Workers in Europe prefer to collect generous unemployment benefits rather than to work for a low wage. Wages are low because the technology shock has made workers' skills obsolete, as in Ljungqvist and Sargent (1998), or has made it increasingly difficult to match workers with existing vacancies, as in Marimon and Zilibotti (1999). The mechanism in these papers operates primarily through the labor supply side. Ljungqvist and Sargent's (2007) study is a refinement that considers a matching framework in which firms adjust labor demand in the aftermath of the shock. The shock considered in Ljungqvist and Sargent (1998, 2007) refers to a general change in the economic environment and is described by an increased degree of economic turbulence.

Recently, a number of economists have emphasized the potential significance of embodied technical change to explain the differences in labor market outcomes across countries. Hornstein, Krusell and Violante (2007) was the first work to highlight the interaction between shocks to capital-embodied technical change and labor market institutions. In their model, an increase in embodied technical change, such as that observed in the mid-1970s, leads to a sharp reduction in firms' labor demand in a (European-type) welfare state economy, whereas it has only mild effects on labor demand in a (U.S.-type) laissez-faire economy. Consequently, unemployment rises by much more in the welfare state.

Much of the work so far on the subject has focused on mechanisms that can successfully reproduce the evolution of an average European unemployment rate but typically fail to account for the large heterogeneity of unemployment rates across European countries. In fact, Blanchard (2005) suggests that discussing "European unemployment" is misleading because high average European unemployment reflects high unemployment in four large continental countries (Germany, Italy, Spain and France), whereas unemployment is low (and comparable to the U.S. rate) in many other European countries. Arguably, a theory that addresses the European unemployment experience but fails to explain the large heterogeneity of labor market outcomes across European economies conflicts with an essential aspect of actuality and is likely to disregard relevant factors.

(2005) is an excellent assessment of the state of the contemporary literature regarding the European unemployment question.

The underlying determinants for the observed divergence are unlikely to be labor market institutions. Although changes in labor market institutions can account for some of the rise in European unemployment, as shown by Nickell et al. (2005), a sizable fraction remains unexplained. Hagedorn et al. (2010) propose a framework in which changes in taxes on labor income and sales affect productivity and drive unemployment. They do not report how much of the diverse unemployment evolution their model can explain, but it is unlikely to be quantitatively substantial. This is because, as reported by McDaniel (2007, 2011), labor income taxes in the OECD have been rising gradually from the 1960s to the 2000s. The increase was uniform across countries, so the dispersion of labor income taxes in 1975 is about the same as the dispersion after the 1990s. Even if labor taxes affect unemployment, it is difficult to reconcile the observed gradual and uniform rise in taxes with the sharp rise of unemployment after the 1970s and the heterogeneous unemployment response across countries.
This paper emphasizes a new dimension of cross-country heterogeneity, namely technological heterogeneity, which has not been considered in the literature thus far but is an important explanatory factor for the observed evolution of OECD unemployment[3]. The framework of this paper paper provides a microstructure for the turbulence approach proposed by Ljungqvist and Sargent (1998). According to their view, rising unemployment can be explained by a higher degree of economic turbulence after the 1970s. Turbulence is modeled as an ad-hoc increase in the likelihood that workers will loose a fraction of their skills in the event of a job loss. In this paper, by contrast, the degree of skill obsolescence is endogenously determined and driven by firms' technology choice. Thus, this paper provides an explicit rationale for higher turbulence by directly linking increased human capital obsolescence to the observed post-1970 rise in embodied technical change.

Several authors have recently noted that, since the late 1950s, total hours worked per person in Europe have declined relative to the hours worked in the United States. The total amount of hours worked and the unemployment rate are naturally related to each other in an economy because changes in total hours worked per person can be decomposed into changes in the intensive margin (hours per worker) and the extensive margin of labor (employment rate). Therefore, the question emerges whether the literature that considers the evolution of hours worked can shed light on the observed divergence of unemployment rates between Europe and the United States. If so, these studies would arguably be competing with the explanation offered in this paper. This is an important matter and Section 2 addresses it through a brief discussion.

[3]It is not the aim of the paper to explain why this heterogeneity exists in the first place, that is why several countries in Europe have been lagging behind the United States in the implementation and usage of new technologies. Rather, the paper takes the observed differences in technology updating as given and evaluates their effects on labor market and other macroeconomic outcomes.

The remainder of the paper is organized as follows. Section 2 presents the empirical facts that motivate the analysis in this paper. Section 3 introduces the theoretical framework and Section 4 analyzes analytically the main channels between technology updating and labor market outcomes. Section 5 presents the quantitative analysis. This section contains an explanation of the parameterization and calibration of the model and a discussion of the cross-country analysis. Section 6 considers various robustness checks of the model's results. Section 7 concludes and an appendix contains supplementary materials.

2 The Facts

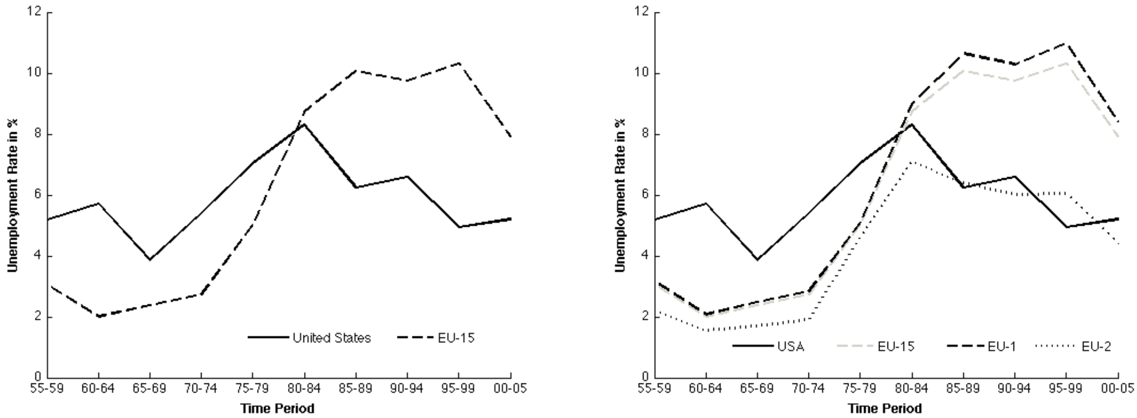
Observation 1: Divergence of OECD Unemployment Rates in the 1980s

In the postwar period prior to the late 1970s, unemployment in Europe was low relative to unemployment in the United States. The graph in Panel (a) of Figure 1 shows that during the entire period prior to the 1980s, unemployment in the United States was significantly higher than in Europe[4]. In the 1960s and early 1970s, the average unemployment rate in Europea was approximately 2.5%, whereas the U.S. figure was approximately 5%. This situation changed substantially after the mid-1970s. Unemployment in Europe experienced a sharp and persistent increase, up to approximately 9%, whereas U.S. unemployment rose by much less.

This rise in Europe, however, was not homogenous across economies. Panel (b) of the same figure shows that until the late 1970s, unemployment rates were fairly uniform across European countries. In the early 1980s, unemployment rates began to diverge because in some countries the increase was much less pronounced than in others. The graph labeled EU-2 represents the group-average unemployment rate for Austria, Denmark, Luxembourg, the Netherlands, Portugal, Sweden and the United Kingdom. Unemployment for this group is similar to the U.S. figure. More importantly, the rise in unemployment was much less pronounced than in the group labeled EU-1, which represents the group-average unemployment rate for Belgium, Finland, France, Germany, Greece, Ireland, Italy and Spain[5]. As a result, the dispersion of unemployment rates across European countries increased substantially. The standard deviation more than doubled, from a value of 1.77 during 1956-1974 to 4.48 during 1980-2000.

[4]The data for the unemployment rate and the duration of unemployment is obtained from the OCED Annual Labour Force Statistics database.

[5]The categorization of countries into EU-1 and EU-2 will be maintained throughout the paper. The following two criteria served as the basis for selecting countries: (1) a 1980-2007 average unemployment rate of above 8% and (2) a percentage points change in 1980-2007 unemployment with respect to the long-run average of more than 2.5 percentage points. All countries which fulfill at least one of the two criteria are placed in the group EU-1, all others are in EU-2. Average unemployment rates are obtained by weighting the unemployment rate of each group member by the population share.



(a) (b)

Figure 1: Average annual unemployment, in %, by subperiod for the United States and the EU-15, and for the group EU-1 (B, FIN, F, GER, GRE, IRE, ITA, ESP) and the group EU-2 (AT, DK, LUX, NLD, POR, SWE, UK).

Table 1: Observations on Unemployment, Hours Worked and Technology Adoption

	Unemployment			**Duration**			**Hours**		**Tech. Adoption**		
	56-07	80-07	Δ	*Avg.*	$f_{\leq 3}$	$f_{\geq 12}$	H	H^*	$\frac{I_{90}}{Y}$	$\frac{I_{04}}{Y}$	*Gap*
United States	5.6	6.1	0.5	3.7	70.1	8.9	0.0	0.0	3.1	4.1	0.0
EU-15	6.3	9.2	2.9	10.7	19.8	47.2	12.4	7.9	1.8	2.4	25.3
EU 1	6.6	9.7	3.1	11.0	17.3	49.5	15.5	10.6	1.7	2.1	33.7
EU 2	4.3	5.9	1.6	8.9	28.6	32.5	4.8	1.4	2.2	3.0	6.5
Belgium	7.1	10.3	3.2	12.8	14.5	59.8	24.6	19.4	2.4	1.7	35.4
Finland	5.8	8.5	2.7	7.1	35.2	24.0	1.8	-3.3	2.1	3.7	20.1
France	5.8	8.9	3.1	10.3	20.9	40.6	15.8	11.7	1.2	1.8	30.2
Germany	4.9	7.6	2.7	11.2	18.1	48.0	15.6	11.4	2.1	2.2	23.7
Greece	6.5	8.6	2.1	11.8	14.4	51.1	-4.8	-7.2	0.9	2.2	28.8
Ireland	8.6	10.7	2.1	11.9	17.1	52.0	2.6	-0.6	1.0	1.5	-0.6
Italy	7.5	10.1	2.6	13.1	11.1	61.2	13.1	10.7	1.9	2.4	57.7
Spain	10.1	16.5	6.4	11.3	19.8	49.0	24.1	12.9	1.7	2.1	27.4
Austria	2.9	3.8	0.9	6.9	40.0	25.7	1.9	1.6	1.8	2.3	11.3
Denmark	5.2	7.1	1.9	7.6	33.5	24.9	3.9	-0.9	2.2	3.4	-8.7
Luxembourg	1.6	1.9	0.3	8.8	24.0	30.5	-4.6	-4.6	3.2	2.2	..
Netherlands	4.6	6.7	2.1	11.0	18.3	44.6	18.7	15.6	1.7	2.7	15.9
Portugal	4.9	6.4	1.5	10.2	21.1	44.9	-2.8	-4.9	2.1	2.1	8.4
Sweden	3.8	5.4	1.6	6.4	46.0	19.9	1.2	-1.1	2.4	3.9	7.6
United Kingdom	5.3	7.8	2.5	8.9	31.4	34.2	3.4	-0.8	1.6	3.1	5.8
Australia	5.2	7.5	2.3	7.4	43.4	26.2	1.2	-3.2	2.2	3.6	3.1
Canada	7.4	8.8	1.4	4.8	59.1	11.6	1.8	-0.5	2.1	3.4	-4.3
Japan	2.5	3.3	0.8	7.2	42.0	22.9	-18.6	-18.8	2.0	3.2	2.1
Norway	2.7	3.8	1.1	4.8	58.9	13.1	7.3	5.9	...	2.6	..

Avg.: Average duration of unemployment in months. $f_{\leq 3}$ ($f_{\geq 12}$): Fraction of unemployed jobless for less than 3 (more than 12) months. H (H^*): Actual (hypothetical) 1980-2005 average percentage gap in hours worked per person between a country and the United States. See Section 2 and Appendices D.1 and D.2 for data sources and details. I_{90}/Y (I_{04}/Y): Average ICT investment to GDP ratio over the period 1980-90 (1998-2004). The data is taken from the Total Economy Growth Accounting Database maintained by the Groningen Growth and Development Centre and the EU KLEMS Growth and Productivity Accounts. *Gap*: Technology gap of a country to the United States. See Section 2 and Appendix D.3 for data sources and details.

Based on this observation, one may conclude that the use of the average rate of unemployment to describe the labor market performance in Europe is misleading. The first three columns of Table 1 reveal that there is, in fact, substantial variation of unemployment rates across European economies. The first two columns report the average unemployment rates for each country from 1956 to 2007 and from 1980 to 2007, respectively. The third column reports the percentage points change in 1980-2007 unemployment with respect to the long-run average. Over the period 1980-07, for instance, seven out of the 16 European labor markets reported in Table 1 produced unemployment rates that were slightly above or even below the U.S. rate. Thus, when we exclude some of the major European countries, particularly Germany, France, Italy and Spain, the so-called *European unemployment puzzle* vanishes[6]. High unemployment is not a phenomenon that is specific to Europe, per se, but rather to a certain group of countries.

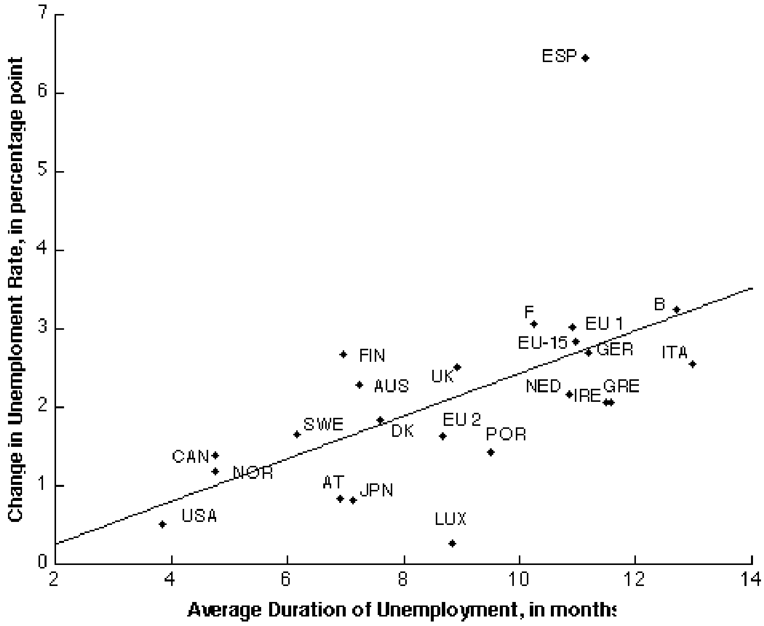


Figure 2: Unemployment Duration and the post-1970s Change in Unemployment

A distinguishing feature of the U.S. labor market is its fluid nature. The average duration of an unemployment spell in the U.S. is low relative to many European countries (see column (4) in Table 1), and the incidence of long-term unemployment is rare. Columns (5)-(6) in Table 1 show that during 1985-2007, 70.1% of unemployed people in the U.S. were jobless for less than three month, whereas this rate was less than 25% in Germany, France, Spain and Italy. In contrast, only 9% of unemployed people in United States remain jobless for more than one year, whereas the number for Germany, France, Spain and Italy is between 40-60%. As shown in Figure 2, there is a close relationship

[6]The "*European Unemployment Puzzle*" refers to high and persistent rates of unemployment in Europe relative to that in the United States.

between the post-1970 change in the rate of unemployment (depicted on the y-axes) and the duration of unemployment in the period thereafter (on the x-axes). Countries with short spells are those that previously experienced a comparatively smaller rise in the rate of unemployment. This finding suggests that the observed rise in unemployment in the 1980s was mainly driven by a decline in the flow of workers from unemployment back into employment, as previously observed by Blanchard (2006) and Ljungqvist and Sargent (2007). Evidently, high unemployment rates in some European countries are the result of a massive rise in the share of the long-term unemployed population.

Observation 2: Faster Embodied Technical Change

There is evidence, most notably by Cummins and Violante (2002), Greenwood and Yorukoglu (1997) and Pakko (2002), that the rate of arrival of new technologies has increased quite substantially since the late 1970s. Table 2 provides an overview of the existing empirical work. For example, Cummins and Violante (2002) follow the approach of Gordon (1990) and construct an aggregate index of investment-specific technological change (ISTC), which is based on a constant-quality price index for investment goods. They find that average annual growth rates were stable at around 3.6% until the late 1970s and experienced a sharp acceleration in the 1980s, which led to annual growth rates of more than 5.5% in the subsequent decade. The growth rates of ISTC reported in Table 2 vary due to different data source and time periods considered as well as different types investments. A closer look at the varieties of investments reveals that ISTC is especially prominent in computers, communication equipment, and software, whereas durable equipment and structures exhibit lower rates. This finding leads many of the aforementioned authors to argue that a sizable fraction of the observed acceleration can be attributed to the intensified adoption and usage of new information and communication technologies (ICT). The majority of empirical work establishes an economically significant acceleration of ISTC of 1.5 to 2.5 percentage points per annum.

As argued by Hornstein and Krusell (1996) and Yorukoglu (1998), an increase in the arrival rate of new technologies has important consequences for the process of technology adoption. A higher rate of technological change means that new technologies, which have characteristics that differ substantially from existing ones, are introduced at a faster rate. This situation raises the issue of compatibility problems between consecutive vintages. The improved technology embodied in new capital changes technological standards and decreases compatibility between old and new vintages. Yorukoglu (1998) argues that the more advanced the new technology is relative to the existing one, the poorer the initial experience is with the new production technology.

Thus, as the rate of technological change increases, agents are less familiar with the new technology, and its adoption is more costly. Therefore, in times of rapid technological change we should see an increase in the technology gap and a rise in the adoption costs. Regarding the former, Cummins and Violante (2002) find that the technology gap in the United States (which they define as the gap between the productivity of the best technology and the productivity of the average practice in the economy) was 15% in 1975. In 2000, this figure had jumped to 40%, suggesting that firms were not able to keep up with the accelerated process of technical change. Or in other words, the increased speed of technological change outpaced firms' technology updating.

Table 2: The Rise in Investment-Specific Technical Change

source	**investment type**	**data source**	**growth in ISTC p.a.**	
			period 1	**period 2**
GY (1997)	producers' durable equipment	Gordon, NIPA	$1954-74: 3.3\%$	$1975-1990: 4.0\%$
KORV (2000)	capital equipment	Gordon	$1963-79: 3.6\%$	$1980-1992: 6.0\%$
KORV (2000)	capital equipment	NIPA	$1963-79: 0.3\%$	$1980-1992: 2.6\%$
CV (2002)	equipment & software	CV	$1960-79: 3.6\%$	$1980-2000: 5.5\%$
Fisher (2006)	equipment & software	CV	$1955-82: 3.2\%$	$1983-2000: 5.8\%$
RT (2010)	equipment & software	CV, RT	$1977-80: 2.6\%$	$1980-1990: 5.5\%$
Pakko (2002)	total private NFI	Pakko	$1950-82: 2.0\%$	$1983-2000: 4.0\%$
JPT (2011)	consumer durables & PDI	CV	$1954-81: 1.2\%$	$1982-2000: 3.1\%$
JPT (2011)	consumer durables & PDI	NIPA	$1954-81: 0.6\%$	$1982-2000: 2.4\%$

NFI: nonresidential fixed investment, PDI : private domestic investment , GY (1997): Greenwood and Yorukoglu (1997), KORV (2000): Krusell, Ohanian, Rios-Rull, and Violante (2000), CV (2002): Cummins and Violante (2002), RT (2010): Rodríguez-López and Torres-Chacón (2010), JPT (2009): Justiniano, Primiceri, and Tambalotti (2011)

Concerning the costs of updating technology, Bessen (2002) provides evidence that adjustment costs rose sharply during 1974-83 and more than doubled from the early 1960s to the late 1980s. He finds that the costs associated with adopting a new technology amounted to \$0.35 per dollar of investment in 1961-73. In 1974-83, adjustment costs rose sharply to \$0.79 per dollar of investment and peaked at \$0.90 in 1984-88. As a result, adoption costs as a percentage of aggregate output increased from 2.4% in 1973 to 6.5% in 1983. Bessen (2002) argues that the rise in costs is specifically associated with a change in firms' investment towards new technologies.

Observation 3: Technology Gap across Countries

Economic growth in Europe was strong until the 1980s but became weaker in the subsequent decades. As a result, a persistent gap in both GDP growth and labor productivity growth between the United States and most European countries has emerged since the 1980s. By examining data on relative manufacturing output per person, Scarpetta et al. (2000) show that the productivity level for Germany and other European countries was converging toward the U.S. level until the 1980s but has since diverged.

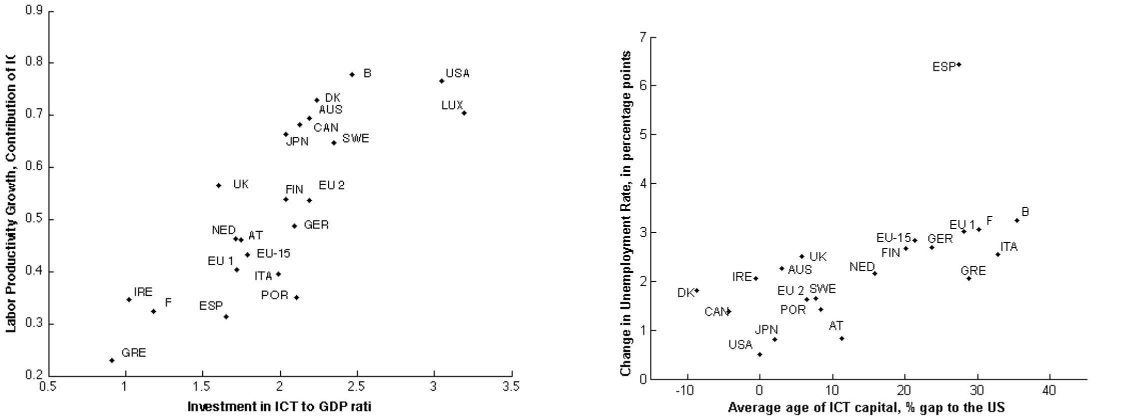
Several Europe economies have lagged behind the United States in terms of the adoption and usage of new technologies. Timmer et al. (2003) report that many European countries have fallen seriously behind the U.S. in the share of ICT investment in GDP. Lower investment rates in ICT mean that newer technologies have been adopted less forcefully. Daveri (2002) and van Ark et al. (2002), among others, find that the diffusion of new technologies in Europe is following a similar pattern to that observed in the U.S., albeit at a considerably slower pace. Moreover, these authors show that ICT investment intensities increased in all countries over time but (a) most European countries began investing in ICT with a significant delay, and (b) the gap between the United States and most European economies has not narrowed significantly.

The lagging technology diffusion is not a feature that applies to Europe in general. Columns (9)-(10) in Table 1 report the average ICT investment to GDP ratios over the periods 1980-90 and 1998-2004 (labeled, respectively, by $\frac{I_{90}}{Y}$ and $\frac{I_{04}}{Y}$). It is evident that there is, in fact, a considerable cross-country heterogeneity with respect to investment in new technologies. Several European countries - most notably, those that belong to EU-2 - have investment rates that are quite comparable to the U.S. rate. Other countries, such as Spain, Italy or France, seem to be not only lagging behind but also losing ground over time. A comparison of the two time periods in columns (9) and (10) reveals that the slack investment in EU-1 countries is not a temporary phenomenon of the 1980s. Rather, the investment gap between EU-1 and EU-2 has not narrowed over time but; if anything, it has been widening over time and remained prevalent in the 1990s. Due to this unequal investment rates, some countries can be expected to be closer than others to the technology frontier or to the United States (as alternative reference point).

To operationalize the concept of the technology gap, I compute, for each country, the average age of the installed aggregate ICT capital stock and compare it to the U.S. figure. The reason for focusing on ICT capital instead of aggregate physical capital is that technological capital, particularly ICT, played a central role in the massive, economy-wide restructuring process in the 1970s and 1980s. This process led to a higher usage of ICT capital in production and a steadily rising share of ICT investment in total investment. Moreover, ICT capital has been identified as the major driver of faster capital-embodied technical change since the 1970s. Thus, it is reasonable to argue that focusing on the average age of ICT capital offers the most insight because it best characterizes the process of technological turnover in the 1970s and 1980s. Column (11) in Table 1 reports the percentage difference between the average age of ICT capital in a given country to that in the United States over the period 1980-2007.[7]. The average age obtained for the United States is 1.89 years, which is almost identical to the 1.8 years reported in the Bureau of

[7]A detailed explanation of how the average age of capital is computed can be found in Appendix D.3.

Economic Analysis' fixed assets accounts for the average age of computer equipment and software in 1970-2000. To obtain the value for a specific country, such as Italy, one must compute (1+57.7/100)*1.89, which yields 3 years. In tranquil times, a gap of one year may seem negligible, but in times of rapid technical change and annual ISTC growth rates of more than 5.5%, such a difference implies a substantial productivity gap.



(a) ICT Investment and Productivity Growth (b) Technology Gap and Unemployment Change

Figure 3

It is well known that lower ICT investment rates are key in explaining the poorer productivity performance of Europe. Panel (a) of Figure 3 illustrates the strong and positive relation between the level of investment in new technologies and the average annual labor productivity growth[8]. Oliner and Sichel (2000) and Jorgensen and Stiroh (2000) provide evidence that, to a large degree, the U.S.-EU productivity gap can be traced to the delayed adoption of new technologies in Europe. This finding is confirmed by a number of studies, including Daveri (2002), Colecchia and Schreyer (2002) and van Ark et al. (2002). Panel (b) of Figure 3 compares the technology/unemployment performance across countries. The x-axis represents a country's technology gap (measured as described previously), and the y-axis represents the deviation of the country's unemployment rate over the period 1980-2007 from its long-run average. Countries with a smaller gap had a more moderate rise of unemployment in the 1980s and 1990s. Countries belonging to the EU-2 group exhibit technology adoption behavior similar to the United States, and the unemployment rates of those economies are comparable to the U.S. rate. Moreover, unemployment rates increased only slightly in the 1980s. By contrast, economies of the EU-1 group seem to adopt new technologies at a substantially slower rate while suffering from persistently high unemployment.

[8]Panel (a) of Figure 3 reports labor productivity growth that is due to ICT-capital deepening.

A question that arises in this context is why technology adoption differs so significantly across economies. A number of empirical studies, such as McGuckin and van Ark (2001) and McGuckin et al (2005), argue that structural impediments in product markets hamper the successful implementation of new technologies across industries in certain European countries. These barriers appear primarily in the form of burdensome regulations. Regression estimates by Nicoletti and Scarpetta (2003) suggest that strict product market regulations that curb competition hinder the adoption and diffusion of new technologies and thus have a negative effect on productivity. Additional evidence provided by Gust and Marquez (2002) suggests that countries with more burdensome regulatory environments tend to adopt new technologies more slowly and have slower productivity growth. These studies argue that because adoption costs differ across countries, countries with low adjustment cost adopt new technologies first. Additional evidence in this direction is provided by Colecchia and Schreyer (2002) and Jerzmanowski (2006).

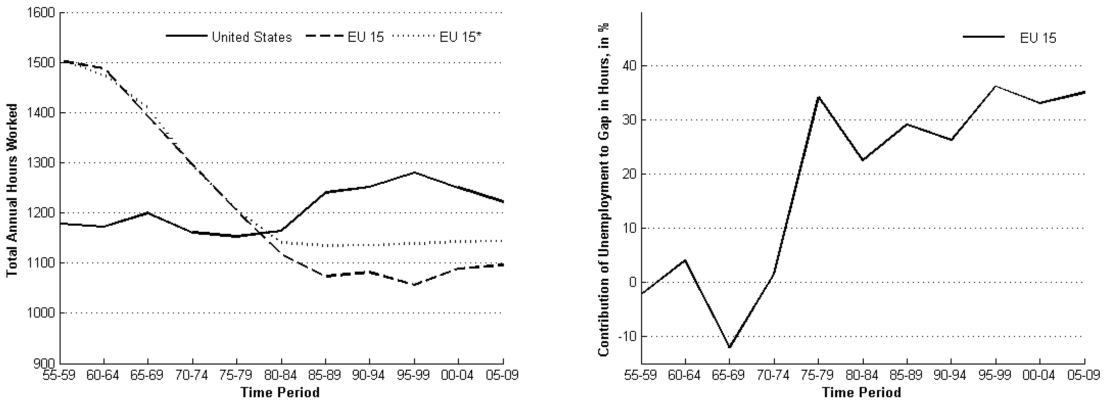
Unemployment and Hours Worked - A Brief Discourse

A recent strand in the literature has found that total annual hours worked per person in Europe has gradually deteriorated relative to the United States since the late 1950s. As a result, European hours worked now fall substantially short of the U.S. figure. Panel (a) of Figure 4 depicts this evolution[9]. Column (7) of Table 1 reports the 1980-2005 average percentage gap in hours between each country and the United States. Several explanations have been offered for this phenomenon. Most prominent are those that emphasize the role of income taxes (Prescott 2004, Ohanian et al. 2008), taxation and home production (Rogerson 2006, 2008, McDaniel 2011), inequality (Bell and Freeman 2001, Bowles and Park 2005), preferences (Maoz 2010, Blanchard 2004) and unions (Alesina et al. 2006).

A decline in the total amount of hours worked can potentially result from rising unemployment. As more people are out of work, all else equal, the total number of hours worked naturally declines. An important question, therefore, is whether the insights of the literature on the evolution of the Europe-U.S. gap in hours can shed light on the observed Europe-U.S. divergence of unemployment rates. Rogerson (2008) argues that the evolution of the differences in hours worked and differences in unemployment rates are two distinct phenomena. The key differences concerns the timing: the decline in European hours worked began in the late 1950s, long before unemployment rates began to diverge, and continued at a steady pace until the mid-1980s. The major part of the decline was over when unemployment began to diverge, as illustrated in Figure 1. Thus,

[9]The total annual hours worked per worker are computed as annual hours worked per worker times the number of persons employed and the result divided/normalized by the population aged 15-64 years. This is the standard way in this literature to express total hours worked. A detailed description of how the data series are constructed together with the data sources can be found in Appendix D.1 .

even with perfect understanding of the evolution of hours worked, it is not possible to explain why unemployment rates in the 1980s began to evolve differently across countries. Consequently, the insights provided by the literature on hours worked offer little guidance concerning the evolution of unemployment rate differences.



(a) Actual and counterfactual hours (b) Hours gap explained by unemployment

Figure 4

However, the converse does not necessarily apply. Panel (a) of Figure 4 shows that in the early 1980s, hours worked in Europe and the United States were roughly equal. The current hours gap originated in the 1980s and was caused by an additional (but short-lived and moderate) decline in European hours and an increase in U.S. hours of roughly the same magnitude. The gap emerged at the time when the unemployment rates in Europe and the United States began to diverge. To assess the impact of the latter on the evolution of hours, I perform an exercise similar to that in Rogerson (2006). In particular, I compute the hypothetical hours worked in Europe that would have prevailed if the unemployment-to-population ratio in Europe had - counterfactually - evolved like that in the United States. I am, thus, able to quantify the contribution of changes in the Europe-U.S. unemployment differential to the gap in hours worked[10]. The result of this exercise is depicted by the dotted line in Panel (a) of Figure 4, which represents the hypothetical hours worked in Europe. Prior to the 1980s, the contribution of unemployment was negligible. This is not surprising because in this period, unemployment rates in Europe and the United States moved very similarly. During the 1980s, however, the rise of European unemployment led to a substantial widening of the hours gap. Without the change in the unemployment differential, European hours would have been higher by approximately one-third. This can be seen in Panel (b), which reports the percentage contribution of changes in the unemployment differential to the observed hours gap.

[10]For a detailed description of the counterfactual experiment see Appendix D.2.

Column (8) of Table 1 reports the hypothetical hours gap of a country (denoted H^*) to the United States over the period 1980-2005. It is perhaps most notable that, like unemployment rates, total hours worked are very different within Europe. EU-2 countries are very similar to the United States, with a difference in hours that amounts to approximately 5%. By contrast, EU-1 countries exhibit a gap that is more than 3 times as large. The divergence of unemployment rates within Europe can help to explain the divergence of hours worked over time. The coefficient of variation of total hours worked for the sample of European countries averages 10.2 over the period 1959-1974, and it rises by more than 20% to 12.5 for the period 1980-2000. If European economies had experienced the same change in the unemployment-to-population ratio as the United States, implying no unemployment divergence, the coefficient of variation would remain constant.

Two conclusions follow. First, a non-negligible part of the difference in the observed hours worked between Europe and the United States can be traced to the different evolution of unemployment rates since the 1980s. Second, to understand the divergence of hours within Europe, one must understand why unemployment rates evolved so differently across European economies. Therefore, it is reasonable to argue that a good understanding of unemployment performance is important for understanding (at least partly) the prevailing differences in hours worked across countries.

3 The Model

Vintage Technology and Skills

As an analytical framework, I use a vintage technology model with a frictional labor market. Time is discrete and denoted by t=$0, 1, 2, ...$ The economy is populated by a continuum of individuals who can be employed or unemployed. Individuals face a constant probability of death, given by σ. All individuals are risk neutral, and they have no access to savings technologies. An agent's objective is to maximize expected wealth, which is given by the infinite stream of discounted future income.

At each point in time, there exists a range of production technologies denoted by $a_{t,\tau}\in \{a_{t,0}, a_{t,1}, ..., a_{t,T}\}$ that differ with respect to their date of creation. The vintage (or age) of a certain technology is denoted by τ=$0, 1, ..., T$. The leading edge technology is given by $a_{t,0}$ whereas $a_{t,T}$ is the oldest that is still in use. T is determined endogenously and can be interpreted as the critical age at which a technology is scrapped. A new technology arrives deterministically in each period and grows in productivity at rate g. Hence $a_{t+1,0}$=$ga_{t,0}$, where $a_{t+1,0}$ and $a_{t,0}$ denote the leading edge in period t+1, and t, respectively. The productivity of an existing technology remains constant throughout time.

There is a single homogeneous consumption good in the economy that is produced by a continuum of firms. Each firm has a single job that is either vacant or filled with a worker. Firms are heterogeneous with regard to the vintage of the implemented technology τ. When a new firm is created it installs the most advanced technology that is available at the given time, that is $a_{t,0}$. An employed worker supplies one unit of labor inelastically to the firm. Labor is the only input to production. The output of a firm is a function of the installed technology, and it produces according to $y_t(\tau)=a_{t,\tau}$. In each period, a firm with a filled job has the choice to keep the currently installed technology, to upgrade by installing the frontier technology, or to destroy the job. When a firm upgrades, it incurs a cost $\chi_t(\tau)$, which is assumed to depend on the firm's technology gap - that is, the distance of the currently installed technology to the leading edge technology.

To operate a technology, a worker is required to possess specific knowledge. This particular form of human capital will be referred to as production knowledge. It does not add to worker's productivity, but is required to operate a certain technology. I follow Violante (2001) and assume that worker's production knowledge is characterized by its limited transferability across vintages. That is, each technology vintage requires specific knowledge, and the knowledge associated with a given vintage cannot be fully applied to another technology of a different vintage. Moreover, the transferability decreases with the distance between two vintages. When a workers is reassigned to a newer technology, her knowledge must be made compatible with the new procedure. Therefore, $\chi_t(\tau)$ is interpreted as representing the training costs the firm incurs to enable the worker to operate the new procedure. When $\partial\chi/\partial\tau\geq 0$, firms with older technologies pay more to upgrade because a smaller proportion of the workers' human capital can be transferred. The decreasing transferability of skills implies that technical progress leads to human capital obsolescence. Newer technologies require a different set of skills than existing ones. With new technologies emerging over time, a worker can utilize only a gradually declining fraction of her current human capital at the frontier. In the conventional vintage-technology models of the labor market, such as that in Mortensen and Pissarides (1998), workers are not constrained by skill requirements when moving across technologies of different levels of advancement. Individuals in these models can switch to more advanced technologies without any extra cost. I find this to be an overly stark assumption and relax it by allowing for a potential dependence of the costs on the worker's skill gap.

Unemployment and the Labor Market

An existing match can be dissolved for two reasons: exogenous destruction that occurs with probability $0<\rho<1$ or endogenous destruction by firms. A firm destroys a job when its production technology is too obsolete and updating was not optimal in the past. Individuals are entitled to government-sponsored unemployment insurance, which pays out

b_t>0 in each period of unemployment[11]. After a job loss, workers' production knowledge remains fully preserved. That is, each unemployed worker continues to possess the knowledge associated with the technology assigned to her prior to displacement. Thus, we can conveniently use τ to indicate the technology vintage for which an unemployed person possesses skills. Due to technical progress, the human capital of the unemployed gradually deteriorates in the same way as the human capital of the employed workers. Hence, the longer it takes an unemployed person to find a job, the more obsolete her skills will be.

The labor market is frictional. This means that at each point in time, there exists a certain number of open vacancies, denoted by v_t, and a pool of job-searching individuals, u_t. To find a worker, a firm posts a vacancy, which is costly. Let κ>0 be the per-period cost of keeping the vacancy open. There are no barriers to entry, so any firm that pays κ can enter the labor market and create a job opening. The total number of unemployed workers is given by $u_t = \sum_\tau u_t(\tau)$, where $u_t(\tau)$ is the mass of unemployed workers with knowledge of vintage τ. New job matches are denoted by m_t and are determined by a matching function that is homogeneous of degree one, bounded above by $min\{v_t, u_t\}$ and increasing in both arguments. The matching function that is adopted here has become the standard choice in the search and matching literature:

$$m_t = m\left(v_t, u_t\right) = min\left\{\bar{m} v_t^d u_t^{1-d}, v_t, u_t\right\}, \tag{1}$$

where $\bar{m}$>0 is a shift factor and $0<d<1$ is the elasticity of matches with respect to vacancies. The probability of a firm meeting an individual with skills for vintage τ is:

$$q_t(\tau) = \frac{m(v_t, u_t)}{v_t} \frac{u_t(\tau)}{u_t} = m\left(\theta_t\right) \theta_t^{-1} \phi_t(\tau), \tag{2}$$

where $\theta_t = v_t/u_t$ is a measure of labor market tightness, and $\phi_t(\tau) = u_t(\tau)/u_t$ is the mass of unemployed individuals with human capital τ. Similarly, let p_t denote the probability of an unemployed worker encountering a firm with an open vacancy:

$$p_t = m\left(v_t, u_t\right)/u_t = m\left(\theta_t\right). \tag{3}$$

Vacancies are all identical; hence, p is the same for all individuals. The existence of a matching frictions in the labor market implies workers looking for a job trigger a congestion effect. The greater the number of individuals looking for a job, the lower the probability of encountering a vacancy. The same holds for firms with open vacancies. Therefore, firms' incentive to post vacancies is governed by the tightness of the market.

[11]The government in this economy levies a lump-sum tax on employed individuals to finance the insurance system, and it is assumed to run a balanced budget every period.

The Value Functions

The constant growth in the technology frontier induces a natural trend in several of the model's endogenous variables. To render the model stationary, all growing variables are divided by the common growth factor given by the productivity at the frontier $a_{t,0}$.

All decisions within a match, including matching, wages and technology upgrading, are made jointly by the firm and the worker. The timing of decisions is such that a firm and a worker first decide on the technology upgrade and, conditional on the outcome, they then bargain over wages. The value functions for an employed worker and a firm are, respectively, $\bar{E}$ and $\bar{J}$ after the upgrading decision, whereas before the upgrading decision, they are given as E and J. The state of a match is described by the vintage of the installed technology, τ. Hence, for a given wage rate $\omega\left(\tau\right)$ we can write $\bar{J}$ as follows:

$$\bar{J}(\tau) = y\left(\tau\right) - \omega\left(\tau\right) + \beta g\left(1-\sigma\right)\left(1-\rho\right) J\left(\tau+1\right). \tag{4}$$

ρ is the rate of exogenous job destruction, with probability σ the worker dies between two consecutive periods and β is the discount factor. The instantaneous return for a firm is given by the output net of wage payments, $y\left(\tau\right)$-$\omega\left(\tau\right)$. If the match survives to the next period, the age of the installed technology becomes τ+1. The value of a job for an employed worker after the upgrading decision is:

$$\bar{E}\left(\tau\right) = \omega(\tau) + \beta g(1-\sigma)\left[(1-\rho)E(\tau+1) + \rho U(\tau+1)\right]. \tag{5}$$

The total value consists of the current period's wage income $\omega(\tau)$ and the discounted future surplus. The latter term takes into account that the job might be hit by an exogenous destruction shock, in which case the worker becomes unemployed. The value of unemployment is given by $U(\tau)$. The joint surplus of a job is defined as the sum of the job values for the firm and the worker, net of the respective outside options. The outside option for a worker is the value of unemployment U, and for a firm is it the value of an unfilled vacancy, which in equilibrium, is equal to zero. For a job with vintage τ<T, the joint surplus is defined as $\bar{\mathcal{S}}(\tau)$=$\bar{J}(\tau)$+$\bar{E}(\tau)$-$U(\tau)$. A match is dissolved when the joint surplus of remaining in the match falls below zero. Using the firm's and the worker's value functions, as stated in (4) and (5), we can rewrite $\bar{\mathcal{S}}$ as follows:

$$\bar{\mathcal{S}}(\tau) = \max_{T\in\mathbb{N}_0}\left\{\sum_{t=\tau}^{T-1}\tilde{\beta}^{t-\tau}y(t) - \sum_{t=\tau}^{T-1}\tilde{\beta}^{t-\tau}\left[U(t) - \beta g(1-\sigma)U(t+1)\right] + \tilde{\beta}^{T}\bar{\mathcal{S}}(T)\right\}, \tag{6}$$

where $\tilde{\beta}$=βg(1-σ)(1-ρ) is the effective discount factor, and T is the age of the technology at which it is scrapped. The joint surplus consists of three parts. The first term represents the discounted stream of output that the technology produces over its lifetime. From that term is deducted the present discounted value of what the worker can get elsewhere. This term (in square brackets) is equal to $b+\beta g(1-\sigma)\left[\bar{E}(0) - I^E(t+1) - U(t+1)\right]$, and it is the sum of the value the worker can get in unemployment b and the expected discounted value of a new job net of training cost I^E. The third term in Equation (6) is the value of the match at the time when the current technology is scrapped. At T, the firm can upgrade to the frontier, in which case it must pay $\chi(T)$, or it can destroy the job. Therefore, we can write $\mathcal{S}(T)$=max$\{\bar{\mathcal{S}}(0)$-$\chi(T), 0\}$. The key decision of a firm amounts to finding the optimal scrapping age T. Notice that T is the same for all firms and is constant over time. The former is true because there is no match heterogeneity other than the vintage heterogeneity. The latter holds because the frontier grows at a constant rate. In the following section, the scrapping decision is examined in more detail.

The Updating Problem and Wage Setting

The decision-making process is sequential. Before the firm and the worker bargain over the wage, they decide whether to upgrade the production technology. At each point in time, a firm/worker pair seeks to maximize the joint surplus of the match. This rule also applies to identifying the optimal time to scrap the existing production technology and adopt a new technology. In this set-up, upgrading means that a firm jumps to the frontier and adopts the current leading-edege technology. Here, updating to the frontier comes by assumption. This assumption is essentially irrelevant because the same result is obtained if firms can choose the vintage[12]. Retooling is costly, and a firm that upgrades must invest in its worker's human capital to make it compatible with the new technology. Upgrading occurs when the joint value net of costs is positive:

$$\bar{J}(0) + \bar{E}(0) - \chi(\tau) > \bar{J}(\tau) + \bar{E}(\tau). \tag{7}$$

The scrapping value of an old technology is zero because no secondary markets exist in this economy. The upgrading costs are shared between the firm and the worker. More precisely, the total costs, $\chi(\tau)$, are allocated to maximize the surplus:

$$\max_{I^E, I^J} [\bar{J}(0) - I^J - \bar{J}(\tau)]^\eta [\bar{E}(0) - I^E - \bar{E}(\tau)]^{1-\eta} \tag{8}$$

$$\text{s.t.} \qquad I^J + I^E = \chi(\tau).$$

[12] The reason for that is the following: The cost of updating from vintage τ to $\tau' < \tau$ depends only the distance between τ and τ'. After t periods the vintages will be equal to $\tau + t$ and $\tau' + t$ but the cost is still the same as the distance obviously has not changed. At the same time, the relative productivity gain of retooling is given by $g^{-\tau'}/g^{-\tau} = g^{\tau-\tau'}$, which is also a function of the distance $\tau - \tau'$ only. Therefore, the net surplus (productivity gain minus cost) of updating from τ to τ' is the same as that of moving from $\tau - \tau'$ to 0. It does not pay off for firms to wait for a technology to fall behind the frontier and then to adopt it. The payoffs of adopting a technology right away and adopting it later are the same.

I^J and I^E are the costs borne by the firm and the worker, and the parameter $\eta \in [0,1]$ indicates the firm's weight in the bargain. The solution to the problem in (8) is a sharing rule that satisfies the first-order condition $(1-\eta)[\bar{J}(0) - I^J - \bar{J}(\tau)] = \eta[\bar{E}(0) - I^E - \bar{E}(\tau)]$. The second step in the decision making sequence concerns the wage bargain. The firm and the worker engage in a bilateral bargaining process in which they choose a wage rate to maximize the joint surplus of the match. This optimization problem reads as follows:

$$\max_{\omega} \bar{J}(\tau)^{\eta} \left[\bar{E}(\tau) - U(\tau)\right]^{1-\eta}. \tag{9}$$

Optimality implies (1-η)$\bar{J}(\tau)$=η[$\bar{E}(\tau)$-$U(\tau)$], which holds for all $\tau<T$. The wage ω can be expressed by combining the first-order condition with the value functions in (4)-(5):

$$\omega(\tau) = \underbrace{(1-\eta)y(\tau)}_{\text{worker's share in current suplus}} + \eta \left[\underbrace{U(\tau) - \beta g(1-\sigma)U(\tau+1)}_{\text{worker's outside option}}\right]. \tag{10}$$

Match Formation

All newly created jobs are assumed to embody the leading-edge technology. That is, after matching with a worker, a firm installs the technology a_0. This assumption will be relaxed later on. A newly created firm incurs re-training costs $\chi(\tau)$ to make the skills of the new worker compatible with the installed technology. The principle of cost sharing applies not only to ongoing matches that update but also to newly formed matches. Similar to the problem above, the total re-training costs for a new match are allocated according to:

$$\max_{I^E, I^J} [\bar{J}(0) - I^J]^{\eta} [\bar{E}(0) - I^E - U(\tau)]^{1-\eta} \tag{11}$$
$$\text{s.t.} \qquad I^J + I^E = \chi(\tau).$$

The value of the worker's outside option affects how the training costs are shared. For instance, a worker who receives generous unemployment benefits has a valuable outside option and thus a high opportunity cost of working. For such a worker to agree to form the match and leave unemployment, the firm must offer a greater share of the total surplus by allowing the worker to pay a smaller fraction of the total costs. In contrast, $U(\tau)$ is decreasing in τ. A worker with more obsolete skills has a lower outside option and, therefore, pays a larger fraction of the total costs. The value function of an unemployed worker with the skills for vintage τ is given by:

$$U(\tau) = b + \beta g(1-\sigma) \left\{p(\theta) \left[\bar{E}(0) - I^E(\tau)\right] + (1-p(\theta))U(\tau+1)\right\}, \tag{12}$$

with probability $p(\theta)$ that an unemployed worker encounters a vacancy and becomes employed. The value of the match, net of training costs, is $\bar{E}(0) - I^E(\tau)$. If no matching takes place in the current period, the worker remains unemployed in the next period. In this case, the obsolescence of her production knowledge increases to $\tau+1$.

With free entry into the labor market, all gains from posting vacancies must be exhausted in equilibrium. In other words, the cost of opening a vacancy must equal the expected return. The implied zero-profit condition of the firm is:

$$\kappa = \beta g(1-\sigma) \sum_{\tau} q(\tau) \left[\bar{J}(0) - I^J(\tau) \right], \tag{13}$$

with probability $q(\tau)$ the firm encounters a worker with the human capital for vintage τ, in which case the net surplus of a match is $\bar{J}(0) - I^J(\tau)$. All new jobs yield the same value, $\bar{J}(0)$, but the training cost depends on which worker the firm meets. There is no directed search in the model, so the firm can expect to be matched with any worker. This is taken into account by summing over all possible skill states τ. With the definition of $q(\tau)$, as stated in Equation (2), the zero-profit condition writes:

$$\kappa = \beta g(1-\sigma) m(\theta)\theta^{-1} \left[\bar{J}(0) - \sum_{\tau} \phi(\tau) I^J(\tau) \right]. \tag{14}$$

The term in square brackets is the expected surplus for a firm conditional on matching, and $\sum_\tau \phi(\tau) I^J(\tau)$ is the expected training cost. Condition (14) pins down the equilibrium market tightness, θ, and thereby determines other endogenous variables such as the unemployment rate. The average obsolescence of workers' skills plays an important role in shaping aggregate labor market outcomes. The incentives for a firm to create a new job depend on the surplus it can expect, which is a function of the quality of human capital among the unemployed. The dependence of aggregate job creation on average skill obsolescence gives rise to an externality: when firms optimally set T they do not take into consideration the effect of their decision on the average human capital obsolescence of unemployed individuals. The higher T is, the longer technologies are kept in operation and the older, on average, the vintages from which workers eventually separate. Therefore, the average human capital obsolescence among the unemployed is higher. This affects the expected hiring costs of all unmatched firms and their incentive to create new jobs.
We can now state the definition of a stationary equilibrium in this model

Definition. *A stationary equilibrium in this economy consists of a set of value functions* $\bar{S}$ *and* U *together with a maximum age* T *that solve the updating problem stated in (6), a set of sharing rules* I^J, I^E *that solve the cost sharing problem in (8) for existing, and in (11) for new matches, a value of market tightness* θ *that satisfies the zero-profit condition in (14), and a distribution of unemployed workers* ϕ *that is time-invariant.*

A Different Representation of the Firm's State

Let z denote a firm's relative productivity with respect to the technology frontier, and define it as $z = g^{-\tau}$=a_τ/a_0, with $z \in \{\bar{z}, ..., g^{-1}, 1\}$. Then, 1-$z$ represents the percentage difference of a firm's current productivity to the frontier, which is referred to as a firm's technology gap. The size of the gap is a function of a firm's vintage τ and the growth rate of the technology frontier. Until now, a firm's state has been described by the vintage of it's technology, τ. From this point, I use a firm's relative productivity z. This has several advantages. τ was chosen mainly for illustrative purposes. Each vintage is closely liked to the time dimension; therefore, τ allows for an intuitive depiction of the vintage structure that prevails in the economy. However, from a technical point of view, it is more convenient to work with z because it is better suited to evaluate the obsolescence of a given technology. The vintage τ says how "old" a technology is but not how it compares to the frontier in terms of productivity. Metaphorically speaking, when the frontier does not move at all (that is, when g=1), then any two different technologies (for example, of vintage τ=5 and τ=100) are equally productive. In both cases, z=1. Therefore, in any experiment that involves changes in g, such as the one implemented here, z is the preferred choice over τ to describe the state of a firm. When the state is z, the decision of the firm is to choose the cutoff productivity for its technology, that is $\bar{z}$=g^{-T}.

4 The Analytical Part - Gaining Intuition

The model at hand is too complex to allow for closed-form results and to analytically examine the channels between technology updating and labor market outcomes. However, a good understanding of these channels is fundamental for interpreting the results of the quantitative section. To foster the understanding of the model, a stripped-down, continuous-time analog is studied very briefly in the next section. More precisely, the full model of the previous section is simplified as follows: (a) the firm's bargaining power η is set to unity, implying that the entire surplus of the match accrues to the firm (that is $\bar{J}(z)$=$\bar{\mathcal{S}}(z)$) and that the worker is payed her reservation wage $\omega(z)$=ω=b; (b) the firm incurs all the costs from technology updating and worker training (i.e. $I^J(z)$=$\chi(z)$ and $I^E(z)$=0). An immediate implication is that the value of unemployment is constant and independent of the worker's skill level: $U(z)$=U; (c) the per-period probability of dying σ is set equal to zero to reduce notational clutter. These simplifications remove only as many parts as necessary to make the model analytically tractable. The main tradeoff and channels underlying the full model are preserved[13]. The switch to continuous time is made because the discreteness of the updating choice prevented closed-form calculations. Instead, with continuous time, the choice is a continuous variable.

[13] Appendix A deals with the complete description of the model's elements, the derivation of the equilibrium, and questions concerning the existence and uniqueness of equilibrium.

The first key equation describes the problem of the firm. Equation (15) states that the firm optimally chooses the cutoff productivity $\bar{z}$ to maximize the job surplus:

$$\mathcal{S}(1) = \mathcal{S} = \max_{\bar{z}\in[0,1]} \left\{ \frac{1}{g} \int_{\bar{z}}^{1} z^{\frac{r+\rho-g}{g}-1} [z-b]\, dz + \bar{z}^{\frac{r+\rho-g}{g}} \mathcal{S}(\bar{z}) \right\}. \tag{15}$$

The total surplus consists of (a) the discounted stream of output y net of the worker's outside value b, and (b) the present value of the match that has reached the cutoff productivity. At $\bar{z}$, the choice of the firm is to decide whether to retool or to destroy the job; hence, $\mathcal{S}(\bar{z})$=max $\{\mathcal{S} - \chi(\bar{z}), 0\}$. In the following section, I focus on the case in which updating is the optimal choice[14]. The worker's outside value comprises only the flow value of unemployment b because, for η=1, the surplus that the worker can receive in any other job is equal to zero. If updating is optimal (that is, when $\mathcal{S}$>$\chi(\bar{z})$), the first-order condition for the problem is obtained by setting $\partial\mathcal{S}/\partial\bar{z} = 0$ which yields the following:

$$\underbrace{\bar{z} - b}_{\text{value of keeping current technology}} = \underbrace{(r+\rho-g)\left[\mathcal{S} - \chi(\bar{z})\right] - \bar{z}g\chi'(\bar{z})}_{\text{discounted value of updating}}. \tag{16}$$

A firm that decides when to upgrade trades off the following considerations. On the one hand, by scrapping the technology now, the firm foregoes the future (net) output the current technology can produce. On the other hand, by delaying the updating of the technology, the firm foregoes the productivity gains of a newer technology and faces higher costs of retooling in future. The latter is a consequence of updating costs χ being a function of the firm's technology gap, which is gradually widening with time. Condition (16) states that at the optimum, the net output of the match with the old technology $\bar{z} - b$ must be equal to the net flow value of the match with the frontier technology $(r+\rho-g)[\bar{\mathcal{S}} - \chi(\bar{z})]$ plus the marginal costs of waiting $-\bar{z}g\chi'(\bar{z}) = \frac{\partial\chi}{\partial z}\frac{\partial z}{\partial\tau}|_{z=\bar{z}}$. The first-order condition can be combined with condition (15) to obtain the following expression, which implicitly determines the optimal cutoff productivity $\bar{z}$:

$$\frac{1}{g}\int_{\bar{z}}^{1} z^{\frac{r+\rho-g}{g}-1}[z-\bar{z}]\, dz = \chi(\bar{z})\left[1 + \epsilon_{\chi,z}\left(1 - \bar{z}^{\frac{r+\rho-g}{g}}\right)\frac{g}{r+\rho-g}\right], \tag{17}$$

where $\epsilon_{\chi,z} = \chi'\bar{z}/\chi$. Appendix A establishes conditions for which $\bar{z} \in (0,1)$ exists and is unique. It can be shown that $\bar{z}$ is negatively related to the updating costs χ. When it is more costly to retool, the optimal cutoff productivity is lower, and firms wait longer before scrapping the technology. From (17), it emerges that the cutoff productivity $\bar{z}$ is only a function of the model's deep parameters and is independent of any endogenous variable or of the value of unemployment benefits b. The first-order condition (16) can be rewritten to express the value of a new job as $\bar{\mathcal{S}}$, which can then be combined with the zero-profit condition $\kappa = p(\theta)\theta^{-1}[\mathcal{S} - E(\chi)]$ to obtain:

[14]The case of job destruction being the optimal choice is studied in Appendix A.

$$\kappa = p(\theta)\theta^{-1}\left[\frac{\bar{z} - b + \bar{z}g\chi'(\bar{z})}{r + \rho - g} + E\left[\chi(\bar{z}) - \chi\right]\right]. \tag{18}$$

$E(\chi) = \int_0^1 \chi(z)d\Phi_z$ is the expected value of re-training costs, and Φ_z is the cumulative distribution of unemployed individuals over skill states z. Φ_z can be expressed in closed-form, as shown in Appendix A. The term inside the square brackets is the expected surplus of a job for a firm, conditional on meeting a worker. The first term, $\frac{\bar{z}-b+\bar{z}g\chi'(\bar{z})}{r+\rho-g}$, is equal to $\mathcal{S} - \chi(\bar{z})$, and it represents the value of a match with a new technology net of upgrading costs. With $\bar{z}$ determined by (17), Condition (18) pins down the equilibrium labor market tightness θ and thus the equilibrium unemployment rate $u = \frac{\rho}{\rho+p(\theta)}$.

A firm with a filled job can install a new technology in two ways: it can upgrade the technology within the existing job, or it can destroy the job (which involves firing the currently employed worker), create a new one and find a new employee. In the first case, the incurred costs are $\chi(\bar{z})$, whereas in the second case, the costs depend on the skill level of new worker. The second term in (18), given by $E\left[\chi(\bar{z}) - \chi\right]$, measures the expected difference in costs between retooling on the job and upgrading through the destruction of the job. This difference can be positive or negative, depending on the average human capital obsolescence among the unemployed.

Condition (18) describes a negative relationship between the expected surplus of a job for a firm $\mathcal{S}$-$E(\chi)$ and the equilibrium unemployment rate u. The intuition behind this relation is straightforward and common to a large class of labor market matching models. The zero-profit condition implies that any change in the expected surplus is accompanied by an adjustment in the labor market tightness θ. Firms that face a lower return on creating a job require compensation so that they are able to recoup the vacancy costs κ. The compensation comes in the form of a lower market tightness θ, which raised the contact rate for the firm $p(\theta)\theta^{-1}$ and reduces the time until the job is filled. At the same time, a lower θ implies a decreased probability for an unemployed worker to find an open position. This, in turn, depresses the flow of unemployed workers back into employment and causes the duration and the level of unemployment to rise.

In what follows, the analytical model is used to study (a) the effects of technical change on unemployment and (b) the role firms' technology choice plays in how faster technical change affects labor market outcomes. The experiment that is considered is a permanent rise in g, which is meant to simulate the observed 1970s acceleration in the rate of embodied technical change. Two equations are central in the analysis: Equation (17), which determines firms' optimal cutoff $\bar{z}$, and Equation (18), which pins down the equilibrium labor market tightness θ. The first step determines how firms respond to faster technical change. From condition (17), it is clear that the updating decision is independent of any endogenous variable, which greatly facilitates the analysis of the optimal cutoff $\bar{z}$.

Proposition 1. *A firm's optimal cutoff level for productivity $\bar{z}$ is weakly decreasing in the growth rate of the technology frontier g. (Proof is in Appendix C)*

The proposition establishes that in times of faster technical change, firms tolerate a larger critical productivity gap to the frontier $1 - \bar{z}$. This is an interesting finding. It implies that firms do not entirely keep up with the pace of innovation, but rather allow the marginal technology $\bar{z}$ to fall behind the technological frontier. As an immediate implication, the productivity range in the economy $\{\bar{z}, ..., 1\}$ expands, which causes the average practice in the economy to deteriorate.

The next step explores the effects of a higher g, together with the implied drop in $\bar{z}$, on labor market variables. To this end, we focus our attention on Equation (18). To isolate the different effects individually, we first analyze the (partial equilibrium) effects on the net value of a job $\frac{\bar{z}-b+\bar{z}g\chi'(\bar{z})}{r+\rho-g}$, and then focus on the term $E[\chi(\bar{z})\text{-}\chi]$. Two opposing effects are at work: first, a rise in the growth rate g lowers the firm's net discount rate, given by r+ρ-g. This is the rate at which a firm capitalizes future income emerging from the current technology and any future upgrading. A higher g means that future profits are discounted at a lower rate. This leads to a rise in the discounted stream of profits and therefore to a rise in the value of the job. Second, as illustrated above, a larger g lowers the cutoff productivity $\bar{z}$. Allowing for higher technological obsolescence of the job lowers the value of the job[15]. These two effects are respectively referred to as the *capitalization effect* and the *obsolescence effect*. Which of these two effects dominates is crucial for the effect of faster technical change on the total surplus and, ultimately unemployment.

Proposition 2. *An increase in the rate of embodied technical change g leads to a rise (fall) in the net value of a job $\frac{\bar{z}-b+\bar{z}g\chi'(\bar{z})}{r+\rho-g}$ if the updating cost χ are sufficiently low (high). There is a unique value of χ for which the net value of a job remains unchanged. (Proof is in Appendix C)*

The proposition says that the net effect of g on the value of a job depends on how frequently firms retool their technologies (which is itself govern by the underlying updating costs χ). The capitalization effect dominates when updating is cheap. The underlying logic is as follows: when costs are low, firms retool frequently and stay close to the frontier. In this way, they can directly participate in the higher productivity growth at the frontier. In contrast, when updating costs are high and retooling occurs only sluggishly, then the obsolescence effect dominates and leads to a decline in match surplus.

[15] The first term in the numerator unambiguously declines with g. The second term is irrelevant if costs are constant χ'=0, and if $\chi'(z)$>0, a sufficient condition for the numerator to decline is $|\frac{\partial \bar{z}}{\partial g}\frac{g}{\bar{z}}|<1$.

The implications for unemployment follow straightforwardly from Equation (18) and are depicted in Figure 5. There, the lower solid line represents equilibrium unemployment (y-axis) in the benchmark economy, where costs are given by χ (x-axis). When g rises, we observe a drop in unemployment in those economies that face low costs and, therefore, update frequently. In that case, the capitalization effect dominates, which leads to a rise in the job surplus and a drop in unemployment. By contrast, for economies to the right of the pivotal point, the obsolescence effect dominates, which causes unemployment to rise. The more sluggish the updating is, the stronger the obsolescence effect and the more pronounced the rise in unemployment[16].

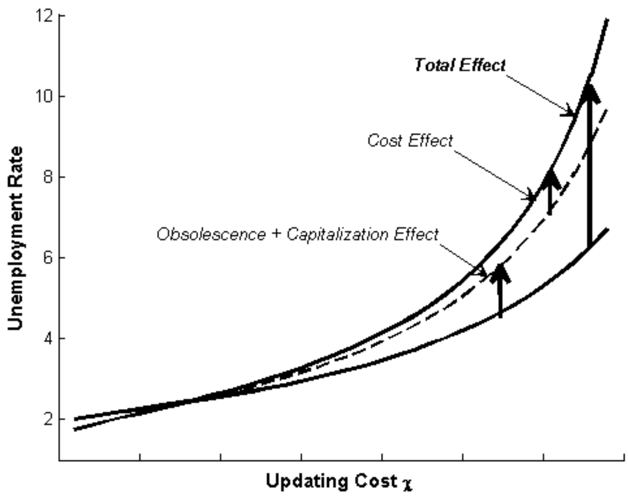


Figure 5: Decomposing the Total Unemployment Change

After considering the value of a job, the final step explores how the second term in Equation (18) $E[\chi(\bar{z})\text{-}\chi]$, changes when growth accelerates. This expression measures how much a firm expects to additionally pay for installing a new technology on the job instead of hiring and training a new worker for a newly created job. It is impossible to formally establish how $E[\chi(\bar{z})\text{-}\chi]$ behaves when g changes. Therefore, in what follows, the focus is on the change in expected costs $E(\chi)$, which can be expressed in closed-form (see Appendix A)[17]. When g rises, $E(\chi)$ changes for the following reasons: (a) a higher g implies that the human capital of the unemployed becomes obsolete at a faster rate; (b) the drop in the cutoff $\bar{z}$ (see above) implies that workers are matched, on average, with more outdated technologies. Hence, when workers eventually separate from the job and enter unemployment, their skills are, on average, more obsolete; (c) a decreased θ (see above) means that unemployed workers find new jobs at a lower rate.

[16] The parameter values underlying Figure 5 are as follows: $\rho = 0.1$, $r = 0.05$, $b = 0.25$, $\bar{m} = 1$, $\kappa = 1$, $d = 0.5$, $g = 0.01$, $g' = 0.04$, and the functional form for χ is $\chi(z) = a - z$, with $a \in [1, 4.5]$.

[17] Evidently, by disregarding the change in $\chi(\bar{z})$ we miss an important aspect, but, nevertheless, the analysis of $E(\chi)$ in itself allows for important insights.

They remain in unemployment for a longer time and have longer exposure to the process of skill depreciation. All three factors lead to a deterioration of the average skills of the unemployed, implying that in times of faster technical change, it becomes more costly to hire and train a new employee. The increase in costs worsens the incentives to create new jobs and tends to raise unemployment. This third effect is referred to as the *cost effect*, which occurs in addition to the capitalization effect and the obsolescence effect. In Figure 5, the cost effect is illustrated by the shift from the dashed line to the upper solid line.

5 The Quantitative Analysis

This section uses the quantitative model to explore the effects of faster embodied technical change on labor market variables and other macroeconomic outcomes. The analysis is divided into two parts. After calibrating the model, I first examine the effects in the benchmark economy, that is, the calibrated U.S. economy, and in two stylized versions of European-type welfare state economies. This first part is intended to illustrate the main channels at work and their quantitative importance. The second part performs a cross-country analysis, in which I match the observed technology gap for each country relative to the United States and then simulate the increase in technical change and observe the extent to which the model fits the country's observed path of unemployment.

Calibration and Parameterization

The quantitative model is calibrated to a selected set of U.S. micro- and macro-observations. The model period is one month. The personal discount factor β=0.99633 is chosen so that the implied annualized interest rate equals 4.5%. Individuals face a per-period probability of dying σ=0.00185; thus, on average, they spend 45 years in the labor force[18]. I follow the standard practice in the search-matching literature and set both the firm's bargaining weight η and the elasticity of matches with respect to vacancies d equal to 0.5. The value of unemployment benefits b is taken from the Labour Market Institutions Database assembled by Nickell and Nunziata (2001). b is set equal to 0.26, which corresponds to the 1960-1995 average of U.S. first-year unemployment benefits (averaged over family types of recipients), measured in terms of the percentage of average pre-tax earnings.

The rate of growth of the frontier technology g is calibrated as in Parente (2000) and set so that the annualized rate of embodied technical change is equal to 2%. The choice of the functional form and the parameters of the updating cost function $\chi(z)$ is not an easy task, and the empirical literature does not provide guidance on this matter. Therefore, I choose to be cautious and proceed by adopting a specific functional form,

[18] σ>0 is needed for computational reasons as it ensures the existence of finite support for the distribution of unemployed workers.

and later, in Section 6, I check the robustness of the results to alternative choices of χ. Here, the cost function is chosen as $\chi(z)=(1+\pi)\ z^{-\mu}$, where $\pi\geq 0$ and $\mu>0$ are parameters. I follow Parente and Prescott (1994) and interpret π as a distortion parameter, which is country-specific and measures the size of the barriers to technology adoption for firms in a given country. In the baseline calibration, which refers to the United States, $\pi=0$. This normalization is unimportant because, in the analysis that follows, we are interested in a country's technology gap relative to that in the United States. π will be calibrated subsequently and separately for each country to fit the observed technology gap.

Four parameters remain for which values must be assigned. The values of κ, ρ, $\bar{m}$ and μ are tied down by the following four U.S. observations: (i) an average unemployment rate for 1948-2007 of 5.5926%, as reported by the Bureau of Labor Statistics (BLS); (ii) an average monthly unemployment-to-employment transition probability for 1967-2007 of 32.11%, taken from Shimer (2005); (iii) a monthly job filling rate of 71%, taken from denHaan et al. (2000) and Hagedorn and Manovsky (2008); and (iv) the ratio of equipment investment to real output for 1948-2007 of 4.9804%, as reported by the Bureau of Economic Analysis (BEA)[19]. The resulting values of the parameters are reported in Table 3, and Table 4 describes the performance of the model in matching the targets. The monthly cost of an open vacancy κ is 0.40252. Given an equilibrium (average) wage equal to 0.9192, this value yields an average recruitment cost (computed as $\kappa\theta/p(\theta)$) of 2.7 weeks of workers' earnings. This is only slightly lower than Hamermesh's (1993) estimate, who estimates average hiring costs per worker, on average, to be one month's wages. At the same time, the implied total recruiting costs as a fraction of aggregate output is 0.0156, which is close to Andolfatto's (1996) estimate of 0.01. The scale parameter of the matching function $\bar{m}=0.4775$ and the monthly probability of exogenous job destruction ρ is found to be 0.017169. This value implies that a worker is laid off due to exogenous reasons, on average, after 4.8 years. In the benchmark calibration, exogenous job destruction is the only source of match separation. Endogenous job separation is not performed in equilibrium. For the calibrated value of ρ, the model generates a median job tenure of 3.3 years. This compares well to Hall's (1982) estimate and to more recent figures provided by the BLS. Hall (1982) finds median tenure in the United States to be 3.6 years in 1978, and the BLS reports a median tenure of workers for 1996-2009 in the range of 3.5-4.1 years.

The curvature parameter of the cost function μ is found to be 7.6323, which is also equal to the elasticity of adoption costs with respect to firm's technology gap 1-z. This value implies that adoption costs are increasing and mildly convex in the technology gap. Two years after the last update, a firm incurs costs equal to 1.4 months of output when

[19]The investment data is taken from BEA's fixed assets accounts, and the ratio is computed as gross private domestic investment in equipment and software (without transportation) divided by real GDP.

updating to the frontier. After 5 years and 10 years, the adoption costs amount to 2.1 and 4.5 months of match output, respectively. The empirical literature lacks direct, firm-level estimates to which these numbers could be compared. Thus, we rely on information about the aggregate adoption costs to evaluate the model's fit. Bessen finds adoption costs in the U.S. manufacturing sector, as a percentage of (manufacturing) output, of 2.4% in 1973. This is very close to the model's outcome of 2.7%.

Table 3: Calibrated Parameter Values

Parameter	Definition	Value
β	Discount rate	0.99633
η	Firms' bargaining power	0.5
b	Unemployment income	0.26
d	Elasticity of matches w.r.t unemployment	0.5
σ	Probability of dying	0.001852
g	Growth rate of technology frontier	1.0017
π	Cost shift parameter	0
κ	Per-period cost of a vacancy	0.40252
$\bar{m}$	Matching function: Scale parameter	0.4775
μ	Curvature parameter of the cost function	7.6323
ρ	Probability of exogenous job destruction	0.017169

The equilibrium labor market tightness θ is obtained directly from Equations (2) and (3), which imply that $\theta = p/q$. Both, p and q served as targets in the calibration, so we can derive θ straightforwardly from $\theta = 0.32114/0.71 = 0.4523$. This value accords well with the number 0.539 obtained by Hall (2005) from the Job Openings and Labor Turnover Survey (JOLTS). After a job loss, the model predicts that an individual will remain unemployed, on average, for 3.1 months before finding a new job. This is only slightly lower than the 3.4 months the OECD reports for the average U.S. unemployment spell over the period 1968-2005. Admittedly, the good fit of the model with regard to the unemployment duration comes naturally because the empirical unemployment-to-employment transition probability served as a target in the calibration of the model.

Table 4: Matching the Calibration Targets

	Value	
Target	Data	Model
Unemployment rate, u	0.05592	0.05593
Unemployment-employment transition probability, p	0.32114	0.32114
Job filling rate, q	0.71	0.71
Investment to output ratio	0.04981	0.04980

In the baseline scenario, the optimal scrapping age of a technology is 3.7 years. With 2% annual growth, this implies a critical value for a firm's productivity gap of 1-$\bar{z}$=1-g^{-T}=7%. T indicates the age of the oldest technology in the economy and thus marks the cutoff point for the range of vintages that are installed. T can be combined with the stationary distribution of firms $\phi^f(\tau)$ to compute the average age of the technologies installed[20]. The average age is found to be 1.6 years which is in line with the 1.8 years reported by the BEA for the average age of computer equipment and software over the period 1970-2000. Overall, the calibrated model produces a good fit of all targeted moments and of a number of non-targeted empirical observations on labor market outcomes and technological variables. I consider this as a first success of the quantitative model.

Laissez-Faire vs. Welfare-State Economies

In this section, I examine the effects of rapid embodied technical change in the benchmark case and in two stylized versions of European-type welfare state economies. Section 4 above isolated the main transmission channels analytically. Now these channels are studied quantitatively. To that end, an experiment is performed that simulates a one-time, permanent increase of 2 percentage points per annum in the rate of technical change g. This value marks the mid-point of the 1.5-2.5% range determined by the empirical literature for the 1970-rise in embodied technical change (see Section 2).

In addition to the calibrated U.S. benchmark economy, the experiment considers two different versions of stylized European welfare state economies. For convenience, the former is referred to as LF economy (short for "Laissez-Faire"), and to the two latter are referred to as WS-1 and WS-2 economies. The common characteristic of the welfare state economies is that jobless workers receive more generous unemployment benefits (than in the LF economy). In both, the WS-1 and the WS-2, b=0.38 which is the 1960-1995 average of benefits (as a percentage of pre-tax earnings) received by unemployed individuals in the EU-15. This value is obtained from the aforementioned Labour Market Institutions Database[21]. What distinguishes WS-1 from WS-2 economies is the cost firms incur when adopting a new technology. The evidence presented in Section 2 argued that certain European economies have lagged behind the rest of Europe and the United States in the implementation and usage of new technologies. Moreover, this pattern has been found to be caused by differences in the strictness of regulatory environments across countries, which translates into differences in the underlying adoption-cost structure.

Two cost scenarios are considered to account for these differences. In WS-1, the policy distortion parameter π=0, so firms in this economy face the same conditions as the firms in the LF economy. In WS-2, $\pi = 0.4$ so the implied technology gap (to the LF economy) matches the observed 25% technology gap of the EU-15 to the United States (see Table 1). The quantitative results for the different regimes are reported in the three panels of

[20]The distribution of firms over vintages, $\phi^f(\tau)$, is straightforward to compute and it can be expressed as $\phi^f(\tau) = \frac{[(1-\rho)(1-\sigma)]^\tau}{\sum_{t=0}^{T-1}[(1-\rho)(1-\sigma)]^t}$ for $0 \leq \tau < T$, and $\phi^f(\tau) = 0$ for $\tau \geq T$.

[21]The EU-15 value of b is obtained by averaging the b's of all countries and using population as weights.

Table 5. Notice that all other parameters, except for b and π, are the same across the cases.

The first row in each panel depicts the model's results for the initial steady-state, in which $g = 2\%$, whereas the second row is for $g = 4\%$. The cutoff productivity $1 - \bar{z}$ is the same in LF and WS-1 but is larger in WS-2. Higher costs curb firms' incentives to scrap old technology, so we observe firms in WS-2 updating relatively less frequently. In all the three cases, we observe the technology gap $1 - \bar{z}$ widening as g increases. This is in line with the analytical result from Section 4: firms extend the run-time of their technologies and allow for a higher critical gap when technical change accelerates. A lower cutoff productivity implies a higher average obsolescence of the installed vintages and of workers' production knowledge associated with these vintages. Eventually, workers separate from their jobs, due to job destruction and move into unemployment. As a result, the average human capital of unemployed individuals $\bar{z}_u$ deteriorates, as illustrated in the second column of Table 5. The skill obsolescence of an unemployed worker determines the amount of training that is necessary in the event of a match. As average skills are more outdated, firms expect larger training expenses $E(I^J)$ when hiring a worker (third column). Higher costs of job creation reduce firms' incentives to post vacancies v (fourth column). In turn, this leads to a decline in job creation, which makes it more difficult for unemployed workers to find new jobs. Consequently, the number of people who flow back into employment declines, causing both the average duration d_u and the rate of unemployment u to rise.

The labor markets in the LF and the WS-1 economies evolve, in general, very similarly. Unemployment rises in the laissez-faire economy by about 0.7 percentage points (or 12.5%) and by only slightly more in the first welfare-state economy. The more generous unemployment insurance induces a higher initial rate of unemployment, but, apart from this level effect, it does not seem to have a dynamic effect on how unemployment responds to faster technical change[22].
In the second welfare state economy, the picture is very different because the rise in unemployment is much more pronounced. The explanation for this pattern proceeds along the same lines identified within the analytical model of Section 4. The total increase in unemployment can be decomposed into three factors: the obsolescence, the capitalization and the cost effect. The contribution of each of these to explaining the total effect is reported in columns (6)-(8) of Table 5 and labeled as $\Delta_{obs.}$, $\Delta_{cap.}$ and Δ_{cost}. The obsolescence and, even more, the cost effect are key in explaining the stronger rise in WS-2 unemployment. The capitalization effect plays only a minor role. The cost effect captures the deterioration of the unemployed human capital. Individuals remain unemployed for

[22]The level effect comes quite naturally and is common in this class of models. A higher b raises a worker's outside option and her share in the total surplus. The firm is compensated for the loss in surplus through a higher vacancy filling rate q, which, in turn, implies a lower job finding rate p for the worker. The compensation is necessary to make the zero-profit condition hold.

longer in the WS-2 economy. With moderate technical change, this is not problematic because human capital depreciates slowly. However, when technical change accelerates, prolonged spells of unemployment lead to a substantial deterioration of the unemployed human capital. This increases firms' expected training costs, depresses job creation and leads to a sharp decline in the equilibrium number of vacancies.

Table 5: Laissez-Faire and the Welfare-State Economies

	1-$\bar{z}$	1-$\bar{z}_u$	$E(I^J)$	v	u	Decomposition			d_u	g_{LP}	σ_{wage}
						$\Delta_{obs.}$	$\Delta_{cap.}$	Δ_{cost}			
$Panel(a)$: LF-Regime with $b = 0.26$ and $\pi = 0$											
	7.0%	3.5%	1.33	2.53	5.59				13.5	1.4%	1.029
	8.7%	4.9%	1.51	−12.9%	+12.5%/0.7	4.6%	−0.5%	8.4%	15.3	3.4%	1.038
$Panel(b)$: $WS1$-Regime with $b = 0.38$ and $\pi = 0$											
	7.0%	3.6%	1.34	2.09	6.60				16.1	1.4%	1.029
	8.7%	5.2%	1.55	−15.8%	+15.9%/1.05	5.9%	−0.6%	10.6%	18.9	3.4%	1.038
$Panel(c)$: $WS2$-Regime with $b = 0.38$ and $\pi = 0.4$											
	8.7%	4.4%	2.02	1.47	8.98				22.5	1.1%	1.038
	10.2%	6.7%	2.50	−27.6%	+30.1%/2.71	10.4%	−0.5%	20.2%	30.1	2.5%	1.047

1-$\bar{z}$: Firms' cutoff productivity, 1-$\bar{z}_u$: Average skill obsolescence of unemployed individuals, computed as $\sum_z \phi(z)(1-z)$, $E(I^J)$: Expected costs of training a new employee, v: Vacancy rate, u: Unemployment rate, $\Delta_{obs.}$ ($\Delta_{cap.}$), [Δ_{cost}]: Percentage rise in unemployment due to obsolescence (capitalization), [cost] effect, d_u: Average weekly duration of unemployment, g_{LP}: Annualized aggregate labor productivity growth, σ_{wage}: Cross-sectional wage dispersion measured by the 90-to-10 wage ratio. The first (second) row of each panel is for $g = 2\%$ (4%).

Finally, columns (10)-(11) in Table 5 report the results for two more macro-outcomes, namely labor productivity growth and wage inequality. Labor productivity rises as g increases. This occurs mechanically because productivity growth at the technology frontier is the only driver of aggregate labor productivity. What is more interesting is that labor productivity growth is substantially lower in the WS-2 economy than in the other two cases. This difference is related to the slower technology updating in WS-2. When upgrading is slack, each period, only a small fraction of existing firms adopts the leading edge technology. These firms experience a jump in their productivity, whereas the productivity of all other firms remains unchanged. Given the small fraction of up-graders, their contribution to aggregate productivity growth is minimal.

In the model, wage inequality is generated by the vintage-induced productivity differences across firms. Firms with new and more productive technologies pay higher wages than firms with older technologies that are less productive. The dispersion of productivity across firms is generally wider than the dispersion of wages. The wage compression occurs because workers in unproductive jobs can threaten to leave the firm for more productive jobs. The wage inequality, measured by the 90/10 ratio, is very modest compared to what is observed in the United States and in Europe. The model predicts that faster technical change causes more wage inequality. When technical change increases, firms lower their cutoff productivity $\bar{z}$, which leads to a wider range of observed productivities in the economy and larger wage inequality. The rise in wage dispersion predicted by the model is less than 1% for all the three cases under consideration. This compares very poorly to the observed rise in many industrialized economies over the last few decades. Obviously, for this dimension of the data, our model has very little explanatory power.

Cross-Country Analysis

This section performs a cross-country analysis to explore how well the quantitative model fits the observed unemployment dynamics for a set of 23 OECD countries. Countries are considered to differ from one another along two dimensions: unemployment benefits b and the policy distortion parameter π. For each country, b is set equal to the 1960-1995 average of unemployment benefits obtained from Nickell and Nunziata's (2001) Labour Market Institutions Database. The distortion parameter π is calibrated for each country so that the model matches the observed technology gap relative to the United States. The choice of b does not affect firms' technology choice, so all of the cross-country heterogeneity in technology updating is captured by π. The remaining parameters are left unchanged and are considered to be the same across countries. Table 8 reports the calibrated values of b and π. The equilibrium for this calibration is called the initial steady-state of a country. The experiment which is considered simulates, for each country separately, a permanent, 2-percentage point increase in the annual rate of technical change. The model's success is evaluated based on the extent to which the model can capture each country's actual change in labor market outcomes, specifically unemployment.

Obviously, the country-specific values b and π generate an unemployment rate in the initial steady-state that differs from what is observed in the data. This is a standard problem in the literature, and it is addressed here by correcting for the higher initial unemployment. More precisely, I follow the strategy of Hornstein et al. (2007) and re-calibrate, for each country separately, the exogenous job separation rate ρ so that the initial steady-state matches the country's average unemployment rate over the 1956-2007 period as reported in Table 1)[23].

The results of the quantitative exercise are concisely summarized in Table 6 and Figure 6. Table 8 also reports the results of the quantitative model in which ρ was not re-calibrated to match a country's initial steady-state. The first two columns of Table 6 depict the percentage-point change in the actual unemployment rate of a country that occurred after the 1970s and the change predicted by the model. Panel (a) of Figure 6 provides

[23]Ljungqvist and Sargent (1998, 2007) face the very same problem and introduce layoff taxes to correct for higher initial unemployment. This step would not work her. As emphasized by Mortensen and Pissarides (1999) layoff taxes reduce the incentives to create jobs and to destroy them. The net effect on unemployment turns out to be ambiguous. In this framework, a firing tax would inevitably raise unemployment since, for the current calibration, endogenous job destruction is not performed in equilibrium. The only source of job destruction is exogenous separations. Hence the channel through which firing taxes could potentially lower unemployment, i.e. via locking workers into their jobs, does not take effect.

a scatterplot of both series. The fit of the model is remarkable. Most of the country observations are clustered closely around a hypothetical 45-degree line. For each country, I compute how much of the actual unemployment change the model can explain and then build the weighted average over all 23 country observations[24]. According to this measure the model can explain, on average, 74% of the observed change in unemployment (see Panel (a) of Table 6).

Table 6: Results of the Quantitative Model

	Change in unemployment rate					Duration		$\mathbf{g}_i^{LP}/\mathbf{g}_{USA}^{LP}$	
	Data	Model	π_i=0	$b_i=\bar{b}$	$\rho_i=\bar{\rho}$	**Data**	Model	**Data**	Model
United States	**0.5**	0.7	0.7	0.7	0.7	**3.7**	3.5	**1.00**	1.00
EU-15	**2.9**	2.4	0.9	0.8	0.7	**10.7**	8.3	**0.57**	0.64
EU-1	**3.1**	3.3	1.1	0.9	0.7	**11.0**	10.1	**0.53**	0.58
EU-2	**1.6**	0.9	0.7	0.5	0.7	**8.9**	5.1	**0.71**	0.94
Belgium	**3.2**	3.2	0.9	0.9	0.7	**12.8**	9.4	**1.02**	0.50
Finland	**2.7**	1.6	0.8	0.7	0.7	**7.1**	6.2	**0.70**	0.71
France	**3.1**	3.1	0.9	0.7	0.7	**10.3**	10.4	**0.42**	0.57
Germany	**2.7**	2.3	0.7	0.6	0.7	**11.2**	9.2	**0.64**	0.62
Greece	**2.1**	3.2	1.1	0.8	0.7	**11.8**	9.9	**0.30**	0.58
Ireland	**2.1**	1.4	1.3	1.1	0.7	**11.9**	4.3	**0.45**	0.89
Italy	**2.6**	2.5	0.9	0.9	0.7	**13.1**	7.4	**0.52**	0.58
Spain	**6.4**	5.1	1.9	1.4	0.7	**11.3**	10.7	**0.41**	0.64
Austria	**0.9**	0.6	0.4	0.4	0.7	**6.9**	4.7	**0.60**	0.83
Denmark	**1.9**	0.9	1.1	0.6	0.7	**7.6**	4.8	**0.95**	1.10
Luxembourg	**0.3**	0.4	0.3	0.2	0.7	**8.8**	4.8	**0.92**	1.06
Netherlands	**2.1**	1.8	0.8	0.6	0.7	**11.0**	8.1	**0.61**	0.73
Portugal	**1.5**	1.4	0.9	0.6	0.7	**10.2**	6.5	**0.46**	0.91
Sweden	**1.6**	1.4	0.7	0.5	0.7	**6.4**	7.4	**0.85**	0.96
United Kingdom	**2.5**	0.8	0.7	0.6	0.7	**8.9**	4.1	**0.74**	0.93
Australia	**2.3**	0.7	0.6	0.6	0.7	**7.4**	3.5	**0.91**	0.94
Canada	**1.4**	1.5	1.7	0.9	0.7	**4.8**	5.6	**0.87**	1.03
Japan	**0.8**	0.4	0.3	0.3	0.7	**7.2**	4.3	**0.89**	1.00
Norway	**1.1**	0.5	0.4	0.3	0.7	**4.8**	4.4	**-**	1.03

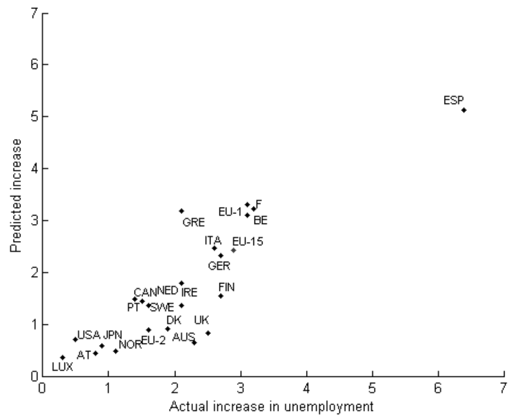
—— *Panel (a): Change in unemployment rate* ——					
% Explained:		74%	38%	30%	30%
—— *Panel (b): Change in dispersion of unemployment* ——					
σ_{56-06}	**2.01**	2.01	2.01	2.01	2.01
σ_{80-06}	**3.06**	3.02	2.37	2.28	2.01
% Explained:		96%	34%	26%	0%
—— *Panel (c): Duration of unemployment* ——					
% Explained (of level):		72%	46%	39%	38%
Dispersion σ	**2.68**	2.43	0.68	0.13	0.00
% Explained (of dispersion):		91%	26%	4%	0%

Model, (π_i=0), [$b_i=\bar{b}$], {$\rho_i=\bar{\rho}$}: Percentage-point change in unemployment rate in the calibrated benchmark model (without technological heterogeneity), [and without institutional heterogeneity], {without any country heterogeneity}, *Duration*: Average monthly duration of unemployment, g_i^{LP}/g_{USA}^{LP}: Ratio of aggregate annualized labor productivity growth in a given country i to labor productivity growth in the United States. σ_{56-06} (σ_{80-06}): Sample standard deviation of 1956-06 (1980-06) average unemployment rates.

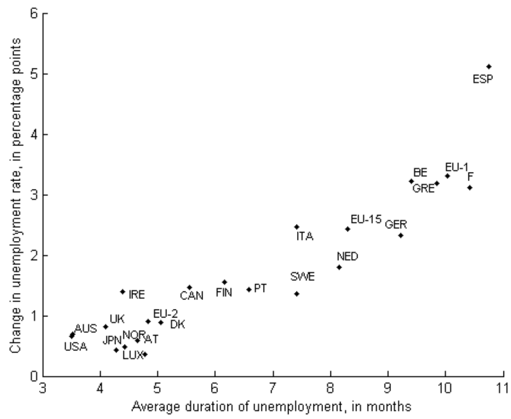
A key observation of this paper is that unemployment has evolved very differently across countries since the 1980s, which is reflected by a rising dispersion of unemployment

[24]The weighted average of the country-specific deviations is computed as $\sum_{i=1}^{23}\left(1-|\frac{\Delta_i^{Data}-\Delta_i^{Model}}{\Delta_i^{Data}}|\right)\omega(i)$, where $\omega(i) = \Delta_i^{Data}/\sum_i^{23}\Delta_i^{Data}$ is the weighting factor. ω is taken so that more weight is put on countries which experienced a large unemployment change.

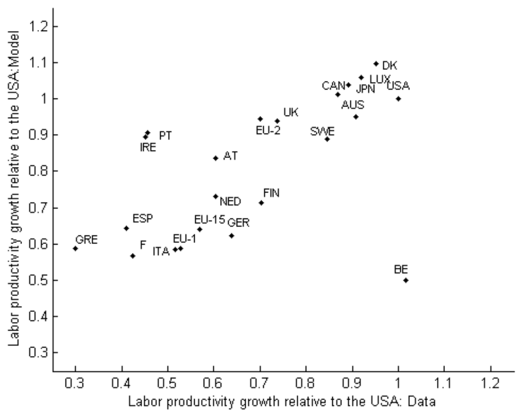
rates across economies. Panel (b) of Table 6 reports the long-run standard deviation of unemployment (denoted σ_{56-06}) and documents that it increased substantially after the 1980s. The model captures this feature very well and can account for 95% of the actual increase in the standard deviation. The implemented shock to technical change triggers a relatively modest unemployment change in the United States, the EU-2 and some other countries such as Canada or Japan, but a large change in the EU-1.



(a) Unemployment Change: Model vs. Data



(b) Duration of and Change in Unemployment



(c) Labor Productivity Growth: Model vs. Data

Figure 6

The model also predicts the average duration of unemployment very well. As reported in Panel (c), it matches, on average, 72% of a country's actual duration, and 91% of the dispersion in the entire sample. Moreover, the model is in line with the empirical observation that, in most countries, the rise in unemployment was driven primarily by a drop in the worker's reemployment probability, leading to longer unemployment spells (see Section 2). Panel (b) of Figure 6 depicts the model outcome for the average unemployment duration and the change in the unemployment rate. The relation between the two variables is broadly consistent with the empirical pattern found in Section 2.

The last result concerns aggregate labor productivity growth. For each country, I report the growth differential to the United States, computed as the ratio of labor productivity growth in a given country to labor productivity growth in the United States[25]. The actual and the predicted growth differentials are in Table 6 and are also depicted in Panel (c) of Figure 6. Some countries exhibit a sizable productivity growth differential, whereas for others, the gap is negligible or even negative. The model does a good job in explaining these differences. However, all observations are consistently above the 45-degrees line, which suggests that the selected empirical counterpart of productivity growth is, arguably, a slightly imperfect proxy of what is captured by the model.

The Importance of Technological Heterogeneity

In the quantitative analysis, countries differ from one another along three dimensions: (1) technology updating captured by π, (2) institutions b, and (3) the rate of job separation ρ. This section assesses the contribution of each source of heterogeneity in explaining the results. To this end, I remove one dimension of heterogeneity after another and evaluate the contribution of each dimension based on the extent to which the empirical fit of the calibrated model changes.

The results of are reported in Columns (3)-(5) of Table 6. First, all cross-country differences in technology upgrading are eliminated. This is achieved by setting the distortion parameter π equal to zero for all countries. Consequently, all firms in all countries face the same costs of technology adoption and upgrading as firms in the United States. Shutting down the technological heterogeneity worsens the empirical fit of the model considerably. Only 38% of the observed country-specific unemployment changes are accounted for by the model, which is about half of what the full model was able to explain. Moreover, the model without technological heterogeneity can account for only 34% of the rise in the cross-country dispersion of unemployment rates. The full model could match 96%, suggesting that differences in technology updating costs is an important source of country heterogeneity. Next, all institutional heterogeneity is eliminated by setting unemployment income b equal to the U.S.-value of $\bar{b}$=0.26. This further reduces the fit of the model, but the quantitative effect is comparatively small compared to the effect triggered by the removal of the technological differences. Finally, the rate of exogenous job separation ρ is set equal to the U.S.-value of $\bar{\rho}$=0.017169. All countries are now alike, and they all exhibit the same increase in unemployment. Obviously, the model without heterogeneity cannot explain any of the increase in cross-country unemployment dispersion.

[25] Actual aggregate labor productivity growth is affected by a variety of factors, many of which are not a part of the model. To make the model outcome comparable with the data I decompose labor productivity growth and focus only on the part which is driven by ICT-capital as this is most closely to what is captured by the model. The data is taken from the Total Economy Growth Accounting Database maintained by Groningen Growth and Development Centre.

The previous analysis has shown that the observed cross-country differences in technology updating, captured by the underlying country-specific technology costs, are quantitatively important for explaining the different evolution of unemployment rates. Institutional differences are of lesser importance.

6 Robustness Checks

This section discusses three robustness checks of the quantitative model. First, the assumption is relaxed that firms always install the state-of-the-art technology. Instead, firms can endogenously choose their preferred technology. Second, alternative functional forms are considered for the updating cost function, including linear and constant costs. Third, in the spirit of Ljungqvist and Sargent (1998), turbulence is modeled explicitly by introducing a probability of instantaneous skill depreciation after a job loss.

Check 1: Endogenizing the Technology Choice

The first check is motivated by the following concern. In the benchmark model, all new firms are assumed to install the leading edge technology, irrespective of the skill level of the new worker. This feature may artificially depress aggregate job creation. If the average worker with whom a firm expects to match has obsolete skills, the firm incurs a large cost to bring this worker to the frontier. This reduces a firm's surplus and the number of vacancies posted. If, instead, the firm can choose the technology, it may be optimal to choose not the state-of-the-art technology but one that is less advanced and requires less training. I now consider the case in which a firm optimally chooses the technology after observing the new worker. The model is modified in two places to incorporate this choice. First, the zero-profit condition is reformulated and now reads as follows:

$$\kappa = \beta g(1-\sigma)m(\theta)\theta^{-1}\left[\sum_{z\in(0,1]}\phi(z)\max_{z^*\in[z,1]}\left\{\bar{J}(z^*)-I^J(z^*,z)\right\}\right].$$

As before, z describes the productivity associated with the skill level of an unemployed individual, and z^* is the productivity level associated with the firm's optimal choice. We shall refer to z^* as the targeted productivity. The total training costs are $\chi(z^*,z)$=[1-$(z^*-z)]^{-\mu}$. The total costs and, therefore, the firm's share I^J depend on the technology gap the firm overcomes by upgrading the worker's skills from z to z^*. For z^*=1, the model is equivalent to the previous version without the technology choice. The technology choice also applies to existing firms. That is, a firm that decides to upgrade can optimally choose the vintage it wants to employ. The condition for upgrading now reads as follows:

$$\max_{z^*\in[z,1]} \left\{\bar{J}(z^*) + \bar{E}(z^*) - \chi(z^*, z)\right\} > \bar{J}(z) + \bar{E}(z).$$

The focus here is on the decision of new firms rather than the upgrading decision of existing firms[26]. Appendix B shows, in a simplified and analytically tractable framework, that the optimal choice of z^* is weakly increasing in the skills of the unemployed worker z and satisfies $z \leq z^* \leq 1$. More precisely, there are two values z_0 and z_1 for which:

$$z^* : \begin{cases} z^* = 1 & \text{if } z \geq z_1 \\ z^* \in (z,1) & \text{if } z_0 < z < z_1 \\ z^* = z & \text{if } z \leq z_0 \end{cases}$$

These conditions indicate that a firm installs (a) the state-of-the-art technology if the worker's skills are sufficiently advanced and above z_1, (b) a technology that is behind the frontier but more advanced than the worker's current skills if these are in (z_0, z_1), or (c) the technology that exactly coincides with the worker's current skill. The latter occurs when the skills of the unemployed worker are more obsolete than z_0. In the quantitative model, these results are found to hold in exactly the same form.

Table 7: Results of Robustness Checks

	Change in unemployment rate					**Unemployment dispersion**			**Duration**		
	USA	EU15	EU1	EU2	$\%_E$	σ_{56-06}	σ_{80-06}	$\%_E$	Level	σ_d	$\%_E$
—— *Panel (a): Data and benchmark model* ——											
Data	**0.5**	**2.9**	**3.1**	**1.6**	-	**2.01**	**3.06**	-	-	**2.68**	-
Benchmark	0.7	2.4	3.3	0.9	74%	2.01	3.01	95%	71%	2.41	90%
—— *Panel (b): Endogenous technology choice* ——											
ETC	0.7	2.7	3.7	0.9	74%	2.01	3.22	85%	72%	2.39	89%
—— *Panel (c): Linear and constant costs* ——											
χ_{lin}	0.8	1.7	2.2	0.9	63%	2.01	2.65	61%	65%	1.60	60%
χ_{cst}	0.2	0.4	0.4	0.2	14%	2.01	2.13	12%	54%	1.28	48%
—— *Panel (d): Turbulence shock* ——											
$\gamma_{1\%}$	0.2	0.3	0.3	0.2	12%	2.01	2.09	9%	42%	0.49	18%
$\gamma_{5\%}$	1.5	1.9	2.0	1.3	64%	2.01	2.39	37%	51%	0.69	26%
$\gamma_{5\%}+\pi_i$	1.5	2.5	2.9	1.4	75%	2.01	2.88	83%	72%	1.88	70%

$\%_E$: Fraction of (full sample) data outcome explained by the model, σ_{56-06} (σ_{80-06}): Standard dev. of 1956-06 (1980-06) average unemployment rates, σ_d: Standard dev. of unemployment duration. χ_{lin} (χ_{cst}): Linear (constant) updating costs, $\gamma_{1\%}$ ($\gamma_{5\%}$), [$\gamma_{5\%}+\pi_i$]: Low (high) turbulence, [high turbulence and technological heterogeneity]

In the quantitative analysis, all structural parameters are taken to be the same as those used in the benchmark model. This is possible because the inclusion of an endogenous technology choice does not alter the initial steady-state of any of the countries under consideration. In other words, the models with and without the technology choice are observationally equivalent for $g = 2\%$, and the calibration, therefore, remains unchanged.

[26]The reason being that upgrading to the frontier is optimal whenever upgrading is the optimal choice (cf. the line of argument provided in footnote 12.). Therefore, adding an explicit technology choice for existing firms does not alter the results.

As before, I consider the experiment of a 2 percentage point increase in g. The first four columns of Table 7 report the induced change in the unemployment rate for the United States, EU-15, EU-1 and EU-2. The fifth column shows the percentage fit of the quantitative model for the entire sample of 23 countries. The remaining columns show the model outcomes for the dispersion of unemployment rates and the duration of unemployment. To facilitate comparability with previous results, Panel (a) of the same table states the findings of the benchmark model and the data outcome.

Overall, the inclusion of the technology choice affects the results only marginally. For the United States, the EU-15 and the EU-2 the results are virtually unchanged, as for most of the countries in our sample. The exception are the countries belonging to EU-1. For these countries, we observe a more pronounced increase in unemployment. It it worth briefly examining why this is the case. Table 9 compares the models with and without technology choice for the EU-1 and the EU-2 case. In the EU-1 countries, technology adoption is more costly; therefore, upgrading is less frequent, and the average skills among the unemployed are more obsolete (relative to the EU-2). In this environment, not all newly hired workers are retrained to the frontier. Those with very obsolete skills receive little or no training because it is optimal for the hiring firm to install a technology that is closer to the worker's current skill level instead of the frontier technology.

This scenario leads to three effects, two of which directly affect the job-creation decision of firms. First, firms can expect lower training costs because not all workers receive the full amount of training. Second, the average technology installed by a new firm is behind, not at, the frontier and is therefore less productive than the leading-edge technology. The first effect positively affects job creation because it raises the expected surplus of a new job, whereas the second effect works in the opposite direction. The third effect results from an increased incidence of job destruction. Technology updating on the job is no longer optimal for all firms. Firms that began with a very obsolete technology always find it too costly to upgrade. Their technology is kept in operation until the job becomes unprofitable and is destroyed endogenously. In the framework studied previously, endogenous job destruction never occurred in equilibrium. Here, it does occur, which leads to a higher incidence of job separation and a correspondingly larger flow of workers into unemployment. Each of the three effects is quantitatively substantial, as indicated in Table 9. In sum, however, they almost cancel each other. Overall it seems that an endogenous technology choice has only minor implications for the model's aggregate outcomes. For the given calibration, the findings of the benchmark model of Section 3 can be considered fairly robust with respect to the inclusion of a technology choice.

Check 2: The Cost Function

The cost function χ used in Section 5 is mildly convex in the firm's technology gap. Now, I consider linear and constant costs. In both cases, I proceed by implementing the new function into the model, re-recalibrating the model to the same targets as in the benchmark case and, finally, simulating the increase in the rate of technical change. The linear cost function implemented here is given by $\chi_{lin}(z) = 1 + \mu_{lin}(1 - z)$, where the parameter μ_{lin} is calibrated as before. The vertical intercept for $z = 1$ is the same as in the benchmark case and equal to 1. The constant cost function is simply $\chi_{cst}(z) = \mu_{cst}$.

Panel (c) of Table 7 reports the results for both specifications. Broadly speaking, the findings change only moderately for the linear cost function. This is particularly true for countries with a low distortion parameter π, such as the United States and the EU-2. This is explained by the fact that technology upgrading in these countries occurs at medium and high values of z (close to 1). In this range, the calibrated value of $\mu_{lin} = 11.39$ implies updating costs that are only slightly different from the benchmark case[27]. By contrast, for countries belonging to the EU-1(which operate mostly at lower values of z), the convexity of the original cost function is important to generate the large rise in unemployment. Therefore, when using a linear function, the results change slightly. For the entire sample, the fit of the model drops from 74% to 63%. More importantly, with linear costs, the increase in unemployment is more uniform across countries. Consequently, the model misses quite a bit of the observed increase in the dispersion of unemployment rates.

With constant costs, the results are very different. Panel (c) of Table 7 shows that the empirical fit of the model drops drastically. In this scenario, an important channel of the model is entirely disabled. We have found previously that faster technical change leads to a higher rate of skill depreciation among unemployed workers, which translates into higher expected training costs for the firm and discourages job creation. This is the cost effect, which accounts for a substantial part of the unemployment increase. With constant costs, this effect disappears because training costs are now the same for all workers. The skill obsolescence of the unemployed worker is no longer relevant to the model. The analysis of this section suggests that the convexity of upgrading costs is inessential for the performance of the model. However, a very important feature is that costs are positively related to the obsolescence of workers' skills.

[27]In particular, in the benchmark the costs for upgrading after 2, 5 and 10 years amounted to 1.4, 2.1 and 4.5 months of output, respectively, In the case of linear costs this changes to 1.4, 2.1 and 3.1 months.

Check 3: The Source of the Shock

Finally, I focus on the underlying exogenous shock. This section is motivated by the previous literature, particularly by the influential work of Ljungqvist and Sargent. As an explanation for the U.S.-EU unemployment pattern, this strand of analysis emphasizes the interaction between an exogenous shock that is common to all countries and labor market institutions that are country-specific. The shock considered in this literature represents a rise in the degree of *economic turbulence*, and it is modeled as an increase in the likelihood that workers lose a fraction of their skills in the event of a job loss.

This paper considers a different type of common shock, the increase in the rate of embodied technical change, and a different source of country heterogeneity, the costs of technology adoption. The aim of this section is to explore the implications of introducing the turbulence shock **instead** of the technology shock into the current framework. More precisely, the turbulence shock is introduced with institutional heterogeneity into the model, but technical heterogeneity is disregarded. From this analysis, it can be determined whether the shock and the heterogeneity proposed in this paper are quantitatively important or whether, instead, the model can explain the data equally well (or better) with the features emphasized in the previous the literature.

There are several ways to incorporate the notion of turbulence into the model. The way chosen here is closest to the approach by Ljungqvist and Sargent. In particular, turbulence is associated with the likelihood that in the event of a job loss, a worker's production knowledge is hit by an obsolescence shock. Given this possibility, the value of a job to a worker becomes:

$$E(z) = \omega(z) + \beta g(1-\sigma)(1-\rho)E(z') + \beta g(1-\sigma)\rho \int_0^{\infty} U(z/g^{\mathtt{t}}, z) dF_{\gamma}(\mathtt{t})$$

where turbulence is encoded in $\mathtt{t}$, which, for $\mathtt{t}>0$, deteriorates a worker's skills z after a layoff. The larger $\mathtt{t}$ is, the higher the reduction of z. $\mathtt{t}$ is assumed to be drawn from an exponential distribution with cdf $F_{\gamma}(\mathtt{t})=1\text{-}e^{-\gamma\mathtt{t}}$. The degree of turbulence is represented by the parameter $\gamma>0$. For $\gamma=+\infty$, it follows that $dF(\mathtt{t})=0$ for $\mathtt{t}>0$, implying that there is no turbulence and each worker maintains the same skill level after a job loss. For γ being finite, $dF(\mathtt{t})>0$ for $\mathtt{t}>0$. The distributional assumption implies that $dF(\mathtt{t})>dF(\mathtt{t}')$ for $\mathtt{t}<\mathtt{t}'$; that is, a small loss of skills is always more likely to occur than a large loss.

Following the literature, a worker's unemployment income is assumed to be a fraction

b of her wage earned prior to displacement. The value of unemployment reads as follows:

$$U(z, z_l) = b\omega(z_l) + \beta g p(\theta)\left[E(1) - I^E(z, z_l)\right] + \beta g(1-\sigma)(1-p(\theta))U(z', z_l).$$

The state of an unemployed worker consists of the level of human capital prior to displacement z_l and the current human capital z. The former determines the benefit payments, and the latter affects the amount of training required in a new job. This setup nicely captures the key mechanism underlying Ljungqvist and Sargent's approach. Consider a worker who lost a job and was hit by the obsolescence shock such that $z<z_l$. This worker receives high unemployment benefits but is costly to retrain. As a result of the high benefits, the worker has a valuable outside option when bargaining with a new employer about wages and how to divide the training costs. Naturally, such a worker can extract a higher share of the joint surplus than a similar worker with the same current skill level z who was not hit by the shock (and so $z=z_l$). When turbulence rises, more workers lose their skills after a layoff. Thus, there is a higher proportion of unemployed workers, who are costly to retrain and have strong bargaining power. Consequently, a firm with an open position expects to obtain a lower surplus from hiring a new worker, which, in turn, discourages job creation and increases unemployment.

The framework is used for the following analysis. First, the wage replacement rate b of a country is chosen as in the quantitative analysis of Section 5, and π is set equal to zero. Turbulence is set to zero, and the initial steady-state is computed for each country. Then, the turbulence shock is introduced, and the equilibrium is recomputed. Two different scenarios are considered: low and high turbulence. In the low-turbulence case, γ=0.1634, implying that all laid-off workers lose, on average, 1% of their skills[28]. In the high-turbulence case γ=0.0314, implying an average skill loss of 5%. Figuratively speaking, a loss of 1% and 5% imply that when the frontier grows at an annual rate of g=2%, a laid-off worker falls further behind the frontier by about half a year and 2.5 years, respectively.

Panel (d) of Table 7 reports the results. A turbulence shock of 1% is clearly insufficient to generate a rise in unemployment that is comparable with the observed rise. The model can account for only 12% of what is observed. Furthermore, the predictions for other labor market variables come nowhere near the actual outcomes. Considering a larger shock size improves the empirical fit of the model, at least along certain dimensions. In the high-turbulence case, the model generates a stronger increase in unemployment and is, on average, more in line with the data. However, it fails to explain the rising unemployment dispersion. As in previous setups of this type, the unemployment increase after a turbulence shock depends on the wage replacement rate b. Unemployment rises only

[28] The average loss is computed as $1 - \int_0^\infty \frac{1}{g^t} dF_\gamma(t) = 0.01$.

slightly when b is small, and it rises significantly when benefits are generous[29].

The observed institutional heterogeneity is insufficient to explain the evolution of OECD unemployment rates. The values of b are relatively uniform across OECD countries (see Column 8 of Table 8), meaning that the actual differences in wage replacement rates are small. Not surprisingly, the quantitative contribution of these differences is minor and they can account for only 37% of the observed divergence of unemployment rates. When technological heterogeneity is introduced into this framework (via the choice of π), the model does a much better job of explaining the data. The results are displayed in the last row of Table 7. With technological heterogeneity, the model can account for 83% of the divergence, which is considerably more than the previous 37%. Taken together, these results, and also those of Section 5, suggest that labor market institutions (captured by b) are unlikely to be the driving force behind the observed divergent labor market outcomes. Rather, cross-country differences in technology usage mark the key source of heterogeneity to explain the observed patterns.

When considering technological heterogeneity, it appears that the model with the turbulence shock is observationally very similar to the model with the technology shock (c.f. the second and the last row of Table 7). This raises the question what type of shock should be considered the relevant one. First, it must be noted that turbulence is an abstract concept that is difficult to operationalize. No direct empirical evidence exists on its occurrence; thus, it is impossible to identify the timing of the shock from observed data or even to quantify the actual shock. Researchers have acknowledged these limitations and relied on induction to characterize the shock. That is, they infer the existence and timing of the turbulence shock from observing several economic outcomes that could potentially be driven by a turbulence shock. For instance, Ljunqvist and Sargent (2007) interpret the rise in individual earnings variability and higher industry and occupational mobility as evidence in support of the hypothesis that turbulence has increased after the 1970s. Even if one were to accept this way of identifying the shock, it is questionable whether it could be used in a quantitative analysis. The lack of direct evidence leaves the researcher with no guidance about how to incorporate the shock in a rigorous manner. Issues such as the variable(s) in which the shock is encoded or the magnitude of the shock remain unresolved.

These matters are different in the case of a shock to embodied technical change. Section 2 mentioned a large body of empirical literature that finds a significant acceleration of embodied technical change in the 1970s. The identification typically relies on concepts that are generally measurable in a reliable and well-defined way, such as the constant-

[29]The reason is that b determines the bargaining power of the worker and thereby determines by how much the turbulence shock reduces the expected surplus of the firm.

quality price index for investment goods used by Gordon (1990) and Cummins and Violante (2002). On closer inspection, the turbulence shock and the technology shock are conceptually very similar; both lead to the deterioration of workers' human capital after a job separation. The turbulence shock exerts a direct effect because it reduces a worker's human capital stock by a given proportion. In contrast, the technology shock induces faster growth of the technology frontier and indirectly leads to increased obsolescence of the worker's skills. Arguably, the technology shock works also through other channels. However, the channel that involves skill obsolescence has been shown to be quantitatively the most important. Considering this, it is reasonable to ask whether what the literature has called turbulence shock is actually the result of the observed technology shock.

7 Conclusion

This paper uses a labor market matching model augmented with an endogenous technology choice to explore the linkages between an economy's technology adoption behavior, labor market institutions and labor market outcomes. It analytically demonstrates that the degree of obsolescence of an economy's technological capital is a key determinant for how the economy's labor market, particularly the unemployment rate, reacts to an acceleration in capital-embodied technical change. The quantitative part of the paper considers a calibrated version of the model to study the implications of the rise in the rate of embodied technical change after the 1970s for OECD labor markets. The main result is that the observed cross-country differences in technology adoption and usage can account for a large part of the different evolution of OECD unemployment rates since the 1970s. Countries with sizable technology gaps have generally experienced a severe deterioration of labor market outcomes, unlike countries with high technology usage, in which unemployment rates have risen only slightly. In contract to previous work, the framework proposed here can explain (a) the divergence of unemployment rates between the major European countries and the United States and (b) a large part of the observed variation in unemployment rates across European economies. The technological heterogeneity is found to be central for explaining cross-country differences in labor market outcomes. This result of the paper challenges the popular, but controversial, hypothesis that blames generous unemployment benefits for high unemployment in Europe. The analysis shows that the observed institutional heterogeneity is insufficient to explain the diverse evolution of unemployment rates. Moreover, many European welfare-state economies with generous unemployment insurance systems have successfully maintained low rates of unemployment. All of these economies have also had high technology adoption rates.

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A Continuous Time Representation of the Benchmark Model

This section presents the continuous-time version of the model. The first step derives the firm's value functions from its discrete-time counterpart. Consider a time interval of length Δ (with discrete time Δ=1) and use $\beta=\frac{1}{1+r\Delta}$ to rewrite the firm's value function:

$$\bar{J}(\tau) = \Delta y(\tau) - \Delta\omega(\tau) + \frac{1}{1+r\Delta}(1+g\Delta)(1-\sigma\Delta)(1-\rho\Delta)\bar{J}(\tau+\Delta) \tag{19}$$

Next, multiply both sides of (19) by $1+r\Delta$, rearrange terms and divide by Δ. Then, let $\Delta\to 0$ and define $\bar{J}'(\tau)=\lim_{\Delta\to 0}\frac{\bar{J}(\tau+\Delta)-\bar{J}(\tau)}{\Delta}$ to obtain the following differential equation:

$$(r-g)\bar{J}(\tau) = y(\tau) - \omega(\tau) - (\rho+\sigma)\bar{J}(\tau) + \bar{J}'(\tau) \qquad \text{for} \qquad \tau < T \tag{20}$$

where $y(\tau)=e^{-g\tau}$ and $0<g<1$ is the growth rate, whereas before it was the growth factor. An employed worker's value function is derived in the same way and given by:

$$(r-g)\bar{E}(\tau) = \omega(\tau) - \rho\left[\bar{E}(\tau) - U\right] - \sigma\bar{E}(\tau) + \bar{E}'(\tau) \qquad \text{for} \qquad \tau < T \tag{21}$$

The total surplus of a job $\mathcal{S}$ is defined as the sum of the surplus to the firm and the surplus to the worker: $\mathcal{S}(\tau)=\bar{J}(\tau)+\bar{E}(\tau)\text{-}U(\tau)$. Using the value functions in (20) and (21), $\mathcal{S}$ can be rewritten and is determined implicitly by the following differential equation:

$$-\mathcal{S}'(\tau) + (r+\rho+\sigma-g)\mathcal{S}(\tau) = e^{-g\tau} - (r+\sigma-g)U(\tau) - U'(\tau)$$

Let T denote the optimal updating horizon, and use $\mathcal{S} = \mathcal{S}(0)$. The solution to the differential equation (evaluated at $\tau = 0$) is:

$$\mathcal{S} = \max_{T\geq 0}\left\{\int_0^T e^{-(r+\rho+\sigma-g)\tau}\left[y(\tau) - (r+\sigma-g)U(\tau) - U'(\tau)\right]d\tau + e^{-(r+\rho+\sigma-g)T}\mathcal{S}(T)\}\right\} \tag{22}$$

where $\mathcal{S}(T)=\max\{\mathcal{S}\text{-}\chi(T),0\}$. The condition $r+\rho+\sigma\text{-}g>0$ has to be satisfied to ensure boundedness of the problem. Section 4 studies a simplified version of this model in which σ is set to 0, the firms' bargaining power η=1 and the firm is assumed to cover the total training or updating costs χ. The latter implies that $U(\tau)$=U, for all τ, and that $U'(\tau)$=0. Furthermore, the model in Section 4 uses the relative productivity z as a firm's state variable, instead of the vintage τ. The switch of state variables is implemented by the change of variables $z=e^{-g\tau}$ (implying $\tau=-\log(z)/g$ and $gd\tau=-dz/z$) which yields the equivalent to Equation (15) in the main text. The optimal cutoff productivity $\bar{z}$ is determined by the solution to the following equation (see Equation (17)):

$$\frac{1}{g}\int_{\bar{z}}^{1} z^{\frac{r+\rho-g}{g}-1}\left[z-\bar{z}\right]dz = \chi(\bar{z})\left[1+\epsilon_{\chi,z}\left(1-\bar{z}^{\frac{r+\rho-g}{g}}\right)\frac{g}{r+\rho-g}\right] \tag{23}$$

The left-hand side is monotonously decreasing in $\bar{z}$, and equal to 0 for $\bar{z}$=1 and equal to $\frac{1}{r+\rho}$ for $\bar{z}$=0. The right-hand side is decreasing in $\bar{z}$, and equal to $\chi 1$ for $\bar{z}$=1, and equal to $\chi 0$ for $\bar{z}$=0. The existence of an interior and unique $\bar{z}\in(0,1)$ requires the following two conditions to hold $\chi(0)<\frac{1}{r+\rho}$ and $\chi(1)>0$. Furthermore, when $\bar{z}$ is such that $\bar{z}[1+g\chi'(\bar{z})]>b$, technology updating is always optimal in equilibrium. When updating is not optimal, that is when $\mathcal{S}$-$\chi(T)<0$ for all $T\geq 0$, the firm destroys the job when the productivity has reached $\bar{z}=(r-g)U=b$. The zero-profit condition stated in (18) is derived from the asset equation for the value of a vacancy V:

$$(r-g)V = -\kappa + p(\theta)\theta^{-1}\int_0^1 [\mathcal{S}-\chi(z)]\, d\Phi_z + V' \tag{24}$$

Φ_z is the cumulative distribution of unemployed individuals over z. In equilibrium, all gains from posting vacancies must be exhausted. This implies V=V'=0 and Equation (24) can be rearranged to yield Equation (18). The distribution function Φ_z is computed in a two-step procedure. In the first step, the distributions of firms and unemployed workers are computed over vintages τ, and in the second step, the necessary change of variables $z=e^{-g\tau}$ is implemented. For tractability, the two-step approach is preferable over the direct computation of Φ_z. Let by m_0 denote the mass of firms at the frontier, composed of newly created firms and those which update. Exogenous destruction is the only source of job separation. Therefore, the mass of firms for any $\tau\in$[0, T] is $f(\tau)=m_0e^{-\rho\tau}$, and $f(\tau)$=0 for all $\tau>T$. The mass of unemployed at the frontier is $u(0)=\rho f(0)$. For any $\tau\in$[0,T], the law of motion of u is $\dot{u}(\tau)=\rho f(\tau)$-$pu(\tau)$. The change in the stock of unemployed with τ is given as the difference between the inflow, i.e. destroyed jobs with τ, and the outflow that is determined by new matches. Using $f(\tau)=m_0e^{-\rho\tau}$ the law of motion can be written as $\dot{u}(\tau)=\rho m_0 e^{-\rho\tau}$-$pu(\tau)$, which, after integrating, yields:

$$u(\tau) = \frac{\rho m_0}{p-\rho}\left[e^{-\rho\tau} - (1+\rho-p)e^{-p\tau}\right]$$

For all $\tau\in(T,\infty)$ there is no further inflow into unemployment since $f(\tau)$=0, $\forall\tau>T$. The law of motion for unemployed with $\tau>T$ can be written as $\dot{u}(\tau)=-pu(\tau)$ which yields $u^*(\tau)=u(T)e^{-p(\tau-T)}$. The total mass of the unemployed $U=\int_0^T u(\tau)d\tau+\int_T^\infty u^*(\tau)d\tau$ is used to compute the density $\phi(\tau)=u(\tau)/U$ for $\tau\in[0,T]$ and $\phi^*(\tau)=u^*(\tau)/U$ for $\tau=(T,\infty)$:

$$\phi(\tau) = \frac{p\rho}{p-\rho}\left[\frac{e^{-\rho\tau}-(1+\rho-p)e^{-p\tau}}{1+\rho-e^{-\rho T}}\right] \qquad \text{for } \tau\in[0,T]$$

$$\phi^*(\tau) = \phi(T)e^{-p(\tau-T)} \qquad \text{for } \tau\in(T,\infty)$$

The change of variables $z=e^{-g\tau}$ implying $\tau=-\log(z)/g$ and $gd\tau=-dz/z$ gives:

$$\phi(z) = \frac{p\rho}{(p-\rho)g}\left[\frac{z^{\rho/g-1} - (1+\rho-p)z^{p/g-1}}{1+\rho-\bar{z}^{\rho/g}}\right] \qquad \text{for } z \in [\bar{z}, 1]$$

$$\phi^*(z) = \phi(\bar{z})\,(z/\bar{z})^{p/g-1} \qquad \text{for } z \in (0, \bar{z})$$

B Robustness Check

The extension in Section 6 allows firms to endogenously choose the production technology after matching with a worker. In the simplified continuous-time version of the model, this extensions leads to the following modified free entry condition:

$$\kappa = p(\theta)\theta^{-1}\int_0^1 \max_{z^*\in[z,1]}\left\{\mathcal{S}(z^*) - \chi(z^*, z)\right\} d\Phi_z$$

The element of interest is z^* which is chosen by the firm to maximize the surplus, given the skill level of the new worker z. That is $z^* = \arg\max\left\{\mathcal{S}(z^*) - \chi(z^*, z)\right\}$. Using the expression for the surplus function $\mathcal{S}(z^*)$ this leads to the following optimality condition[30]:

$$\frac{1}{gz^*}\left[z^* - b - (r+\rho-g)\mathcal{S}(z^*)\right] \gtreqless \partial\chi(z^*, z)/\partial z$$

For a given z, $\mathcal{S}$ and χ are (weakly) increasing in z^*. Therefore, corner solutions are possible leading to the 3 cases for the optimal z^* as stated in the text. When the condition above holds for all z^* with $>$, then z^*=1. In this case, the surplus $\mathcal{S}$ rises by more than the costs, therefore the maximum surplus is obtained at the upper bound z^*=1 (provided that $\mathcal{S}>\chi(1, z)$). When the opposite holds, that is costs are rising more than the surplus, then the optimum is attained at lowest possible value of z^*, which is z^*=z. The third case is given when the condition above holds with equality, implying that there is an intermediate value of $z<z^*<1$ for which the maximum surplus value is attained. As a result, the optimal choice z^* is weakly increasing in the new worker's skill level z.

C Proofs

Proof of Proposition 1. *The proof is established by showing that the right-hand side and the left-hand side of Equation (17) are, respectively, increasing and decreasing in g. This implies that the $\bar{z}$ for which Equation (17) holds with equality, is decreasing in g. Let Γ_R denote the right-hand side of Equation (17) and define $\gamma=\frac{r+\rho-g}{g}$. Therefore,*

[30]To preserve tractability, the possibility of future technology updating is not considered here. Consequently, the term for $\mathcal{S}(\bar{z})$ drops from the surplus equation. This certainly leads to a loss of generality, but for the current purpose it is acceptable as the main focus here is on a firm's technology choice after matching with a worker. It is likely that the relevant trade-offs concerning this choice remain largely unaffected by this simplification.

Γ_R=$\chi(\bar{z})$+$\bar{z}\chi'(\bar{z})\left[\frac{1-\bar{z}^{\gamma}}{\gamma}\right]$ *from which it follows that* $\partial\Gamma_R/\partial\gamma = \frac{\bar{z}\chi'(\bar{z})}{\gamma^2}\left[\bar{z}^{\gamma}\left(1-\gamma\log\bar{z}\right)-1\right]$. *The term in square brackets* $[\bar{z}^{\gamma}\left(1-\gamma\log\bar{z}\right)-1]$*=0 for* $\bar{z}$*=1, and (by L'Hopital's rule)* $\lim_{\bar{z}\to 0}\frac{1-\gamma\log\bar{z}}{\bar{z}^{-\gamma}}$*-1=-1. Moreover, the term is increasing for* $\bar{z}$*∈(0,1] since* $\frac{\partial}{\partial\bar{z}}\bar{z}^{\gamma}\left(1-\gamma\log\bar{z}\right)$ $=-\gamma^2\bar{z}^{\gamma-1}\log(\bar{z})\geq$*0 from which it follows that* $\partial\Gamma_R/\partial\gamma\leq$*0 (with* $=0$ *for* $\bar{z}$*=1), and since* $\partial\Gamma_R/\partial g$ $=\partial\Gamma_R/\partial\gamma\times\partial\gamma/\partial g$ *and* $\partial\gamma/\partial g<$*0 one can establish* $\partial\Gamma_R/\partial g\geq$*0 (with* $=0$ *for* $\bar{z}=1$*). Let* Γ_L *denote the left-hand side of Equation (17) so that* $\Gamma_L=\frac{1}{g}\int_{\bar{z}}^{1}z^{\frac{r+\rho}{g}-1}\left[1-\frac{\bar{z}}{z}\right]dz$*. For* $\bar{z}$*=1 it follows that* Γ_L*=0, and for* $\bar{z}$*=0,* $\Gamma_L=\frac{1}{r+\rho}$*. Both endpoints are independent of* g*. To evaluate the change of* Γ_L *for* $\bar{z}$*∈(0,1), build:* $\frac{\partial\Gamma_L}{\partial g}=-\frac{1}{g^2}\int_{\bar{z}}^{1}(1+\frac{r+\rho}{g}\log(z))z^{\frac{r+\rho}{g}-1}[1-\frac{\bar{z}}{z}]dz$*. The term under the integral* $(1+\frac{r+\rho}{g}\log(z))z^{\frac{r+\rho}{g}-1}\left[1-\frac{\bar{z}}{z}\right]$ *is equal to* 0 *for* $z=\bar{z}$*, and equal to* $1-\bar{z}>0$ *for* $z=1$*. Simple inspection reveals that the term is increasing in* z *as all the three terms, that involve* z *increase as* z *goes up). From that it follows that integral is positive for all* $\bar{z}\in(0,1)$ *and thus* $\frac{\partial\Gamma_L}{\partial g}\leq 0$*, with = for* $\bar{z}=0$ *and* $\bar{z}=1$*.*

Proof of Proposition 2. *The critical productivity* $\bar{z}$ *is determined by the updating costs* χ *and, thus* $\mathcal{N}_{job}=\frac{\bar{z}-b+\bar{z}g\chi'(\bar{z})}{r+\rho-g}$ *can be considered as a function of* χ*. Here, only those values of* χ *are considered for which technology updating is optimal, that is* $\chi\in[0,\bar{\chi}]$ *where* $\bar{\chi}$ *solves* $\mathcal{N}_{job}$*=0* $\iff$ $\bar{z}(1+g\bar{\chi}')$*=b. For* χ*=0, it follows that* $\bar{z}$*=1, and thus* $\mathcal{N}_{job}|_{\chi=0}=\frac{1-b}{r+\rho-g}>$*0. An increase in g moves the vertical intercept* $\mathcal{N}_{job}|_{\chi=0}$ *upwards, whereas the horizontal intercept* $\mathcal{N}_{job}|_{\chi=\bar{\chi}}$ *is shifted inwards. The image of* $\mathcal{N}_{job}$ *is rotated counter-clock-wise implying that an increase in g leads to a rise (fall) in* $\mathcal{N}_{job}$ *if* χ *is sufficiently low (high). Moreover, there is a unique value of* χ *for which the net surplus does not change at all.*

D Data

D.1 Hours Worked: Data Series and Sources

I follow the literature and compute *total annual hours worked per person* by, first, multiplying *annual hours worker per worker* with the number of *persons employed*, and then dividing the product by the *total population aged 15-64 years.* The data on annual hours worker per worker and persons employed is obtained from the Total Economy Database published by the Groningen Growth and Development Centre. The data can be downloaded from http://www.conference-board.org/data/economydatabase/ The two series used here are labeled "Hours" and "Emp". The data on total population aged 15-64 years is obtained from the Annual Labour Force Statistics database maintained by the OECD and can be downloaded from http://stats.oecd.org/index.aspx

D.2 Hours worked: Counterfactual

Here I explain how to compute the hypothetical hours worked per person in country i at time t that would have prevailed if the unemployment to population ratio in country i (denoted $\frac{U_{i,t}}{P_{i,t}}$) had evolved like that in the United States. First, pick a reference year relative to which changes in the ratio $U_{i,t}/P_{i,t}$ are measured. The reference year used here is 1970. Second, compute $\Delta_{i,t} = \frac{U_{i,t}}{P_{i,t}} - \frac{U_{i,70}}{P_{i,70}}$, which measures by how much the unemployment to population ratio of country i is different in year t than in 1970. For instance, in the case of the EU-15, the ratio rises from 0.0148 in 1970 to 0.0713 in 1995, implying that $\Delta_{EU15,95} = 0.0565$. Third, compute the same statistic for the United States: $\Delta_{USA,t}$, For instance, for t =1995 we get $\Delta_{USA,95} = 0.0103$. By comparing $\Delta_{i,t}$ and $\Delta_{USA,t}$, one can infer how much more country i's unemployment to population ratio has rises (fallen) from 1970 to t relative to the United States. The relative increase in the EU-15 in 1995 amounts to 0.0462. Fourth, determine how high unemployed in country i at time t would have to be, so that the change in the unemployment to population ratio were the same as in the United States. That is, compute the hypothetical number of unemployed (denoted $U^*_{i,t}$) for which $\frac{U^*_{i,t}}{P_{i,t}} = \frac{U_{i,t}}{P_{i,t}} - (\Delta_{i,t} - \Delta_{USA,t})$. Fifth, compare this number to the actual number of unemployed: $U^*_{i,t} - U_{i,t}$ from which we learn by how much the number of unemployment individuals would have to decline (rise) to offset the larger rise (fall) in the unemployment to population ratio in country i relative to the United States. Continuing the previous example: $U^*_{EU15,95}$ - $U_{EU15,95}$ = -11,476,820 meaning that in the EU-15 (in 1995) unemployment would have to decline by around 11.5 million. Finally, ask the hypothetical question how would total hours worked per person in country i at time t have looked like, if these additional unemployed individuals were all employed and had worked the same hours like an average worker in i at time t. Let $TH_{i,t}$ and $TH^*_{i,t}$ denote the actual and the hypothetical total hours worked and $AH_{i,t}$ denote the average hours worked per worker. Compute the hypothetical hours worked per person as $\frac{TH^*_{i,t}}{P_{i,t}} = \frac{TH_{i,t} - AH_{i,t}\left(U^*_{i,t} - U_{i,t}\right)}{P_{i,t}}$. For the EU-15 $\frac{TH^*_{EU15,95}}{P_{EU15,95}}$ is equal to 1122.6 hours.

D.3 Computing the Technology Gap

This section outlines the approach which is used to compute the average age of ICT capital for each of the countries in the sample. The data is taken from the 2009 release of the EU KLEMS Growth and Productivity Accounts, and in particular from the "Capital Input Files". In the first step, a perpetual investment method is used to construct a series of the ICT capital stock. Let i indicate a given country and let $K^{ICT}_{i,t}$ denote the ICT capital stock of country i at time t which is computed as $K^{ICT}_{i,t} = \sum_{s=1}^{t}(1 - \delta^{ICT}_i)^{s-1} I^{ICT}_{i,s}$. δ^{ICT}_i is the ICT capital depreciation rate which is taken to be country-specific but constant over time, and $I^{ICT}_{i,s}$ denotes aggregate real gross fixed capital formation of ICT assets at time $s \leq t$. In the original data set $I^{ICT}_{i,s}$ is labeled as "Iq_ICT" and the base year for the price index is the year 1995.

The observations on $I^{ICT}_{i,s}$ range from $s = 1970, 1971, ..., 2007$ (this is different for some countries as reported below), therefore one can construct the following sequence of capital stocks $\left\{K^{ICT}_{i,t}\right\}_{t=1970}^{2007}$. With geometric depreciation, only a fraction $(1 - \delta^{ICT}_i)^{t-s}$ of the period $s \leq t$ investment is still undepreciated at time t and part of the time t

capital stock. Let $\phi_{i,s,t}$ denote the fraction of time s investment in the period t capital stock. It is computed as $\phi_{i,s,t} = \frac{(1-\delta_i^{ICT})^{t-s} I_{i,s}^{ICT}}{K_{i,t}^{ICT}}$, with $\sum_{s=1}^{t} \phi_{i,s,t} = 1$. The average age of ICT capital at time t is denoted $age_{i,t}^{ICT}$. Using the elements from above it can be straightforwardly computed as $age_{i,t}^{ICT} = \sum_{s=1}^{t} \phi_{i,s,t} [t-(s-1)]$. Country i's technology gap (as reported in Table 1) to the United States is then expressed as the percentage difference between the average age of ICT capital in country i and of that in the United States: $Gap_i = 100 \times \left(age_i^{ICT}/age_{USA}^{ICT} - 1\right)$.

The use of the perpetual investment method implies that the capital stock, and therefore also the age of capital, are not accurately measured for the first few time periods of the sample. This has to be taken into account and is solved by cutting off an initial period of a certain length. Due to high values of δ_i^{ICT}, this period can be kept relatively short as the time series of $age_{i,t}^{ICT}$ stabilizes already after only a few periods. For some countries this takes slightly longer than for other countries, therefore, the number of periods which are cut off can differ across countries. Column 1 of Table 8 reports the time period for each country in the sample over which the data on I^{ICT} is available, and Column 2 of the same table reports the final number of periods (= total - initial cutoff) over which the average age of capital $age_{i,t}^{ICT}$ is computed.

The rate of ICT-capital depreciation δ_i^{ICT} is taken to be country specific. I do not make use of the depreciation rates provided by the EU-KLEMS since these are all identical across countries and are, therefore, not suited for our purpose. The concept of capital depreciation as it is considered here, is analogous to the definition of the BEA which describes depreciation as "the decline in value due to wear and tear, obsolescence, accidental damage, and aging" and it is thus a combination of physical decay and obsolescence. The degree of "wear and tear" is unlikely to be the same across countries and consequently I refrain from using the depreciation rates of the EU-KLEMS. Instead, δ_i^{ICT} is constructed for each country separately. The approach which is used builds on the notion that the rate of depreciation should be related to the degree of utilization of the capital. Capital that is intensely used is likely to wear out more quickly and is subject to a higher rate of depreciation.

There is no comprehensive data available on the utilization of ICT capital. Thus I use a proxy which is taken to be the ratio of ICT-capital services (denoted $S_{i,t}^{ICT}$) to the ICT-capital stock. The idea behind this concept is that the amount of services produced by a given amount of capital should be related to how intensely the capital stock is utilized. The data for the capital stock is taken from the EU-KLEMS data base, and given by the series for the real fixed ICT-capital stock (computed for 1995 prices). To compute capital services, the reported series for ICT-capital services per hour worked is multiplied by the reported number of total hours worked. The rate of capital depreciation for country i is then computed as $\delta_i^{ICT} = \frac{1}{T} \sum_{t=1}^{T} \frac{S_{i,t}^{ICT}}{K_{i,t}^{ICT}}$.

The results obtained from this procedure are reported in Table 8. The literature generally lacks empirical estimates of ICT-depreciation rates to which one could compare these numbers. Luckily, however, there exist good estimates for the rate of depreciation of physical (non-ICT) capital[31]. The annual rate of physical capital depreciation in the United States is typically found to be the interval from $0.09 - 0.14$. To get a sense of how the proposed proxy compares to these estimates, I also compute the rate of depreciation of non-ICT capital. These results are reported in Column 4 of Table 8. The rate for the United States is found to be 0.122 which lies in the aforementioned interval. This makes me confident that also the proxy for ICT-capital depreciation is, in fact, a good measure of the actual depreciation rate.

E Tables

Table 8: Supplementary Information, Data and Results

	Period	**Yrs**	**Depreciation**		**Technology Gap**			**b$_i$**	π_i	**% Unemployment Change**			
			δ_i^{ICT}	δ_i	80-95	95-07	78-07			**Data**	Model	π_i=0	$b_i=\bar{b}$
USA	1970-07	30	0.461	0.122	0.0	0.0	0.0	0.26	0.00	**9.1**	12.5	12.5	12.5
EU-15					25.7	25.6	25.3	0.38	0.64	**44.7**	30.1	15.9	12.5
EU-1					35.9	34.5	33.7	0.39	0.75	**45.3**	37.4	16.3	12.5
EU-2					7.4	5.8	6.5	0.38	0.21	**37.7**	18.7	15.8	12.5
BE	1980-04**	20	0.324		32.7	49.2	35.4	0.31	0.92	**45.8**	28.3	13.6	12.5
FIN	1970-07	20	0.375	0.081	19.4	21.7	20.1	0.32	0.52	**46.1**	24.9	13.9	12.5
F	1980-04**	10	0.364			30.1	30.2	0.40	0.77	**52.3**	46.0	16.7	12.5
GER	1970-07	30	0.374	0.082	24.9	23.1	23.7	0.39	0.70	**53.9**	33.5	16.4	12.5
GRE	1980-04**	10	0.315			28.8	28.8	0.39	0.74	**31.4**	37.1	16.1	12.5
IRE	1980-04**	20	0.492		2.2	-4.9	-0.6	0.37	0.04	**23.8**	14.4	15.3	12.5
ITA	1970-07	30	0.260	0.085	57.4	60.5	57.7	0.29	0.73	**33.8**	35.1	13.1	12.5
ESP	1970-07	30	0.352	0.087	27.9	25.8	27.4	0.44	0.59	**63.9**	49.3	18.2	12.5
AUT	1976-07	30	0.398	0.077	13.5	11.5	11.3	0.27	0.38	**27.5**	17.7	12.7	12.5
DK	1970-07	30	0.493	0.067	-9.2	-7.7	-8.6	0.51	-0.13	**34.7**	16.1	22.9	12.5
LUX	1980-04**	20	0.315					0.39	0.15	**15.8**	15.9	15.9	12.5
NED	1970-07	35	0.381	0.077	17.4	15.3	15.9	0.43	0.52	**47.0**	28.4	18.1	12.5
POR	1980-04	13	0.439	0.133	6.5	10.0	8.4	0.46	0.26	**28.4**	26.3	19.6	12.5
SWE	1993-07	10	0.439	0.138		7.6	7.7	0.48	0.32	**43.4**	27.8	20.5	12.5
UK	1970-07	30	0.434	0.094	6.1	4.6	5.8	0.29	0.14	**47.1**	15.4	13.2	12.5
AUS	1970-07	30	0.433		4.8	-0.7	3.1	0.21	0.09	**43.6**	12.7	11.6	12.5
CAN	1980-04*	30	0.456	0.082	-4.4	1.5	-4.3	0.52	-0.05	**18.7**	19.3	23.8	12.5
JPN	1970-06	30	0.461	0.122	-2.4	7.4	2.0	0.32	0.17	**31.8**	14.8	14.1	12.5
NOR	+							0.36	0.14	**43.8**	15.0	15.1	12.5

Note: * The data for these countries is taken from the 2008 release of the EU KLEMS Growth and Productivity Accounts. ** The data for these countries is taken from Total Economy Growth Accounting Database maintained by the Groningen Growth and Development Centre (The EU KLEMS does not provide capital data for these countries). + No ICT-capital data is available for Norway. The average age of ICT capital is assumed to be the same as in the United States, *Period*: Time interval for which ICT data is available, *Yrs*: Number of most recent observations used to compute the capital age, δ_i^{ICT} (δ_i): Depreciation rate of (non) ICT-capital, 80-95 (95-07) [78-07]: Technology gap to the United States in period 1980-95 (1995-2007) [1978-2007], b_i: 1960-1995 average of first year unemployment benefits measured in terms of the percentage of average pre-tax earnings, π_i: Distortion parameter affecting technology adoption costs, *Model* (π_i=0) [$b_i=\bar{b}$]: Percentage change in unemployment rate in the calibrated benchmark model (without technological heterogeneity), [and without institutional heterogeneity]. Notice: In this version of the model ρ was not re-calibrated to match a country's initial steady-state.

[31] See Epstein and Denny (1980), Bischoff and Kokkelenberg (1987) and Nadiri and Prucha (1996).

Table 9: Endogenous Technology Choice: EU-1 vs EU-2

		1-$\bar{z}$	1-z_u	1-z_0	$E(J)$	$E(I^J)$	j_{dest}	u	Δu	Δ_I	Δ_{II}	Δ_{III}
—— *Panel (a): EU-1* ——												
BM/ETC	$\mathbf{g = 2\%}$	**8.5%**	**4.9%**	**0.0%**	**2.9**	**2.6**	**0.0%**	**6.6**				
BM	$g = 4\%$	9.9%	8.1%	0.0%	3.8	3.6	0.0%	9.9	+3.3	+0.856	+0.578	-1.005
ETC	$g = 4\%$	9.9%	10.5%	3.4%	3.4	3.3	6.3%	10.4	+3.8			
—— *Panel (b): EU-2* ——												
BM/ETC	$\mathbf{g = 2\%}$	**7.0%**	**3.9%**	**0.0%**	**2.1**	**1.7**	**0.0%**	**4.3**				
BM	$g = 4\%$	8.7%	5.7%	0.0%	2.3	1.9	0.0%	5.2	+0.9	+0.008	+0.006	-0.008
ETC	$g = 4\%$	8.7%	5.8%	0.1%	2.3	2.0	0.2%	5.2	+0.9			

Note: The initial steady-state for $g = 2\%$ is the same for BM and *ETC*, BM: Benchmark model, *ETC*: Model with endogenous technology choice, g: Annualized growth rate of technology frontier, 1-$\bar{z}$: Firms' cutoff productivity, 1-$\bar{z}_u$: Average skill obsolescence of unemployed individuals, 1-z_0: Average technology gap of newly created jobs, $E(I^J)$: Expected costs of training a new employee, $E(J)$: Expected costs of training a new employee, j_{dest}: Fraction of existing jobs that will be endogenously destroyed, u: Unemployment rate, Δu: Percentage-point change in unemployment when $g = 2\% \rightarrow 4\%$, Δ_I (Δ_{II}) [Δ_{III}]: Additional percentage-point increase of u in the *ETC* case relative to the BM case due to lower expected surplus (higher endogenous job destruction), [lower expected costs].