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the Dynamics of Unemployment

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**EUROPEAN UNIVERSITY INSTITUTE  
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# Technology Adoption, Turbulence and the Dynamics of Unemployment\*

Georg Duernecker<sup>†</sup>

## Abstract

The divergence of unemployment rates between the U.S. and Europe coincided with a substantial acceleration in capital-embodied technical change in the late 70's. Furthermore, evidence suggests that European economies have been lagging behind the U.S. in the adoption and usage of new technologies. This paper argues that the pace of technology adoption plays a fundamental role for how an economy's labor market reacts to an acceleration in capital-embodied growth. The framework proposed offers an appealing and novel explanation for the 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 behavior. Moreover, we challenge the conventional wisdom that high European unemployment is the result of institutional rigidities by claiming that institutions are not the principal cause per se but they rather amplify certain forces that promote the emergence of high unemployment.

**JEL classification:** J24, J64, O33

**Keywords:** Unemployment, Labor Market Search and Matching, Turbulence, Skill Loss, Technology Adoption, Training

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# 1 Introduction

After low levels of unemployment until the late 1970s, European unemployment rates became high relative to that in the United States. Labor markets in Europe started to deteriorate at a time when there was a substantial acceleration in the arrival of new technologies as measured by capital-embodied technical change. As documented in 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 decreased substantially from  $-2\%$  before the mid-70s to  $-4.5\%$  in the 1990s, suggesting an acceleration in embodied technical change<sup>1</sup>. There is convincing empirical evidence, some of which is provided by Oliner and Sichel (2000), Jorgenson and Stiroh (2000) and van Ark et al. (2002), indicating that - with a few exceptions - European economies have been lagging behind the U.S. in the adoption and usage of new technologies. This is reflected by a persistent growth and technology gap relative to the U.S. - as measured by per capita GDP growth, labor productivity growth in the manufacturing sector, the share of information and communication technologies (ICT) in investment and its contribution to output growth. The coexistence of a technology deficit - resulting from slack technology adoption - and the divergence of unemployment rates across economies are not coincidental. The main hypotheses of this paper is that the pace of technology adoption plays a fundamental role for how an economy's labor market reacts to an acceleration in capital-embodied growth. We challenge the conventional view that high rates of European unemployment are the result of labor market institutions by claiming that institutions are not the principal cause of high unemployment per se but they rather show the tendency to amplify certain forces that promote the emergence of high levels of unemployment<sup>2</sup>. These forces are generated through the interaction of (a) the rate of arrival of new technologies, (b) the speed of their adoption and (c) the speed with which workers accumulate technology-specific skills and (d) the degree of turbulence, i.e. the order of magnitude of worker's skill depreciation during spells of unemployment.

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<sup>1</sup>A number of authors, starting from Greenwood et al. (1997) have suggested to measure the speed of embodied technical change through the rate of decline of the relative (quality-adjusted) price of capital.

<sup>2</sup>Researchers and policy-makers very often stress the importance of various labor market institutions for explaining high rates of unemployment in major European countries. Their line of argument is that institutions create rigidities in the labor market and prevent a fluid reallocation of labor. This argument is highly controversial. Blanchard and Wolfers (2000), for instance, notice that the institutions which generate these rigidities were also present in the 1960s and in the 1960s unemployment was much higher in the U.S. than in Europe. Taking the same line, Oswald (1997) claims that "Despite conventional wisdom, high unemployment does not appear to be primarily the result of things like overly generous benefits, trade union power, taxes or wage "inflexibility".", (Oswald, 1997, p.1) By contrast, in a recent empirical analysis of unemployment patterns in OECD countries Nickell et al. (2005) find that changes in labor market institutions explain around 55% of the rise in European unemployment from the 1960s to the first half of the 1990s.

The framework provided in the paper offers an appealing and novel explanation for the divergence of unemployment rates across economies that are hit by the very same shock (i.e. the acceleration in embodied technical change) but differ with respect to their ex-ante technology updating behavior. The main forces at work are the following. When firms in an economy update their production technology rather sluggishly, workers operate a certain technology for a relatively long time, hence they accumulate substantial amounts of skills on that technology. The effect of these skills on wages we will refer to as "skill effect". If these skills are technology specific than a displaced worker loses parts, or all, of his skills upon lay-off. This loss of human capital implies that new wage offers - that reflect a worker's current level of skills - are potentially lower than the pre-displacement wage<sup>3</sup>. In an environment where institutions provide generous unemployment benefits (that are proportional to the worker's previous wage income), displaced workers, therefore, possess a valuable outside option in the wage negotiation which reduces firms incentives to create new jobs. If there is high technology turnover in an economy - in the sense that firms renovate their production technology rather often - then the amount of accumulated experience on a specific technology is relatively low. However, frequent updating also implies that workers operate technologies which are, on average, closer to the technology frontier, which has a positive effect on wages. This effect will be referred to as the "vintage effect". Which of these two effects - the skill and the vintage effect - dominates will determine the impact of learning on wages and consequently on job creation and unemployment. There is a second, potentially important, channel through which the frequency of technology updates influences an economy's labor market performance. Operating a particular production technology requires a certain set of skills and knowledge, e.g. workers need to possess the knowledge of how to operate the machines they are working with. This production knowledge can be considered as partly vintage-specific (rather than general) which implies its limited transferability across technologies. As a consequence, a worker that gets to operate a technology different from her previous can transfer only a fraction of her original production knowledge into the new occupation. Technologies that are "close" to ("far away" from) each other in terms of technological advancement are likely to require a similar (very different) set of skills. Hence the fraction of skills that can be transferred will depend on the relative "distance" between technologies. As the leading edge technology, constantly advances there is a gap emerging between the technologies that were implemented by firms already at an earlier date and the technology frontier.

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<sup>3</sup>There is considerable empirical evidence, some of which is provided by Farber (1993) and Jacobson et al. (1993) saying that the earnings loss suffered by displaced workers is positively related to tenure on the pre-displacement job which is consistent with the destruction of job-specific human capital when a long-term job ends. This gives support for the model's characteristic that for high tenure workers - i.e. the ones that have accumulated a lot of job-specific skills - the difference between the pre- and the post-displacement wage is rather high.

Infrequent updating implies that workers operate technologies for a relatively long time and hence this technology gap will be rather wide. As those workers get attached to more advanced technologies - either through a technology update within a firm or the transition to a new firm - the fraction of their production knowledge that can be transferred will, on average, be small. Hence, there is a discrepancy arising between a worker's current production knowledge and the knowledge that is required to operate the new technology. This discrepancy can be considered as a form of skill obsolescence implied by the limited transferability of workers production knowledge. I.e. a worker's human capital becomes obsolete relative to that required at the frontier given that the amount that can be transferred decreases over time. To make a worker's production knowledge compatible with the state-of-the-art, firms potentially need to invest a substantial amount in costly training. Provided that these expenses do not add anything to workers productivity but are rather sunk they reduce the net present value of a job. These costs are increasing in the size of the gap, therefore slow technology adoption - which implies a high degree of workers human capital obsolescence - reduces firm incentives to open up new vacancies since high training costs reduce the net surplus of creating new jobs. Before we proceed with providing some stylized facts let us briefly summarize the main mechanism that are shaping an economy's rate of unemployment.

- Slack technology adoption implies the accumulation of large amounts of technology-specific skills. This potentially triggers a skill effect that drives a wedge between pre- and post-displacement earnings. Hence, for sufficiently generous unemployment benefits the value of being unemployed, i.e. a workers outside option, is large relative to the value of a new job which strengthens workers' bargaining power and discourages firms to create new jobs. A vintage effect that implies a negative tenure/relative wage profile might counteract.
- Sluggish updating implies that workers, on average, operate technologies that are far away from the frontier. Hence their production knowledge is relatively obsolete. This necessitates costly training in the case of a technology update or a re-match which reduces the net present value of a job for a firm and therefore reduces job creation.
- Rapid technical change implies that the technology gap for displaced individuals (i.e. the gap between the production knowledge used in their previous occupation and that required at the frontier) widens rather quickly. Hence training costs for newly hired workers are expected to be higher on average. This effect is more severe in economies that have slow technology adoption and therefore exhibit a relatively large fraction of long-tenured workers.



## Related literature

In the recent years economists have offered numerous explanations for the emergence of high European unemployment in the late 1970s, involving factors such as overly generous welfare systems, slow TFP growth or capital market imperfections to mention just a few<sup>4</sup>. One particularly influential strand of this literature emphasizes the interaction of 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 went up because of reduced workers' incentives to exit unemployment. Workers in Europe prefer to collect generous unemployment benefits rather than to work for a low wage given that the technology shock made their skills obsolete - as in Ljungqvist and Sargent (1998) - or made it increasingly difficult to match with existing vacancies - as in Marimon and Zilibotti (1999). The mechanism in those papers operates primarily through the labor supply side. Ljungqvist and Sargent (2007) is a refinement that considers a matching framework in which firms adjust labor demand as part of the adjustment process. The shock considered in Ljungqvist and Sargent (1998, 2007) refers to a general change in the economic environment, i.e. an increased degree of economic turbulence, rather than an explicit shock to technological change. Recently a number of economists pointed at the potential importance of embodied technical change for explaining the differences in labor market outcomes across countries. Hornstein, Krusell and Violante (2007) were the first that highlighted the interaction between capital-embodied technical change and labor market institutions. In their model an increase in embodied technical change leads to a sharp reduction in firms labor demand in the welfare state economy whereas it has only mild effects on labor demand in the laissez-faire economy and consequently unemployment rises by much less. These models, however, suffer from a serious shortcoming. They are designed to reproduce the movements of an average European unemployment rate ignoring the large heterogeneity of unemployment rates across European countries. Recently Blanchard (2005) pointed out that talking about "European unemployment" is misleading since high average European unemployment reflects high unemployment in four large continental countries, Germany, Italy, Spain and France, whereas unemployment is low (and even below the U.S. level) in many other European countries. Arguably, a theory that addresses the issue of European unemployment but fails to explain (or ex-

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<sup>4</sup>See Nickell (2003) for a recent survey of research on the issue of European unemployment. Blanchard (2005) is an excellent assessment of what we know already and what remains to be explained regarding the European unemployment question.

ante ignores) the large heterogeneity across European labor markets clearly conflicts with an essential aspect of actuality and is likely to disregard relevant factors related to the issue. The determinants of the observed heterogeneity are unlikely to be of an institutional nature. Even though welfare states across Europe differ in some respects the main properties are predominant in almost all states. Explicitly accounting for (small) differences in institutional settings is not likely to resolve the problem. This paper proposes a framework in which cross-country differences in firms technology adoption behavior can account for a large part of the divergence of unemployment rates across economies that are hit by the very same shock (i.e. the acceleration in capital-embodied technical change). These differences in the adoption behavior are highly consistent with existing empirical evidence and are likely to be result of differences in regulatory environments. The model builds upon the matching framework in Mortensen and Pissarides (1998) that includes an endogenous technology choice by firms. However the model of Mortensen and Pissarides (1998) such as that of Hornstein et al. (2007) displays one stark and clearly unrealistic feature: workers are not constraint by any skill requirements when switching between technologies that differ in the level of technological advancement. Hence, individuals can transit from less to more advanced technologies without any extra cost. This implies that it is equally costly for firms to hire a worker coming from a high-tech or a low-tech job<sup>5</sup>. One might conjecture that technologies are likely to differ with respect to the set of skills and abilities required to operate them. Newer and more advanced technologies require different skills than older and less advanced ones. Evidently, in a framework that considers capital-embodied technical change the issue of workers skill obsolescence is of particular relevance since the set of skills needed (e.g. for the most advanced technology) is subject to changes over time. The framework presented in this paper explicitly models workers' skill dynamics. It can therefore account for increased human capital obsolescence caused by a technology shock which will be an important determinant of how firms adjust their labor demand in the aftermath of a shock. Also Ljungqvist and Sargent (1998, 2007) consider a form of human capital obsolescence but the mechanism proposed in this paper is significantly richer. Unlike Ljungqvist and Sargent (1998, 2007), that are not explicit about the underlying economic mechanism, the degree of skill obsolescence in this paper is partly endogenous and as it is driven by firms technology choice. In this way we are able to add microfoundation to the turbulence approach (pioneered by Ljungqvist and Sargent (1998)) and to provide a rationale for increased turbulence (i.e. skill obsolescence) that was caused by an acceleration in embodied technical change in the mid 1970s.

The remainder of the paper is organized as follows. The next section aims at motivating

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<sup>5</sup>The only cost that is involved in the labor reallocation process is due to search. The explicit acquisition of skills (if there is any) is generally uncoupled from a worker's previous experience.

the analysis by presenting a variety of stylized facts. In Section 3, I lay out the theoretical model and discuss the characteristics of the labor market. Sections 4 and 5 briefly discuss the calibration of the model and the algorithm that was used to solve the model. Section 6 presents and discusses the results and Section 7 performs a variety of sensitivity checks and Section 8 concludes.

## 2 Stylized Facts

### Unemployment

In the postwar period until the late 1970s unemployment in Europe was low relative to that in the U.S. The data summarized in Table 1 shows that during the whole period until the 1980s unemployment in the U.S. was significantly higher than that in Europe. In the 1960s and early 70s the average unemployment rate in European was around 2.5% whereas the U.S. figure was around 5%. However, the picture had changed dramatically after the mid-1970s. Unemployment in Europe experienced a sharp and persistent increase up to a level of around 9%. On the other hand, U.S. unemployment first gradually increased in the late 70s and in the 80s but then declined over time and settled at a rate of around 5%. The use of the average rate of unemployment is, however, misleading. A closer look reveals

	1960 - 69	1970-74	1975-79	1980 - 89	1990 - 99	2000 - 06
U.S.	4,78	5,38	7,04	7,27	5,71	5,11
Euro Area	2,16	2,62	4,76	8,36	9,55	8,43
Austria	2,13	1,30	1,56	2,70	3,87	4,36
Belgium	1,93	2,04	5,96	9,54	8,47	7,74
Denmark	1,11	1,16	5,22	6,67	6,93	4,71
Finland	2,20	2,40	5,16	4,79	11,87	8,84
France	1,75	2,68	4,84	8,54	10,60	9,19
Germany	0,65	0,90	3,12	5,83	6,29	8,46
Greece	5,11	2,70	1,92	6,06	9,03	10,16
Italy	4,86	5,42	6,46	8,39	10,25	8,39
Netherlands	0,84	1,98	5,62	8,16	5,41	3,53
Norway	0,00	1,60	1,90	2,81	4,80	3,99
Spain	2,39	2,92	6,12	15,44	15,89	10,29
Sweden	1,70	2,24	1,86	2,59	7,21	5,96
UK	1,61	2,44	4,54	9,45	8,00	5,01

Source: European Commission, Annual Macroeconomic Database (AMECO)

Table 1: Average annual unemployment, in %, by subperiod

that there is a wide variation of unemployment rates across European countries. Over the period 2000 – 06, for instance, five out of the nine European labor markets in Table 1 produced unemployment rates that are just slightly above or even below the U.S. rate.

This implies that when we exclude some of the major European countries, in particular Germany, France and Italy, the famous *European unemployment puzzle* vanishes<sup>6</sup>. High unemployment is therefore not a phenomenon that is specific to Europe per se but rather to certain countries. A distinguishing feature of the U.S. labor market is its fluid nature. The average duration of unemployment is low relative to European countries which evidences a rapid reallocation of labor across sectors<sup>7</sup>. Table 2 shows that in the period 2000 – 04 the fraction of unemployed being jobless for less than one month is 37.22% in the U.S. while it is around 5% in Germany, France, Spain and Italy. In contrast only 9% of the unemployed in U.S. stay out of work for more than one year whereas the number for Germany, France, Spain and Italy ranges between 40% and 58%. Evidently, high unemployment rates in some European countries are the results of a massive share of long-term unemployed.

	Belgium	Germany	Denmark	Spain	France	UK	Italy	Sweden	U.S.
< 1 month	7.4	5.76	22.18	5.34	4.48	16.2	5.1	21.34	37.22
[1, 3) months	11.18	11.7	18.96	16.78	18.46	23.98	8.92	22.56	30.8
[6, 12) months	17.12	16.64	18.28	18.84	19.48	15.68	15.66	16.16	8.06
≥ 12 months	50.7	50.32	20.88	41.86	39.7	24.66	58.36	21.28	9.02

Source: OECD, Numbers indicate the fraction of unemployed by duration

Table 2: Average duration of unemployment

### Increased Arrival Rate of New Technologies

There is evidence, some of which is provided by Cummins and Violante (2002), Greenwood and Yorukoglu (1997) and Pakko (2002) that the rate of arrival of new technologies has increased by the late 1970s. Cummins and Violante (2002) construct an aggregate index of investment-specific technological change and find that average annual growth rates were stable around 4% in the postwar period until the late 1970s but then there was a sharp acceleration in the 1980s that led to annual growth rates of more than 6% in the 1990s. 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 differ substantially in their characteristics from existing ones are introduced at a faster rate. This raises the issue of compatibility problems between consecutive vintages. The improved technology embodied in new capital changes the technological standards and hence decreases the compatibility between old and new vintages. Yorukoglu (1998) argues that the more advanced the new technology is relative to the existing one the lower is the initial experience with the new production technology. This implies that as the rate

<sup>6</sup>The so-called "European Unemployment Puzzle" refers to high and persistent rates of unemployment in Europe relative to that in the United States.

<sup>7</sup>Farber (1999) finds that in the U.S. half of all new jobs end in the first year and at any point in time about 20% of workers have been with their current employer for less than one year.

of technological change increases the less familiar agents will be with the new technology and hence it will be more costly to adopt it. In times of rapid technological change we should therefore see an increase in the technology gap and a rise in total adoption costs. Regarding the former, Cummins and Violante (2002) find that the technology gap in the U.S. (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 the figure had jumped to 40% suggesting a substantial decrease in the frequency of technology updates. These findings are consistent with results provided by Bessen (2002) who estimates technology adoption costs in the U.S. manufacturing sector from 1961-96. He finds that adjustment costs rose sharply during 1974-83 and more than doubled from the early 1960's to the late 1980's. Adoption costs as a percentage of aggregate output had increased from 2.4% in 1973 to 6.5% in 1983. Bessen (2002) argues that the rise in costs is specifically associated with a switch in firm's investment towards new technologies.

### **Technology and Growth Gap**

Economic growth in Europe was strong until the 1980s but became weaker in the subsequent decades. As a result a persistent growth gap between the U.S. and most European countries has emerged since the 1980s in GDP growth as well as in labor productivity growth. By taking data on relative manufacturing output per person, Scarpetta et al. (2000) shows that the productivity level for Germany and other European countries was converging toward the U.S. level until the 1980s but has diverged since then. At the same time Europe has lagged behind the U.S. in adoption and usage of new technologies. Timmer et al. (2003) report that almost all EU countries have been seriously lagging behind the U.S. in the share of ICT investment in GDP. Consequently, IT capital stocks are much lower in Europe. It is a well established fact that slower rates of ICT investment are key in explaining the poorer European productivity performance. Figure 1 illustrates the strong positive relation between the level of investment in new technologies and labor productivity growth. van Ark et al. (2002) find that ICT contributes nearly as twice as much to labor productivity growth in the U.S. as in Europe. The total gap in aggregate productivity growth was 1.09 percentage points in 1995-2000. Roughly 75% of this differential can be explained by industries that are using new technologies. Lower investment rates in ICT mean that newer technologies have been adopted less forcefully. In fact Oliner and Sichel (2000) and Jorgensen and Stiroh (2000) provide convincing evidence that the U.S.-EU productivity gap can be traced back in large part to the delayed adoption of new technologies in Europe. This finding is confirmed by Daveri (2002), Colecchia and Schreyer (2002) and van Ark et al. (2002) to mention a few. van Ark et al. (2002), Daveri (2002) among others find that the diffusion of new technologies in Europe is following a similar pattern to those observed in the U.S. but at a considerably slower pace. This

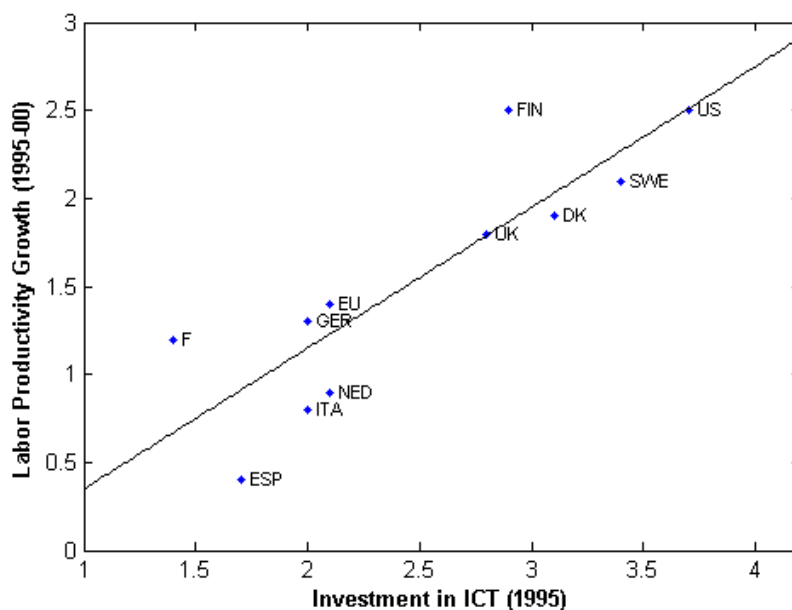


Figure 1: Investment in new technologies and LPD growth, Data is from van Ark et al. (2002) and Timmer et al. (2003)

pattern is clearly observable in Table 3. It shows that ICT investment intensities were increasing in all countries over time but (a) most European countries started investing in ICT with a significant delay and (b) the gap between the U.S. and most European economies has not narrowed much.

Evidently the slower diffusion of new technologies is the principal factor in explaining the weaker European productivity performance. Questions arising in this context are (a) why is Europe generally lagging behind and (b) what explains the heterogeneous investment patterns among European countries? There is a bulk of empirical studies, see for instance McGuckin and van Ark (2001) and McGuckin et al (2005), arguing that structural impediments in product and labor markets hamper the successful implementation of new technologies across industries in Europe. These barriers mostly come 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. More evidence provided by Gust and Marquez (2002) suggests that countries with more burdensome regulatory environments tend to adopt new technologies more slowly and also have slower productivity growth. These studies argue that adoption costs may differ across countries so that low adjustment cost countries adopt new technologies first. This pattern is also reflected in Figure 2 that plots the strictness of an economies regulatory environment and the degree of technology diffusion as measured by the ICT investment

	1980	1985	1990	1995	2001
U.S.	2.5	3.4	3.3	3.7	4.2
EU	1.2	1.9	2.2	2.1	2.6
Denmark	1.5	2.3	2.9	3.1	3.6
Finland	1.1	1.5	1.9	2.9	4.3
France	1.0	1.4	1.5	1.4	2.1
Germany	1.3	2.2	2.4	2.0	2.5
Italy	1.5	1.9	2.3	2.0	2.5
Netherlands	1.6	1.9	2.4	2.1	2.9
Spain	0.9	1.5	2.5	1.7	2.1
Sweden	1.6	2.5	2.7	3.4	4.7
United Kingdom	0.8	1.6	2.3	2.8	3.0

Source: Timmer et al. (2003)

Table 3: ICT investment as a share of GDP

intensity. The measure of regulation (computed by the OECD) captures the degree of an economy's regulation in product and labor markets, administrative burdens for start-ups and the degree of state controls. 5 (1) indicates a very strict (loose) regulation. Clearly, countries that have a very strict regulatory environment tend to invest less in new technologies. Gust and Marquez (2002) confirm that differences in regulations are causal for the observed cross country heterogeneity in the adoption of new technologies<sup>8</sup>.

The claim that there is a link between the pace of technology adoption, output growth and unemployment is supported by the impressive labor market and growth performance of some European countries like Sweden and the Netherlands<sup>9</sup>. Both countries exhibit productivity growth rates that are close to that of the U.S. and in terms of technology adoption and usage we find no evident technology deficit relative to the U.S. At the same time the unemployment rates of both economies are only slightly higher (Sweden) or even lower (Netherlands) than the U.S. rate.

<sup>8</sup>For more evidence on the hypotheses that the lag in technology adoption can be attributed to stricter regulations in European countries, see Colecchia and Schreyer (2002) and Jerzmanowski (2006).

<sup>9</sup>The view that slack adoption of new technologies in Europe is causal for the observed slowdown in productivity and output growth is reflected by a recent statement in the European Commission's European Competitiveness Report 2001: *"The growing consensus that the strong growth and productivity performance in the United States is related to increased investment and diffusion of ICT goods and services has raised concerns that the weaker economic performance of EU Member States is caused by sluggishness in the adoption of these new technologies ..."*, (European Commission's European Competitiveness Report 2001, p. 10).

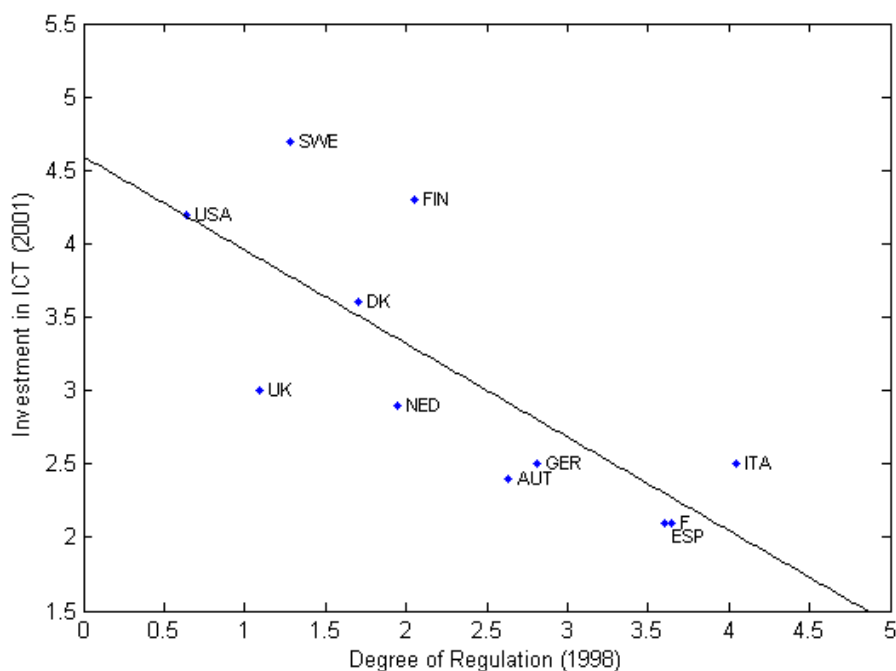


Figure 2: Regulation and investment in new technologies, Data is from Nicoletti et al. (1999) and Timmer et al. (2003)

### 3 The Model

As an analytical framework I use a vintage technology/vintage human capital model with frictional labor markets. Firms are heterogeneous with regard to the installed production technology. When a new job, i.e. a new production unit, is created it adopts the most advanced technology that is currently available. Each period firms have the choice of keeping their old technology, upgrading the existing one, i.e. installing the leading edge technology or destroying the job. Agents are heterogeneous with respect to their human capital endowment. Workers accumulate job-specific skills that are associated with the particular technology they are working with. These skills are scrapped in the event of a lay-off. The accumulation of specific skills captures the notion of technology learning that increases the productivity of an existing production unit over time. This feature is consistent with empirical results. For instance, Jensen et al. (2001) find that the gains in productivity of an existing production plant which are due to the accumulation of experience are high and significant<sup>10</sup>. The specification implies that technologies of different vintages are installed in the economy at the same time. The use of vintage technology is

<sup>10</sup>They find that for a plant that was created in 1967, technology learning accounts for an increase in own productivity of about 57% over the period 1967 – 1992.



supported by empirical findings that evidence a high persistence of firm's technology<sup>11</sup>.

### Vintage Technology and Skills

The economy is populated by a continuum of individuals that are either workers or entrepreneurs. Workers are either employed or unemployed. Individuals are infinitely lived but they face a constant probability of death that is given by  $\sigma$ . At each point in time,  $t$ , there exists a range of sector-neutral technologies denoted by  $a_{t,\tau} \in \{a_{t,0}, a_{t,1}, \dots, a_{t,T}\}$  that differ with respect to their date of creation. The leading edge technology is given by  $a_{t,0}$  whereas  $a_{t,T}$  is the oldest that is still in use.  $T$  can be interpreted as the critical age at which a technology is scrapped. New technologies arrive at a constant rate  $g$ . Hence  $a_{t+1,0} = ga_{t,0}$ , where  $a_{t+1,0}$  and  $a_{t,0}$  denote the leading edge technologies of tomorrow and today respectively. Newer technologies therefore have a higher productivity. Each employed worker is equipped with a certain stock of human capital, denoted by  $h$ , that is proportional to the amount of specific skills that the worker has accumulated on her current job. Specific skills, denoted by  $s$ , can take values  $s \in \{s^0, s^1, \dots, s^I\}$  where  $s^0 < \dots < s^I$ .  $s^0$  and  $s^I$  are, respectively, the lowest and highest potentially attainable skill level in the economy. The transition across skill levels is governed by a Markov process with transition probabilities given by  $p(s, s')$ . More precisely,  $p(s, s')$  denotes the probability that a worker with current skill level  $s$  experiences an upgrade of his technology specific skills to level  $s'$  where  $s' \geq s$ . Furthermore, I assume  $s^0 = 0$ . This condition says that immediately after the creation of a new production unit or the renovation of an existing one, i.e. when  $\tau = 0$  there exists no job/technology specific knowledge. This specification is supported by empirical evidence provided e.g. by Cochran (1960), Garg and Milliman (1961), Rusell(1968) and Pegels (1969). They find that after a change in firm's production technology, productivity initially drops and then gradually rises. The drop suggests that production knowledge does not apply equally across the old and the new production technologies and the subsequent increase evidences the existence of learning. The stock of human capital embodied in a worker is given by

$$h = f^h(s) = (1 + \alpha s) \tag{1}$$

where  $\alpha > 0$ . Thus, the function  $f^h$  is linear in  $s$  and satisfies the following property:

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<sup>11</sup>Work e.g. by Baily et al. (1992) and Bartelsman and Drymes (1998) suggests that each period roughly 60% of the firms keep their current level of technology. Moreover, both studies and the findings by Dunne (1994) confirm that plants with poor relative productivity can restructure their technology and move up in the relative productivity scale. This can be interpreted as clear evidence for firm's updating efforts. More explicitly, Dunne (1994) finds that old and young plants appear to use advanced technology at similar frequencies. Given that old plants had installed a different technology when they were created this implies that at a certain point in time they must have updated their technology.

$$f^h = \begin{cases} 1 & \text{for } \tau = 0 \\ > 1 & \text{for } \tau > 0 \end{cases}$$

The functional form of  $f^h$  implies that the returns to learning are positive. This is consistent with findings, e.g. by Bahk and Gort (1993) and Jovanovic and Nyarko (1995). Bahk and Gort (1993) use plant age as a proxy for the vintage of a technology and find that technology learning accounts for an annual increase in output of 1%<sup>12</sup>. 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 level of technology specific skills embodied by the employed worker and the vintage of the implemented technology. When a new firm is created it installs the most advanced technology that is available in the economy, i.e.  $a_{t,0}$ , hence upon creation  $\tau = 0$ . Firm's output is a function of the installed technology and the worker's stock of human capital. Therefore, the output of a firm employing a worker with skills  $s$  that operates a technology of vintage  $\tau$  is given by

$$y_t(\tau, s) = a_{t-\tau,\tau} f^h(s) = a_{t-\tau,\tau} (1 + \alpha s) \quad (2)$$

Jobs can be distinguished along two dimensions, the vintage of the installed technology,  $\tau$  and the level of specific skills embodied in the employed worker,  $s$ . In each period firms have the choice of keeping their old technology, upgrading the existing one, i.e. installing the frontier technology or destroying the job. When a firm decides to upgrade it has to incur a cost  $\chi$  that is assumed to depend on the technology gap, i.e. the distance of the currently installed technology to the leading edge technology, in the following convex way

$$\chi_t(\tau) = \mu e^{\xi(1-z)^{-1}} \quad (3)$$

where  $\xi > 0$ ,  $\mu > 0$  and  $z = 1 - g^{-\tau}$  denotes the firm's technology gap. Notice that the width of this gap is determined by the growth rate of the technology frontier - when new technologies arrive at a more rapid pace then the technology gap widens rather quickly<sup>13</sup>.

As mentioned previously, workers are equipped with a set of skills and abilities that enables them to operate the technology they are attached to. This particular form of human capital, which we call a worker's production knowledge, is characterized by its limited transferability across vintages<sup>14</sup>. Hence in the case of a technology update within

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<sup>12</sup>For a survey on empirical studies of technology learning see Yelle (1979).

<sup>13</sup>Notice that a firm's technology gap can be measured in terms of time,  $\tau$ , or alternatively in terms of the productivity differential,  $z$ . For the sake of comparability the latter might prove more useful later on when the growth rate  $g$  will be subject to changes.

<sup>14</sup>Notice that, even it can be considered as workers human capital it does not show up in Equation

a firm there is likely to be a discrepancy between a worker's current production knowledge and the knowledge that is required to operate the newly installed technology. This discrepancy can be best understood by considering the limited transferability as an implicit form of human capital obsolescence. The less of a worker's production knowledge can be transferred to a new job (that incorporates a more advanced technology) the more obsolete it is relative to the production knowledge required in that new job. Thus, we can understand  $\chi_t(\tau)$  as a form of training costs the firm has to incur in order to provide the worker with necessary skills that enables her to operate the new technology. The convexity of  $\chi$  follows from the fact that long-tenured workers, that are highly specialized in their jobs, operate technologies that are already far away from the frontier. Hence, a substantial investment is made necessary to make the worker's skills and abilities compatible with the new production technology. However, we find that the convexity of the training cost function is not critical for our results. We obtain virtually the same results for linear costs. Given the paths of the frontier technology and the upgrading costs we know that when it is optimal for a firm belonging to skill class  $s$  to update at age  $T_s$  it is also optimal at each multiple of  $T_s$ . Intuitively, firm's incentive to update or not is driven by the path of the updating costs. If in skill class  $s$  it is never optimal to update then there exists a maximum age  $T_s^+$  at which it is no longer optimal to keep the current production technology in operation and thus the job is destroyed. When a firm renovates it adopts the leading edge technology, hence  $\tau = 0$ . This implies that upon upgrading the currently employed worker loses his technology specific skills, i.e.  $s = 0$ <sup>15</sup>. At the beginning of a period each firm and its employee observe the level of embodied skills and the age of the installed technology. Both parties are involved in a bargaining process that determines the wage. As a bargaining concept I use Nash bargaining.

### Unemployment

When a production unit gets destroyed, either because of exogenous destruction that occurs at the constant rate  $\rho$  or endogenously due to technology obsolescence the worker is released to unemployment. Endogenous destruction occurs when the installed technology in a particular production unit has reached its maximum age  $T_s^+$  and updating was not optimal for the firm. The use of Nash bargaining implies that any break-up of existing job/worker pairs is a consensus outcome. Hence we do not observe unilateral quits by the worker. Upon lay-off a worker that has accumulated skills  $s$  in his previous

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(1). This is due to the fact that we consider production knowledge as having a rather abstract nature. It does not add anything to worker's productivity but it is ex-ante required to actually start operating a certain technology.

<sup>15</sup>Specific skills are not lost in the sense that they fully depreciate upon lay-off but they are not marketable anymore, hence they get implicitly lost.

occupation is entitled to unemployment benefits denoted by  $b(s)$ . Benefit payments are a constant fraction  $\phi$  of the average after-tax wage within the respective skill class, i.e.  $b(s) = \phi(1 - \tau^w) \sum_{\tau} n(\tau, s) \omega(\tau, s)$ , where  $n(\tau, s)$  denotes the measure of workers with skills  $s$  that are operating vintage  $\tau$ .  $\omega(\tau, s)$  denotes the respective wage. Each period, unemployed face a constant probability,  $\gamma$ , of losing their benefit receipts. Unemployed individuals can be distinguished along two dimensions, the amount of job specific skills they have accumulated in their previous occupation and their implicit technology gap, i.e. the relative obsolescence of their production knowledge. Each unemployed individual is implicitly attached to a certain vintage, i.e. the one that was operated in the last occupation, for which the worker still possesses the respective production knowledge. During spells of unemployment the workers production knowledge is subject to depreciation, i.e. it becomes more and more obsolete over time, which is a natural consequence of non-zero growth in the leading edge technology and the limited transferability property. This implies that when an unemployed gets re-matched with new firm (that embodies the leading edge technology) there will be a discrepancy between the individual's production knowledge and that required to operate the new technology. Notice that the nature of this discrepancy is exactly the same firms face when they consider a technology update. As a result, newly hired workers need to be provided with training.

### The Labor Market

The labor market is frictional. This means that at each point in time there exists a certain number of open vacancies denoted by  $v$  and a pool of job-searching individuals,  $u$ . The total number of searcher is given by  $u = \sum_{\tau, s, j \in \{+, -\}} u^j(\tau, s)$  where  $j$  indicates whether or not the individual receives unemployment benefits,  $j = \{+\}$  or not,  $j = \{-\}$ .  $\tau$  indicates the individual's distance to the frontier and  $s$  indicates the amount of skills accumulated in the previous job<sup>16</sup>. New matches are determined by a matching function that is homogeneous of degree one, bounded above by  $\min\{v, u\}$  and increasing in its both arguments.

$$m = m(v, u) = mv^d u^{1-d} \quad (4)$$

where  $m > 0$  and  $d \in [0, 1]$ . The probability that a firm meets an unemployed individual with previous skills  $s$ , benefit entitlement  $j$  and distance  $\tau$  is given by

$$q(\tau, s, j) = \frac{m(v, u)}{v} \frac{u(\tau, s, j)}{u} = m(\theta, 1) \frac{u(\tau, s, j)}{v} \quad (5)$$

The last term is implied by the homogeneity assumption on  $m$ . Note that  $\theta = v/u$  is a

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<sup>16</sup>Notice that the terms "an individual's distance to the frontier" and "the degree of obsolescence of an individual's production knowledge", both captured by the variable  $\tau$ , will be used interchangeably.

measure of labor market tightness. Similarly, let  $p$  denote the probability that a searcher encounters a vacancy <sup>17</sup>.

$$p = m(v, u) / u = m(\theta, 1) \quad (6)$$

The existence of a matching function in the labor market implies that workers looking for a job trigger a congestion effect on each other. The more individuals are looking for a job the lower is the probability of encountering a vacancy. The same is true, of course, for vacancies. Therefore, firm's incentive to post a vacancy is strongly affected by the tightness in the labor market.

### Government

The public sector in this economy levies a taxes on labor income and to redistribute the revenues in the form of unemployment benefits. The government is assumed to run a balanced budget every period, hence  $\tau^w W_t = B_t$ , where  $W$  is the total wage bill,  $\tau^w$  is the tax on labor income and  $B$  denotes total benefit payments.

### Value functions

Given capital-embodied growth there exists a natural trend in the model's key variables. De-trending by  $a_{t,0}$  yields a stationary representation. In order to fill a vacant job firms have to actively search for workers. This is done by posting vacancies. Denote with  $V$  the value of a vacancy and let  $\kappa$  be the cost of keeping the vacancy open. Given free entry, in equilibrium all gains from posting vacancies must be exhausted, hence  $V = 0$ . Or in other words the cost of opening up a vacancy must equal the expected return. The implied zero-profit condition is

$$\kappa = \beta g(1 - \sigma) \sum_{\tau, s, j} q(\tau, s, j) (J^j(\tau, s) - \chi(\tau)) \quad (7)$$

$\sigma$  is the probability that a worker dies between two consecutive periods,  $J^j(\tau, s) - \chi(\tau)$  is the net value of a new job for a firm that gets matched with a worker that has characteristics  $(j, \tau, s)$ . Notice that the term on the right hand side represents the expected profit. Given the possibility of getting matched with any possible worker the firm assigns probabilities to each possible match which are given by Equation (5). Condition (7) pins down the degree of labor market tightness in equilibrium. The relevant state variables for a firm are the level of skills embodied in the worker,  $s$  and the age of the installed technology,  $\tau$ . Each period a firm has a choice set, denoted by  $\Upsilon$ , which contains the following actions:

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<sup>17</sup>Notice that all the heterogeneity comes from the workers side, vacancies are all ex-ante the same.

$$\Upsilon = \begin{cases} 1 - \text{produce with the current technology} \\ 2 - \text{upgrade to the leading edge technology} \\ 0 - \text{destroy the job} \end{cases}$$

Given the wage rate  $\omega(\tau, s)$ , the value of a job for a firm that operates vintage  $\tau$  and employs a worker with skills  $s$  writes:

$$J(\tau, s) = \max_{\Upsilon \in \{0,1,2\}} \left\{ y(\tau, s) - \omega(\tau, s) + \beta g(1 - \sigma)(1 - \rho) \sum_{s' \geq s} p(s, s') J(\tau', s'), \right. \\ \left. J^+(\tau, s) - \chi(\tau), 0 \right\} \quad (8)$$

$\rho$  is the rate of exogenous job destruction,  $\tau'$  is the next periods age of the installed technology,  $\beta$  is the discount factor and  $y(\tau, s) - \omega(\tau, s)$  denotes instantaneous profits. When the current production technology is kept in operation, the value of the job next period is  $J(\tau', s')$  with probability  $p(s, s')$  where  $s' \geq s$ <sup>18</sup>. This captures the notion of worker's technology learning during employment. If the firm decides to update it has to incur training costs  $\chi(\tau)$  that depend on the technology gap, i.e. the firm's distance to the frontier<sup>19</sup>. A worker's value function depends on his status of employment.

- $E(\tau, s)$  - the value of being employed for an individual with skill level  $s$  that is operating vintage  $\tau$
- $W^j(\tau, s)$  - the value of being unemployed for an individual associated with vintage  $\tau$  that was of skill type  $s$  when she got laid-off. If  $j = \{+\}$  ( $j = \{-\}$ ), she is (not) entitled to unemployment benefits

Exogenous job destruction does not apply to newly matched job/worker pairs. Hence, a job/worker relation can not break up for exogenous reasons immediately after the match. The value of being unemployed - that is conditional on the worker's benefit entitlement - can be written as

$$W^+(\tau, s) = b(s) + \beta g(1 - \sigma) \{ p(\theta) E^+(\tau, s) + (1 - p(\theta)) \\ \times (1 - \gamma) W^+(\tau', s) + \gamma W^-(\tau', s) \} \quad (9)$$

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<sup>18</sup>Note that  $p(I, I) = 1$ . This is implied by the assumption that during employment there is no depreciation of specific skills.

<sup>19</sup>Note that the net post-update value of a firm is equal to the value of a new production unit that has been formed with a worker that was entitled to unemployment benefits, hence  $j = \{+\}$ .

$$W^-(\tau, s) = \beta g(1 - \sigma) \{ p(\theta) E^-(\tau, s) + (1 - p(\theta)) \times W^-(\tau', s) \} \quad (10)$$

Note that with probability  $p(\theta)$  a worker encounters a vacancy which results in a match. The value of such a match for a worker is denoted by  $E^j(\tau, s)$ . If no match takes place in the current period the individual might lose his unemployment benefits with probability  $\gamma$ . Notice that we have to keep track of a worker's benefit entitlement because in the case of a match it will determine a worker's bargaining power in the wage bargain. A worker not receiving benefits has a lower outside option and has, therefore, also a lower reservation wage. The choice set of an employed worker, denoted by  $\Xi$ , consists of the following actions:

$$\Xi = \begin{cases} 1 - \text{stay with the current employer} \\ 0 - \text{quit} \end{cases}$$

First, for notational convenience let's define the surplus of a job for a worker that stays with the current firm.

$$\bar{E}(\tau, s) = (1 - \tau^w) \omega(\tau, s) + \beta g(1 - \sigma) \left( (1 - \rho) \sum_{s' \geq s} p(s, s') E(\tau', s') + \rho W^+(\tau', s) \right) \quad (11)$$

The value is determined by the worker's after-tax wage income and the present value of the future surplus. If the firm/worker relation survives to the next period the plant might enjoy an appreciation of the worker's skill level that occurs with probability  $p(s, s')$ . This is captured by the first term inside the bracket. The realized value of employment for a worker is dependent on the actual action of the entrepreneur. If the entrepreneur plans to update (keep) the technology, i.e.  $\Upsilon = 2$  ( $\Upsilon = 1$ ), the worker compares his current outside option with the post-update (continuation) value of the job.

$$E(\tau, s) = \begin{cases} \max_{\Xi \in \{0,1\}} \{ \bar{E}(0,0), W^+(\tau, s) \} & \text{if } \Upsilon = 2 \\ \max_{\Xi \in \{0,1\}} \{ \bar{E}(\tau, s), W^+(\tau, s) \} & \text{if } \Upsilon = 1 \end{cases}$$

Notice that when deciding on  $\Xi$  the worker always considers his current outside option as the relevant one. Also in the case of  $\Upsilon = 2$ . The cooperative nature of decision making within this framework implies that the firm/worker pair seeks to maximize the joint surplus of the job at each point in time. No action can be taken against the will of a particular party. When we take the joint surplus of each joint action as the underlying

value for comparison we get the following condition

$$(\Upsilon, \Xi) = \arg \max \{J(\tau, s) + E(\tau, s) - W^+(\tau, s), J^+(\tau, s) + E^+(\tau, s) - W^+(\tau, s) - \chi(\tau), 0\}$$

Note that what counts for the worker is the net surplus of an update that is given by  $E^+(\tau, s) - W^+(\tau, s)$ . If his current outside option is high relative to the post-update value of the job then the update might not take place. To make the worker agree on an change in the technology the gain in the job-value must be sufficiently high to compensate the worker for a potential reduction in her current outside option<sup>20</sup>. Conditional on the decision that was taken, the joint surplus of a job, defined by  $\Omega(\cdot, \cdot)$ , is given by

$$\Omega(\tau, s) = \begin{cases} J(\tau, s) + E(\tau, s) - W^+(\tau, s) & \text{if } \Upsilon = 1 \wedge \Xi = 1 \\ J^+(\tau, s) + E^+(\tau, s) - W^+(\tau, s) - \chi(\tau) & \text{if } \Upsilon = 2 \wedge \Xi = 1 \\ 0 & \text{otherwise} \end{cases}$$

### Optimizing behavior

The objective of each worker is to maximize expected wealth that is given by the infinite stream of future income

$$\sum_{s=t}^{\infty} (\beta g(1 - \sigma))^{s-t} y^w \quad (12)$$

Conditional on the employment status,  $i \in \{e\text{-employed}, u\text{-unemployed}\}$  and the benefit entitlement status,  $j \in \{+, -\}$  a worker faces the following constraint

$$y^w = I(i = e) (1 - \tau^w) \omega(\tau, i) + I(i = u) I(j = +) b(s) \quad (13)$$

where  $I(i = \cdot)$  and  $I(j = \cdot)$  are an indicator functions that shape the constraint according to the worker's actual employment and benefit status. Without loss of generality I assume the existence of just one entrepreneur that receives all the profits generated in the economy. Given that there is no capital accumulation, the entrepreneur's objective is to maximize the infinite stream of future income

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<sup>20</sup>Notice that, a generous unemployment insurance scheme that naturally creates a valuable worker's outside option could potentially create delays in the adoption of new technologies. This is due to the fact that with a high replacement rate  $\phi$  and for certain combinations of states  $(\tau, s)$  we likely see the case  $W^+(\tau, s) > W^+(0, 0)$  which implies that workers might not be willing to exchange their high (pre-update) outside option  $W^+(\tau, s)$  for the lower (post-update) outside option  $W^+(0, 0)$ .



$$\sum_{s=t}^{\infty} \beta^{s-t} y^e \quad (14)$$

subject to

$$y^e = \Pi - \sum_{\tilde{\tau}} v(\tilde{\tau})\kappa - C \quad (15)$$

The entrepreneur's income is given by profit income  $\Pi$  net of total training costs,  $C$  and vacancy costs.

### Wage setting

In the bargaining process a job/worker pair chooses the wage rate in order to maximize the Nash product which is given by

$$(J(\tau, s))^\eta (E(\tau, s) - W^+(\tau, s))^{1-\eta} \quad (16)$$

We need to distinguish two cases, (a) firm/worker pairs that continue an existing relation and (b) newly matched pairs. The difference stems from (a) the existence of training costs a firm has to pay after a match and (b) the underlying characteristics of the worker the firm got matched with. Newly matched workers differ with respect to  $\tau$  and  $s$  and so does their outside option in the first-period wage bargain. From the second period onwards a worker's current outside option is uncoupled from her previous employment history. As a result we get a two-tier wage system that contains two wage functions - one for continuing relationships and one for newly matched job/worker pairs. A job/worker pair that continues an existing relationship chooses a wage that satisfies

$$\omega(\tau, s) = \operatorname{argmax} (J(\tau, s))^\eta (E(\tau, s) - W^+(\tau, s))^{1-\eta} \quad (17)$$

$\eta$  indicates the firm's weight in the bargain. As before,  $J(\tau, s)$  is the value of a job for a firm and  $E(\tau, s) - W^+(\tau, s)$  is the net value of employment for a worker. Optimality implies that

$$(1 - \eta)J(\tau, s) = \eta (E(\tau, s) - W^+(\tau, s)) \quad (18)$$

Using the value function given by Equations (8) and (11) and the optimality condition (18) that has to hold for all pairs of  $(\tau, s)$  we can write the wage as

$$\omega(\tau, s) = \{(1 - \eta)y(\tau, s) + \eta [W^+(\tau, s) - \beta g \rho(1 - \sigma)W^+(\tau', s)] - \eta \beta g(1 - \sigma)(1 - \rho) \sum_{s' \geq s} p(s, s')W^+(\tau', s')\}(1 - \eta\tau^w)^{-1} \quad (19)$$

Similarly a newly matched job/worker pair solves

$$\omega^j(\tau, s) = \operatorname{argmax} (J^j(\tau, s) - \chi(\tau))^\eta (E^j(\tau, s) - W^j(\tau, s))^{1-\eta} \quad (20)$$

that yields

$$\omega^j(\tau, s) = \{(1 - \eta)(y(0, 0) - \chi(\tau)) + \eta [W^j(\tau, s) - \beta g \rho(1 - \sigma)W^+(1, 0)] - \eta \beta g(1 - \sigma)(1 - \rho) \sum_{s' \geq 0} p(0, s')W^+(1, s')\}(1 - \eta\tau^w)^{-1} \quad (21)$$

## 4 Solving the model

The solution to the model is a set of policy functions that characterize the optimal decision behavior of workers, firms, and firms with dormant jobs. The relevant state variables for an existing job/worker pair are the vintage of the installed technology  $\tau$  and the level of specific skills  $s$ . Given a certain state  $(\tau, s)$  the policy function gives the optimal decision that maps into the action space given by {keep on producing, update the technology, destroy the job}. Notice that decisions are taken jointly. The free entry condition that results in the zero (expected) profit condition implicitly determines the vacancy posting behavior of firms with a dormant job. Notice that when optimizing, firms and unemployed take matching probabilities as given. Solving the model reduces to finding a fixed point  $(\tau^w, \theta)$  that balances the government budget constraint - and yields ex-post matching probabilities that are consistent with agents' ex-ante beliefs. The algorithm that is constructed to this end is structured in the following way. In an inner loop agents solve their maximization problem taking the tax rate  $\tau^w$  and the tightness  $\theta$  as given. At the end of each loop one can compute the stationary distributions of firms, workers and unemployed across vintages and skill levels and use this information to update the value of  $\theta$  leaving the tax rate unchanged. The inner loop has converged when the value of  $\theta$  is found that is consistent with agents' prior beliefs. Using the stationary distributions one can compute aggregate variables, including total government expenditures and revenues. In an outer loop, these values are subsequently used to update the guess of  $\tau^w$  in a way such that the government budget constraint is balanced. Once the fixed point in  $\tau^w$  is found the model is solved. Hence we can characterize the equilibrium of the model as follows. The

equilibrium consists of

- a wage schedule  $\omega(\tau, s)$  and a firm's policy function  $T(\tau, s)$  that maps into the action space  $\{\text{keep, update, destroy}\}$ , so that the joint surplus of each firm/worker pair is maximized
- a labor market tightness  $\theta$  that ensures zero expected profits from posting vacancies and
- a tax rate  $\tau^w$  that guarantees a balanced government budget.

## 5 Calibration

The model period is set equal to half a quarter. In total there are 13 parameters (see Table 4) to be calibrated. Seven of them,  $(\beta, \sigma, \eta, \alpha, \lambda, d, \xi, g)$ , are calibrated "externally" by using existing micro-evidence. The discount factor  $\beta = 0.9945$  is chosen so that the implied annualized real interest equals 4.5%. People of working age face a constant probability of dying  $\sigma = 0.0025$ . Hence, on average, they spend 50 years in the labor force. Firm's bargaining weight,  $\eta$  is equal to 0.5 which is also the elasticity of the matching function with respect to the stock of vacancies. The value of  $\alpha = 0.3347$  is chosen so that the progress ratio i.e the ratio of peak to initial productivity is equal to 1.2. Jovanovic and Nyarko (1995) report progress ratios from dozen empirical studies. Their suggested range is 1.14 – 2.9. Given that 1.2 is a rather conservative choice we will consider alternative values in Section 7. Calibrating the parameters of the cost function is not an easy task given that the empirical literature is silent regarding training/updating costs. However, there exists a consensus that training costs are a convex function of the technology gap<sup>21</sup>. Therefore, I set  $\xi = 1$ . The choice of the second parameter in the cost function  $\mu$  will be discussed shortly. The transition probabilities of the Markov process governing skill accumulation are calibrated so that intra-firm technology learning lasts, on average, for 10 years. This value is consistent with findings by Bahk and Gort (1993) who report that intra-firm capital and organizational learning continues for up to 10 years after birth<sup>22</sup>. Four parameters -  $(\kappa, \rho, m, \mu)$  - are calibrated internally which means that their values are chosen such that the steady state generated by the model matches certain features of the U.S. economy for the period before 1975. The pre-1975 steady state of the laissez-faire economy (henceforth LS) generates (1) an average duration of unemployment of 11.4 weeks which is consistent with BLS-data for the period 1960-75, (2) an average vacancy duration of 6.5 weeks as reported by van Ours and Ridder (1992), (3) a technology adoption cost

<sup>21</sup>However, as mentioned previously, the convexity of the cost function is not critical for our results.

<sup>22</sup>The lower (upper) bound of the range of attainable skills is set equal  $s^0 = 0$  ( $s^I = 0.2$ ).

to GDP ratio of 2.4% as estimated by Bessen (2002) for 1973 and (4) and unemployment rate of 4%. The semi-quarterly vacancy cost  $\kappa = 0.14076$  compares to 1.5 months of wage payment. A value that is in line with findings by Bentitola and Bertola (1990) and Felbermayer and Prat (2007). Exogenous layoffs occur with probability  $\rho = 0.0212$ , i.e. once every 5.9 years. For the welfare-state (henceforth WS) there are two more parameters to calibrate. The replacement rate is set equal to 45%. The OECD reports replacement rate for the early 1970s in Europe lying in the range between 30% (Germany) and 50% (Netherlands). The semi-quarterly probability of losing the benefit entitlement is  $\gamma = 0.0417$ . Hence, people receive benefits, on average, for 3 years. As a benchmark I set the annual growth rate of embodied technical change equal to 2.5%. Given the differences in the institutions, the same LS job destruction rate  $\rho$  rate generates a steady state unemployment rate of 5.2% in the WS economy. However, average unemployment until the early 70s in Europe was around 3.5%. To account for this fact we follow Hornstein et al. (2007) and recalibrate the separation rate for the WS economy. One might conjecture that introducing layoff taxes - as in Ljungqvist and Sargent (2007) - would be equally successful in resolving the problem. As emphasised by Mortensen and Pissarides (1999) layoff taxes reduce incentives to create jobs and to destroy them. The net effect on labor market tightness and hence on unemployment turns out to be ambiguous. In this framework however, a firing tax payed by the firm in the event of an endogenous or an exogenous separation would inevitably raise unemployment. This is due to the fact that, for the current calibration, there exists no endogenous job destruction 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. As a result, layoff taxes would only decrease the surplus of a job for a firm and consequently depress job creation. In order to match low European unemployment in the 70s we set the semi-quarterly separation rate  $\rho = 0.0137$ . A welcome sideeffect of lowering  $\rho$  is that in this way we automatically increase the average duration of unemployment in the WS economy. As reported by Machin and Manning (1999) the duration of unemployment in European countries was substantially higher relative to the U.S. already in the 1970s. We, therefore, believe that our calibration very well captures the main characteristics of (and differences between) European and U.S. labor markets.

## 6 Results

The focus of this paper is on providing a proper understanding of the links between firms' technology adoption behavior, labor market institutions and the labor market performance of an economy. The analysis was motivated by the fact that there are substantial

Explanation	Variable	Value	
Discount Factor	$\beta$	0.9945	
Probability of dying	$\sigma$	0.0025	
Firm's bargaining weight	$\eta$	0.5	
Vacancy cost	$\kappa$	0.14076	
Parameter of production function	$\alpha$	0.3347	
Parameter of matching function	$m$	0.7702	
Parameter of matching function	$d$	0.5	
Parameters of cost function	$\xi$	1	
Growth rate of technology frontier	$g$	0.025	
		LS	WS
Separation rate	$\rho$	0.0212	0.0137
Parameter of cost function	$\mu$	0.024	0.024-0.057
Replacement rate	$\phi$	0	0.45
Probability of losing benefit entitlement	$\gamma$	-	0.0417

Table 4: Parameter Values (One period is half a quarter)

and highly persistent differences in unemployment rates between major European countries and the U.S. These differences emerged after the late 1970's at a time when there was a major increase in the arrival rate of new technologies. Given these observations it is clear that we need to evaluate the model along two different dimensions. First we need to consider a pre-1975 period that is characterized by a low rate of arrival of new technologies. The outcomes of this scenario are then put in contrast with the results of a post-1975 scenario where the arrival rate is high. Secondly, in order to mimic the existing technology gap between (and among certain) European countries and the U.S. we need to account for differences in technology updating which is done by considering various different updating cost scenarios. It is not the aim of the paper to explain why Europe has been lagging behind the U.S. in the implementation and usage of new technologies but it takes the existing technology gap as given and seeks to analyze its consequences for the local labor markets. As mentioned at the outset, cross-country differences in the frequency of technology updating are likely to be the result of different regulatory environments. There is considerable empirical evidence arguing that restrictive regulatory practices in a number of European countries have impinged on firm's incentives to adopt new technologies by raising the costs of a technology upgrade and therefore slowing down the rate of adoption. These studies together with Figures 2 suggest that there is substantial heterogeneity in the nature of regulatory environments across European countries which translates into differences in the underlying adoption-cost structure. In light of this we consider different cost scenarios for the WS economies in order to mimic the observed heterogeneity in technology adoption across European economies. To this end we pick values for the cost parameter  $\mu$  in the range 0.024 – 0.057. This range yields average updating costs that are

comparable with 4.21 – 13.49 weeks of average first period post-update wage payments. Higher costs curb firms’ incentives to adopt new technologies, hence we observe firms with higher costs updating their production technology relatively less frequently. This pattern is reflected in Table 5 which depicts pre-75 outcomes of the calibrated matching model and contrasts the results of the *laissez-faire* economy with that of the different scenarios of the welfare-state economy.

	L-F, pre 75		Welfare state, pre 75				
			Benchmark: $g = 2.5\%$				
Distance to Laissez-Faire, in quarters	0	0.22	2.02	4.37	6.16	8.03	10.2
Average time until update, in quarters	14.44	14.66	16.46	18.81	20.6	22.41	24.64
Average distance to tech. frontier	8.59	8.93	9.6	10.2	10.83	11.44	11.97
Unemployment rate, in %	4.02	3.48	3.73	3.97	4.24	4.58	4.94
Duration of unemployment, in weeks	11.54	14.43	15.51	16.55	17.74	19.2	20.81
% of unemployed w/ spells $\leq 3$ months	81.05	69.94	66.43	63.31	60.05	56.43	53.34
% of unemployed w/ spells [6, 12) months	3.46	8.22	10.00	11.65	13.41	15.38	17.03
% of unemployed w/ spells $\geq 12$ months	0.13	0.82	1.27	1.81	2.55	3.59	4.9
Equilibrium tax rate, in %	0	1.28	1.37	1.45	1.54	1.65	1.77

L-F: Laissez-Faire Economy ( $\phi = 0$ ), Welfare State Economy ( $\phi = 0.45$ )

Table 5: Steady states for the period before 1975

Given the benchmark parametrisation firms in both economies update their production technology every 14.44 quarters in the LS economy and - depending on the respective cost structure - every 14.66 – 24.64 quarters in the WS economy. As a consequence of different costs the WS suffers from a technology deficit relative to the LS in the range 0 – 10 quarters<sup>23</sup>. Given the frequency of updates the implied technology gap - i.e. the average distance of firms to the leading edge technology ranges from 8.59 – 11.97 quarters. Differences in adoption costs, that translate into different updating frequencies do, of course, not leave labor market variables unaffected. For the purpose of understanding how differences in firms technology choice spill over to the labor market we first define two concepts that will prove useful also later on. Denote with  $z_u$  the average technology gap (i.e. the average degree of skill obsolescence) of unemployed individuals. This is given by

$$z_u = (\sum_{s,j,z} u(s, j, z)z)/u$$

and second let  $c_{tr}$  denote expected training costs a firm has to incur in the event of a

<sup>23</sup>Notice that a deficit of 6 quarters between two economies means that the straggler updates its technology, on average, 6 quarters later than the leader.

match, which we can write as<sup>24</sup>

$$c_{tr} = (\sum_{s,j,z} u(s, j, z) \chi(z)) / u$$

Recall that there exists a one-to-one mapping between the maximum age of a technology  $T$  and the corresponding critical technology gap at which it's optimal for a firm to renovate, i.e.  $z^* = 1 - g^{-T}$ . Therefore, differences in updating frequencies directly translate into different values of  $z^*$ , see rows 1 – 2 in Table 6. Clearly, as the updating horizon expands production technologies are kept in operation for a longer period of time. Hence, the average technology gap of firms increases, i.e. firms production technologies are, on average, further away from the frontier. This, however, implies that also workers that are attached to these technologies while being employed exhibit a higher degree of skill obsolescence. As jobs get destroyed these workers transit to unemployed and hence also the average degree of skill obsolescence in the pool of unemployed individuals will be higher, see the third row in Table 6. In other words, as  $z^*$  rises the distribution of unemployed (across  $z$ ) shifts to the right, hence the mass of individuals with relatively more obsolete skills rises. The degree of skill obsolescence of an unemployed worker determines the amount of training that is required in the event of match. Consequently, a higher degree of skill obsolescence in the pool of unemployed implies that firms can expect larger training expenses when opening up a new vacancy. The fourth row in Table 6 reveals that, depending on the cost regime, expected training costs amount to 6.79% – 17.8% of firm's output. Larger job creation costs reduce incentives to post vacancies (see the fifth row in Table 6) and, consequently, lead to higher unemployment (which ranges from 3.48% – 4.9%). Higher unemployment is accompanied by a rise in the average duration of unemployment. The percentage of jobless workers with spells less or equal than 3 months in the laissez-faire economy is around 81.05% which is consistent with U.S. data (81.57%, see OECD). The figures for the WS outcome are substantially lower (53.34% – 69.94%). This is in line with findings by Machin and Manning (1999). They report that the duration of unemployment in Europe was substantially higher than in the U.S. already in the 1970s. The model does well also in predicting the proportion of long-term unemployed in the LS economy. The figure produced by the model, i.e. 3.46% is close to U.S. data, i.e. 4.58%. The figure for the WS is substantially higher - i.e. it ranges from 8.22% - 17.03% - emphasising that long-term unemployment was a severe problem for European economies already in the 70s.

On the whole, the steady states for the laissez-faire and the welfare-state economy

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<sup>24</sup>Recall that  $u(s, j, z)$  is the mass of jobless workers with previous skills  $s$ , benefit entitlement  $j$  and gap  $z$ .  $z$  defines the technology gap in terms of the productivity differential, i.e.  $z = 1 - e^{-g\tau}$  and  $u$  is the total mass of unemployed workers.

	LS		WS				
Average time until update, in quarters	14.4	14.6	16.5	18.8	20.6	22.4	24.6
Average $z^*$ at update, in %	8.63	8.75	9.77	11.1	12.1	13.1	14.3
$z_u$ , in %	7.39	8.44	8.93	9.35	9.81	10.3	10.7
Average job creation costs, in % of firm's output	7.14	6.79	8.81	10.7	12.7	15.2	17.8
Vacancy/employment ratio, $\frac{v}{1-u}$ , in %	2.25	1.23	1.15	1.08	1.01	0.93	0.86
Unemployment rate, in %	4.02	3.48	3.73	3.97	4.24	4.58	4.94

Table 6: Comparison of cost regimes, pre 75

generated by the baseline parametrisation can consistently capture the main features of European and U.S. labor markets of the period before 1975.

One of the stylized facts presented at the outset reveals that, in the late 1970's, there was a substantial acceleration in capital-embodied technical change. To pattern technology growth in the post-75 period we increase the growth rate of the technology frontier, i.e. we set  $g = 4\%$ . Given that the firm's decision to adopt a new piece of technology is state and not time dependent we would expect agents to update more frequently in periods of rapid technical change. State-dependency in this context implies that if it is optimal for a firm to update at a certain critical size of the technology gap, i.e.  $z^*$  than increasing  $g$  just means that the same critical gap is already reached at a lower  $\tau$ . However, as argued previously a higher rate of arrival of new technologies raises the issue of compatibility problems between vintages and therefore adjustment costs are likely to rise. To account for the increase in adoption costs in the post-75 period, for which Bessen (2002) provides empirical evidence, we re-calibrate the cost parameter  $\mu$  and set  $\mu = 0.0668$ . This generates a steady state adoption cost to output ratio of 6.5% which is the same as that of the U.S. in the period after 1975 as reported by Bessen (2002). Given the lack of similar estimates for European countries we determine  $\mu$  for each of the WS scenarios in the following way. Bessen (2002), Cummins and Violante (2002) and Yorukoglu (1998) among others argue that the rise in adoption costs is due to vintage-specific compatibility problems that are triggered by higher rates of technical change. Given that the rate of embodied technical change increased uniformly in the U.S. and in Europe we should observe the same compatibility problems in European countries as well. Hence we can expect European firms being confronted with an increase in costs of a similar order of magnitude as those in the U.S. In the calibration we, therefore, pick the post-75 value of  $\mu$  so that the relative increase in updating costs for each of the different updating scenarios in the WS case exactly matches the increase in costs in the laissez-faire economy. Table 7 depicts the post-75 steady states of the laissez-faire economy and the different scenarios of the welfare state.

Column 1 in Table 7 shows that an increase in capital-embodied technical change raises unemployment in the laissez-faire economy by about 2.27 percentage points. This



	L-F, post 75		Welfare state, post 75				
			Post 75: $g = 4\%$				
Distance to Laissez-Faire, in quarters	0	-1.55	1.26	3.93	6.73	9.61	12.85
Average time until update, in quarters	20.74	19.1	22.01	24.68	27.47	30.35	33.59
Average distance to tech. frontier	9.18	9.15	10.09	10.92	11.76	12.64	13.54
Unemployment rate, in %	6.29	5.48	6.54	7.61	8.84	10.38	12.22
Duration of unemployment, in weeks	18.47	23.22	28.03	32.95	38.82	46.36	55.72
% of unemployed w/ spells $\leq 3$ months	58.2	48.42	41.42	36.45	31.25	26.44	22.36
% of unemployed w/ spells [6, 12) months	14.42	19.52	22.54	24.08	24.93	24.38	23.94
% of unemployed w/ spells $\geq 12$ months	3.05	7.09	11.87	16.9	22.62	29.72	36.33
Equilibrium tax rate, in %	0	1.94	2.27	2.58	2.93	3.34	3.81
L-F: Laissez-Faire Economy ( $\phi = 0$ ), Welfare State Economy ( $\phi = 0.45$ )							

Table 7: Steady states for the period after 1975

matches very well the post-75 increase in U.S. unemployment. In the data we see a jump in U.S. unemployment in the late 1970's that leads to an average unemployment of 6.38% for the period 1975-2000<sup>25</sup>. The increase in unemployment is fueled by an increase in the duration of unemployment which is also well reflected by the data. In the period 1975-2005 the average spell of unemployment lasted for 15.33 weeks which is slightly less than what the model predicts. Not surprisingly the increase in costs leads to a fall in the frequency of technology updates. In the post-75 scenario firms update on average every 20.74 quarters which is roughly 6 quarters later than in the baseline case. Comparing the first columns in Table 5 and in Table 7 we can make the observation that the simulated rise in the arrival rate of new technologies that triggered a rise in updating costs had, on the whole, a rather modest impact on the performance of the labor market in the LS economy. This suggests that the economy did not switch to a different steady state after the jump of arrival rate in the late 1970's. The effects in the WS economy, however, are more diverse. Columns 2 – 7 in Table 7 reveal that the change in unemployment that occurs in response to an acceleration in capital-embodied growth depends crucially on an economy's ex-ante technology updating frequency. For the moment, let's focus on the outcomes in columns 4–8. Increasing  $g$  to 4% and allowing for an initial technology gap of 4 quarters drives up unemployment to 7.61%. A gap of 6 years results in 8.84% whereas a gap of 10 quarters pushes up unemployment to 12.22%. These figures broadly match post-75 unemployment rates of major European welfare state economies that exhibit a sizable technology deficit. Examples are Germany (7.31%), France (10.23%) or Italy (10.74%). The results in columns 2 – 3 in Table 7 reveal that unemployment rates in a welfare state economy that provides generous unemployment insurance need not necessarily be high.

<sup>25</sup>Unemployment in the U.S. was above average mainly in the 80s and early 90s. Our model can account for this movement but not for the subsequent decrease that started in the mid-90s.

In both specifications the cost parameter  $\mu$  implies updating frequencies that are virtually the same as those in the LF economy. Thus, there is virtually no technology deficit. The unemployment rates we get in this case are between 5.48% – 6.54% which is not too far from the LS economy but, more importantly, it is substantially lower than the rates in welfare states that suffer from significant technology gaps. Therefore, the key factor that determines the level of unemployment is clearly the frequency of technology updates. The intuition for that will be provided shortly. Furthermore, unemployment benefits are not the main driving force of high rates of unemployment but they are rather a factor that promotes their emergence in economies that have sluggish technology updating. A closer look at European labor markets reveals that economies that provide generous benefit payments but exhibit a zero - or just a small technology gap perform remarkably in terms of labor market indicators. Notable examples are Sweden (with an unemployment rate of 5.27%), Netherlands (5.72%) or UK (7.47%). Our model can reproduce this pattern reasonably well. The percentage of unemployed with spells greater or equal than 6 months in the welfare state with low frequency updating ranges from 40.98% to 60.27% which is broadly consistent with actual data for welfare states like Germany (39%), Spain (51.6%) or France (55.1%)<sup>26</sup>. Likewise, the results for welfare states with high frequency updating (26.61% – 34.41%) can match up real-world counterparts like Sweden (25.44%) or Austria (37.75%). Also the result for the LS economy (i.e. 17.47%) is consistent with the corresponding U.S. figure, (15.53%)<sup>27</sup>. It is well known that the persistent increase in European unemployment rates was primarily driven by an increase in the fraction of long-term unemployed. Inflow rates into unemployment were roughly the same in the pre- and the post-1980's era. Outflow rates i.e. the hazard rates of gaining employment, however, dropped significantly after the late 1970's. As a consequence, the duration of unemployment and therefore the fraction of long-term unemployed was rising. This phenomenon is captured well by our model. The results in Table 7 show that both indicators experience a significant increase in the post-75 period. The duration of unemployment was generally low in the pre-75 era but experienced a dramatic increase as the rate of arrival of new technologies started to accelerate. The positive relation between the time that passes by until firms update their production technology and the level of unemployment is depicted in Figure 3. There, the solid and the dashed lines graph the outcomes of the welfare state for the pre-75 and the post-75 era respectively. The Figure has to be read as follows. Each point on the solid line represents a particular pre-75 cost scenario that generates a certain a technology gap and a rate of unemployment<sup>28</sup>. After a shock to capital-embodied technical change the economy jumps to the point on the dashed

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<sup>26</sup>See Table 1 in Ljungqvist and Sargent (2002)

<sup>27</sup>Data is taken from the OECD

<sup>28</sup>Note that the indication of gaps in the figure corresponds to pre-75 gaps.

line that is exactly above the respective pre-75 location on the solid line. Evidently, as the rate of arrival of new technologies accelerates unemployment in the WS reaches high levels rather quickly as the technology gap widens.

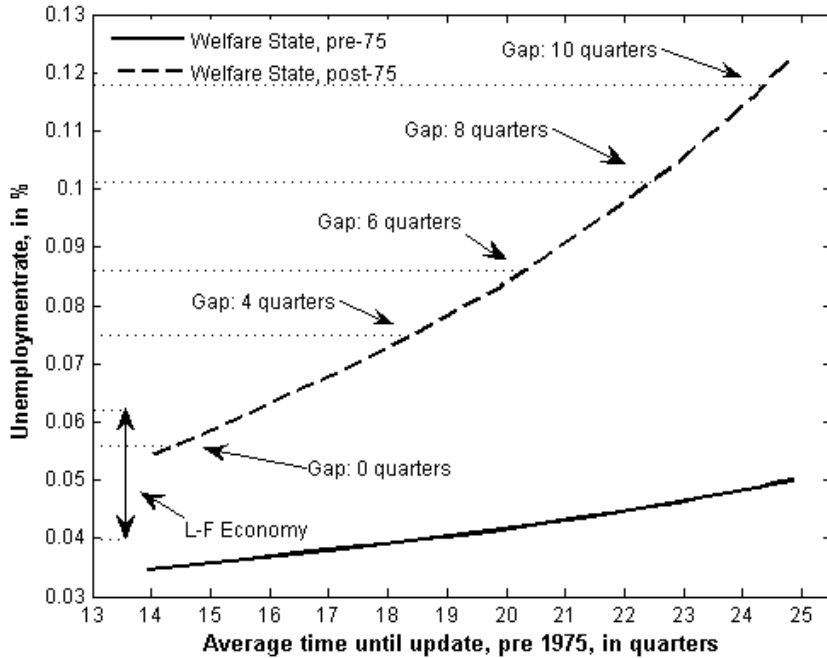


Figure 3: Unemployment Rates

Notice that unemployment rates increase more than proportionally for economies that feature less frequent technology updating. To better understand the intuition behind this important result we make use again of the two concepts we employed previously to interpret pre-75 results, i.e. the average degree of skill obsolescence of unemployed individuals,  $z_u$  and the expected training costs for firms,  $c_{tr}$ . Moreover, in order to get a more complete picture of the driving mechanism we perform the following counterfactual analysis. In a first step we increase just the growth rate of the technology frontier  $g$  to 4%, and leave the cost parameter  $\mu$  unchanged hence we disregard the issue of compatibility. In this way we are able to isolate the effects stemming solely from an acceleration of the arrival rate of new technologies. The results are represented by the first rows in Panels I-III in Table 8. Notice that the numbers indicate the change relative to pre-75 outcomes. In the second step we, likewise, set  $g$  to 4% but we also account for compatibility issues by changing the cost parameter  $\mu$ . In this step we set  $\mu$  so that the resulting adoption cost to GDP ratio in the LS economy equals 4.5%. This is less than in the benchmark scenario for which that ratio was 6.5%. Hence the problems of compatibility considered are less severe relative to the benchmark. The results of this step are given by the respective second rows in Table 8. For matters of comparability, we also report the outcome of the benchmark

scenario in the respective third rows. The key element for understanding the divergence of unemployment rates across economies is the post-75 response of a firm's critical gap, i.e.  $z^*$ . As we saw previously,  $z^*$  determines the degree of skill obsolescence in the pool of unemployed,  $z_u$ , and hence also affects the expected training costs for firms,  $c_{tr}$ . Training costs drive job creation and, therefore, influence also unemployment through their impact on firms vacancy posting behavior. From the second column in Table 8 we can infer that the critical gap  $z^*$  increases for all scenarios, even in the case of constant costs<sup>29</sup>. Notice that economies which feature slow technology updating experience a more than proportional increase in the critical gap. The explanation for that is intuitive. Notice first that the value of an existing firm gradually declines over time as its production technology ages<sup>30</sup>. It continues to decline until the firm's technology gap reaches its critical size, i.e.  $z^*$ , at which the technology gets scrapped. The wage payed within a firm is proportional to the plant's current (relative) productivity, i.e.  $\omega(\tau, s) \propto y(\tau, s) = \bar{a}g^{-\tau}(1 + \alpha s)$ , see Equation (19). As the productivity of new vintages grows faster, implied by a higher  $g$ , wages payed within firms drop. The longer the updating horizon of a firm the longer the time period for which it will benefit from lower wages. Hence firms with less frequent updating (i.e. firms that face higher costs of updating their technology) will benefit more relative to firms that update frequently<sup>31</sup>. This causes a relatively slower decline of the firm's value as its technology ages. As a result technologies will be kept longer in operation, hence they reach a relatively higher degree of obsolescence. Consequently, the increase in the size of the critical gap will be larger in economies that update less frequently<sup>32</sup>. Notice that this effect gets more pronounced as we consider also the issue of vintage compatibility (represented by the middle and far right number in each column). The intuition is the following. First note that according to Equation (8) it is optimal for a firm to update when the current surplus  $J(z, \cdot)$  equals the value of a firm that has just updated, i.e.  $J^+(\cdot, \cdot) - \chi(z)$ <sup>33</sup>. Costs increase uniformly in both updating scenarios. However, since  $J(z, \cdot)$  declines less fast in the slow updating environment the critical gap, at which  $J(z^*, \cdot) = J^+(\cdot, \cdot) - \chi(z^*)$  holds, increases by more than that in the fast

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<sup>29</sup>Recall that the critical gap is defined as  $z^* = 1 - e^{-gT}$  where  $T$  indicates the maximum age of a technology. For constant costs  $T$  naturally decreases as it is optimal for firms to update earlier. This decrease, however, is outweighed by the increase in the growth rate  $g$  so that the overall impact on  $z^*$  is negative. As costs increase the maximum age  $T$  decreases by less or even rises. Hence in the scenarios that consider also compatibility problems the critical gap  $z^*$  rises by more.

<sup>30</sup>This is a consequence of technology obsolescence caused by ongoing productivity advancements at the technology frontier.

<sup>31</sup>Average wages drop by 6.22% in an economy with frequent updating compared to 11.81% in an economy with sluggish adoption.

<sup>32</sup>There is also a second effect that comes through a standard capitalisation effect. A higher  $g$  increases a firm's surplus by lowering the effective discount rate. Again, firms with a longer updating horizon will benefit more from lower discounting.

<sup>33</sup>Hence,  $z^*$  is defined as  $z^* : J(z^*, \cdot) = J^+(\cdot, \cdot) - \chi(z^*)$ .

updating economy. Using the same logic we have developed previously it is straightforward to understand the remaining figures in Table 8. In effect, these results are mostly implied by the response of the critical gap  $z^*$ . Recall that  $z^*$  determines the degree of skill obsolescence in the pool of unemployed,  $z_u$ . Hence, the more than proportional rise in  $z^*$  for late-updating economies translates into a relatively stronger increase in the degree of workers skill obsolescence  $z_u$  (see column 3 in Table 8). This pushes training costs and consequently dampens firms vacancy posting. As a result, the decline in job creation and therefore, the rise in unemployment is more severe for economies with less frequent technology updating.

Cost	$\Delta z^*$ in %p	$\Delta z_u$ in %p	$\Delta JCC$ , in %	$\Delta \frac{v}{1-u}$ , in %	u, in %
Panel I: LS					
=	+3.3	+2.1	+2.4	-9.1	4.4
4.5	+5.3	+2.8	+5.3	-17.5	4.8
6.5	+10.1	+4.8	+14.3	-37.6	6.3
Panel II: $z_{WS}^* - z_{LS}^* = 0$					
=	+3	+2.3	+2.4	-9.7	3.8
4.5	+4.4	+2.9	+5.1	-18.1	4.2
6.5	+8.6	+4.9	+13.7	-37.9	5.5
Panel III: $z_{WS}^* - z_{LS}^* = 10$					
=	+4.8	+3.8	+6.9	-20.7	6.1
4.5	+7.3	+5.2	+14.9	-35.8	7.3
6.5	+14.3	+9.4	+41.3	-62.6	11.6

$z_{WS}^* - z_{LS}^*$  - indicates the technology gap relative to the LS case, %p = change in percentage points,  $\Delta z^*$  = change in firm's critical gap, u = unemployment rate,  $\Delta \frac{v}{1-u}$  = change in vacancy/employment ratio,  $\Delta JCC$  = change in expected costs of job creation,  $\Delta z_u$  = change in average degree of unemployed skill obsolescence

Table 8: Counterfactual Analysis

## 7 Sensitivity Analysis

### The role of unemployment insurance

The existence of generous unemployment benefits is a widely used argument to explain high rates of European unemployment. It is further argued that the removal or a reduction of these would substantially contribute to an improvement in the performance of local labor markets. Evidently, cutting benefits in our model would, for sufficiently sluggish updating, definitely decrease unemployment. However, the results depicted in Table 7, show that even within a welfare state that provides generous payments, low levels of unemployment are achievable. If firms in the welfare state renovate at the same frequency as firms in the LS economy then the increase in unemployment is slightly higher than

under LS though, the unemployment rate however, levels out at relatively moderate levels. Based on these observations we may suppose that what matters for an economy's level of unemployment is primarily the rate of technology turnover or the speed with which firms adopt newly available technologies. The generosity of publicly provided unemployment insurance is rather of second order importance only. To provide further support for this hypotheses we conduct another experiment in which we vary the level of generosity of unemployment insurance. To this end we pick replacement rates of  $\phi \in \{0, 0.25\}$  and compare the outcomes with those of the benchmark<sup>34</sup>. The results of this experiment are depicted in Table 9. For matters of comparability we depict just the two extreme cost cases, i.e. the ones that yield technology gaps of 0 and 10 quarters relative to the LS economy. For the two cases (organized in Panels I and II) we report the results of each policy regime, i.e.  $\phi \in \{0, 0.25, 0.45\}$ . The second column contains the change in unemployment that occurs in response to a shocks to embodied technical change. The order of magnitude of this shock is the same as in the previous sections, i.e.  $g_{post75} = 4\%$ . Evidently, the degree of generosity of unemployment insurance (as measured by  $\phi$ ) plays a rather limited role for explaining both, the post-75 increase in unemployment and the divergence of unemployment rates across OECD countries. In the case of frequent updating (see Panel I) the response of unemployment is virtually independent of generosity of unemployment insurance (henceforth UI). In the benchmark case, i.e.  $\phi = 0.45$ , only 0.55 percentage points of the total post-75 increase in unemployment are due to the existence of UI. Panel II that depicts the results for sluggish updating suggests a slightly higher influence of benefits - 2.37 percentage points of the increase are due to UI - but a large portion of the increase remains to be primarily explained by firms technology choice. The reason why benefits have a bigger impact in the case of slow updating is intuitive. The existence of (generous) UI naturally increases the duration of unemployment, see Column 3 in Table 9. For  $z_{WS}^* - z_{LS}^* = 10$  the difference in the duration is more pronounced than in the case of  $z_{WS}^* - z_{LS}^* = 0$  since job creation is naturally lower. Or in other words the more fluid nature of the labor market in the latter case makes it less vulnerable to distortions coming from UI. A higher duration implies that unemployed workers are exposed to skill decay, that is implied by technical progress, for a longer period of time. The longer workers stay unmatched the further they drift away from the state-of-the-art, meaning that fewer of their original production knowledge can, potentially, be transferred to the next job/technology. This is reflected in Column 4 which confirms that the difference in the average degree of skill obsolescence across UI regimes is higher in Panel II. The degree of skill obsolescence in the pool of unemployed determines firms expected costs of

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<sup>34</sup>Note that the case  $\phi = 0$  is basically equivalent to a LS economy, however it differs from that in the previous section in terms of the replacement rate,  $\rho$ . In this section we keep the original parametrization of  $\phi$  for the welfare state, i.e.  $\rho = 0.0137$  and just lower  $\phi$ .

job creation, see column 5, and therefore governs vacancy posting. For the cases depicted in Panel II workers stay unemployed for a relatively longer period of time implying that they lose a higher proportion of their skills. More importantly, in this case the difference in the duration - and hence  $z_u$  - across UI regimes gets more pronounced as the UI becomes more generous. As a result, the increase in expected job creation costs for  $\phi = 0.45$  ( $\phi = 0.25$ ) is higher by 15.14 (11.54) percentage points than in the case where no UI is provided and consequently the increase in unemployment is stronger. However, this should not conceal that the overall importance of UI for explaining the post-75 increase in unemployment is rather limited. This finding is in sharp contrast to the results of Ljungqvist and Sargent (1998, 2007). In their analysis the existence of UI is the main driving force that generates high levels of unemployment in times of high economic turbulence. Notice that Ljungqvist and Sargent (1998, 2007) refer to turbulence as the instantaneous loss of a worker's human capital in the event of a job loss. If we rather interpret turbulence as the obsolescence of workers human capital during the whole spell of unemployment then we find the feature of increased turbulence also in our setup. The difference is, however, that in this paper the increased degree of turbulence stems directly from an observable change in the economic environment, i.e. the increased rate of arrival of new technologies. This is clearly a refinement of the rationale Ljungqvist and Sargent (1998, 2007) provide for increased turbulence because (a) it adds microstructure to the mechanism to the process of skill depreciation and (b) it directly relates increased human capital obsolescence to the observable acceleration in capital-embodied technical change.

$\phi$	$\Delta_u$ in %p	Duration	$z_u$	JCC	$\Delta_{JCC}$ , in %p
Panel I: $z_{WS}^* - z_{LS}^* = 0$					
0	1.45	17.46	12.99	20.35	-
0.25	1.74	20.35	13.18	20.39	0.47
0.45	2.00	23.22	13.35	20.44	0.92
Panel II: $z_{WS}^* - z_{LS}^* = 10$					
0	4.91	38.07	18.39	56.82	-
0.25	6.61	48.99	19.73	57.51	11.54
0.45	7.28	55.72	20.04	59.02	15.14

$\Delta_u$  - change in unemployment rate, %p - change in percentage points,  $z_{WS}^* - z_{LS}^*$  - indicates the technology gap relative to the LS case,  $\phi$  = Replacement rate, Duration of unemployment is in weeks,  $\Delta_{JCC}$  - change in JCC relative to case with  $\phi = 0$ , JCC = expected costs of job creation,  $z_u$  = average degree of unemployed skill obsolescence

Table 9: The Effect of Unemployment Insurance

Evidently, there is not much gain from making the UI system more stringent. Reducing the replacement rate to 25% would lower total unemployment by a mere 0.65 – 1.31 percentage points depending on the initial technology gap. More importantly, one should not overlook the dramatic increase in unemployment in an economy that provides just

minor unemployment insurance but suffers from large technology gaps. Suppose  $\phi = 0.25$  and updating occurs, on average, every 7.5 years. This would generate an unemployment rate of around 9.25% which exemplifies once again that very slack technology adoption can have serious consequences for the labor market even in economies that do not provide generous benefits.

### **The effects of capital-embodied technical change on the equilibrium**

The key factor that distinguishes the pre- and the post-75 period and drives the results in our model is the accelerated rate of arrival of new technologies. In the previous experiment we set  $g = 4\%$ , but in order to get a more complete picture we consider also growth rates of 3.5% and 4.5%. Arguably, a higher  $g$  - that creates more severe compatibility problems and consequently causes higher adoption costs - further delays the process of adoption, but the relative distance between the laissez-faire and the welfare state economy remains virtually unchanged. This is not surprising given the way we calibrated the post-75 value of the cost parameter  $\mu$ <sup>35</sup>. The effects of a high  $g$  on the average duration and the rate of unemployed are dramatic. This is best reflected by Figure 4 that plots post-75 unemployment rates for  $g = 3.5\%$  and 4.5% respectively. An important observation we can make is that economies in which firms update rather frequently are least affected by high rates of arrival of new technologies. The difference in unemployment rates for  $g = 3.5\%$  and  $g = 4.5\%$  are comparatively small. However, this gap widens quickly as we move to the right that is as we lower the frequency of updating. The underlying intuition behind this pattern is as follows. A rise in  $g$  that is accompanied by an increase in adoption costs triggers two effects that are reinforcing each other. Higher costs slow down the process of updating, consequently workers will be operating a certain technology for a longer time. This implies that when becoming unemployed their individual distance to the frontier will, on average, be bigger than it would be under a lower  $g$ . As a consequence, the training costs that are required to update a workers skills in case of a re-match will be higher, which in turn discourages firms of opening up new vacancies and hence it increases unemployment. Moreover, a high  $g$  means that the individual technology gap for already unemployed workers is widening at a faster rate which again causes higher training costs and therefore discourages job creation.

### **Do skills matter? The effects on wages and unemployment**

The purpose of this section is to analyze to what extent the accumulation of job/technology specific skills affects the outcomes presented in the previous sections. To this end we first

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<sup>35</sup>Recall that the post-75 value of  $\mu$  is chosen so that relative increase in updating costs is the same for the WS and the LS economy.



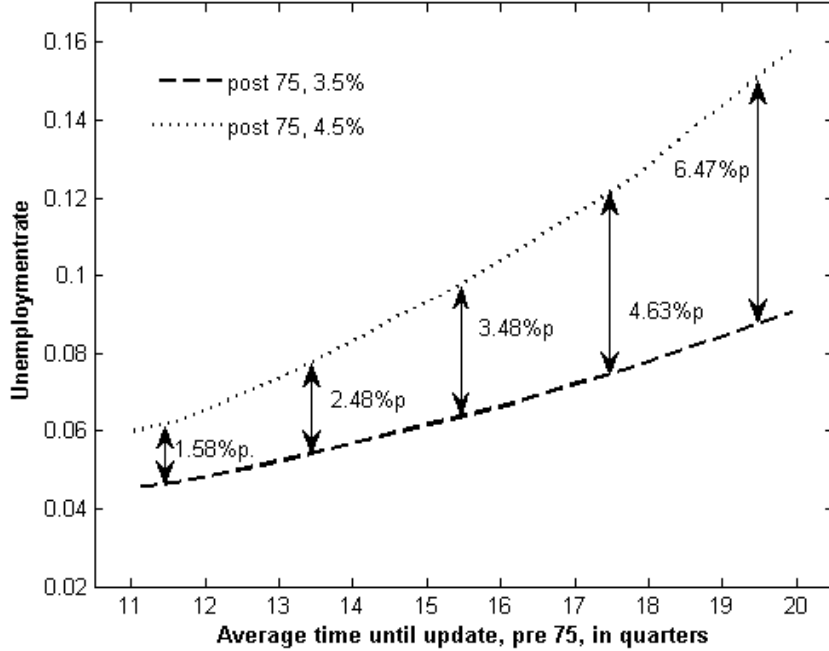


Figure 4: Unemployment for  $g = 3.5\%$  and  $4.5\%$

try to get a better understanding of how specific skills interact with firm's technology choice and potentially affect the model's steady state. Sluggish technology updating implies that workers operate a certain technology for a relatively long period of time, hence they accumulate a substantial amount of specific skills. In the benchmark case presented in Section 6 the average skill level is up to 21% higher in an economy that updates less frequently. The amount of accumulated skills determines an individual's wage and also her unemployment benefits. Thus a high degree of specialization implies that displaced workers with high tenure have a valuable outside option which strengthens their bargaining power when getting re-matched. To compensate firms for the implied loss in surplus they would experience *ceteris paribus*, labor market tightness  $\theta$  has to adjust in a way so that firms can fully recover the expected cost of creating new jobs. As a result, the vacancy finding rate declines which raises the average duration of unemployment.

However, there is another effect that suggests a negative relative-wage/tenure relation and therefore potentially counteracts the first effect. When firms update rather frequently, they operate technologies that are more productive. Higher productivity translates into higher wages and therefore fast-updating/high-productivity firms are expected to pay higher wages<sup>36</sup>. Which of these two effects dominates is a quantitative question and will

<sup>36</sup>Put differently, wages in fast-updating economies are high because workers operate technologies that are, on average, very productive, whereas wages in slow-updating economies are high because workers have accumulated a lot of skills that make them more productive.

depend on the speed and the scope of technology learning. If workers accumulate specific skills rather rapidly then the productivity enhancing effect might initially offset the negative effect that is induced by shifts in the technology frontier. However, the scope for technology learning is bounded. Consequently, after a certain amount of time the negative effect stemming from a widening technology gap will dominate implying that the within-firm wage will grow slower than the wage payed at the frontier. Under the baseline calibration, the effects of technology learning on the accumulation of skills, wages and the unemployment rate are rather modest. This is implied by the fact that (1) the scope for technology learning is rather limited and (2) the speed of learning is relatively slow. On average, agents tap the full potential of a technology only after 10 years, which, given (1) a separation rate of  $\rho = 0.0137$  and (2) technology updates that occur, on average, every 4.75 – 8.25 years will happen very rarely. Moreover, the progress ratio, that is the ratio of initial to peak productivity is 1.2. This means that advances in productivity induced by technology learning amount to 20% at most. This value lies in the range 1.14 – 2.9 of possible progress ratios reported by Jovanovic and Nyarko (1995) but to get a more complete picture and to better assess the effects of learning on wages and unemployment we consider alternative learning scenarios in this section. In the baseline model we find that net wages in the economy with frequent technology updates are, on average, 11.8% higher than wages in the economy with low technology turnover<sup>37</sup>. This is not surprising given the light effect of skills on wages. The relatively higher wage stems from the fact that workers in an economy with frequent updating operate technologies that are closer to the frontier and are, therefore more productive. In order to isolate the net effect of skills on wages (henceforth called "skill effect") we first compute the wages that would be payed in an economy in which no learning occurs. In this way we are able to identify the relative difference in wages that is solely due to the different vintages that are in place (this effect we call the "vintage effect"). We find that the vintage effect accounts for 15.46% of the wage differential between in/frequent updating economies. We next reintroduce technology learning according to the baseline calibration and we find that the wage differential shrinks to 11.8%. In an economy that updates rather infrequently technologies are kept longer in operation. Hence workers accumulate more skills which translates into higher wages. Given only the skill effect, wages in late-updating economies would be, on average, 3.57% higher than the average wage in fast-updating economies. This is rather modest. Increasing the speed of learning does not change much. If we increase the speed with which skills are accumulated so that the full potential is reached, on average, after 5 (2.5) years the skill effect amounts to a wage differential of 4.41% (4.7%). However,

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<sup>37</sup>Notice that we refer to an economy that provides unemployment insurance according to the baseline calibration.

the picture changes substantially when we consider higher values of the progress ratio, i.e. when we increase the scope of learning. When we set the progress ratio to 1.5 and consider 10, 5 and 2.5 years of learning we get that the skill effect amounts to 8.33%, 10.65% and 11.4% respectively. More and faster learning therefore leads to higher wages. In an economy that provides unemployment insurance one would expect higher wages causing higher unemployment. This is not the case in our model, though. Comparing two otherwise identical economies that differ just with respect to the speed or the scope of technology learning we see that unemployment will always be lower in the fast-learning economy. This is intuitive. Technology learning implies that workers can raise a plant's level of productivity at no cost. Consequently, firms exhibit a higher average productivity in economies that feature learning. This implies further that the value of a job for a firm will be higher which is expected to stimulate job creation. This feature is also generated in our model. In the baseline scenario average workers productivity exceeds that of an otherwise identical economy that features no technology learning by 14.3%, as a result job creation is higher by 19.18% and the unemployment rate is lower by 1.73 percentage points<sup>38</sup>. If we increase the speed or the scope of learning these effects clearly become more pronounced. The conclusion we can draw is the following. The more workers can learn about a certain technology, i.e. the more they can raise its productivity above its initial level, the higher will be the value of a job for a firm and hence, the more profitable it will be creating new jobs.

## 8 Conclusion

The aim of this paper is to provide a proper understanding of the linkages between an economy's technology adoption behavior, labor market institutions and the dynamics of unemployment. To this end, a labor market matching model was constructed that has been augmented by an endogenous technology choice by firms and a skill accumulation technology for workers. The outcomes of this model suggest that the frequency of technology updates in an economy is a key determinant of the performance of the local labor market. Moreover, the divergence of unemployment rates between major European countries and the U.S. can be understood taking account for the different speed of technology adoption across both countries. The analysis suggests that the acceleration in capital-embodied technical change in the mid-1970s is the main driving force of the divergence of unemployment rates across countries. Furthermore, the results of the paper reject the

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<sup>38</sup>These numbers result from the scenario with sluggish updating. In an economy that updated at the frequency of the benchmark LS economy the corresponding figures would be as follows: the average productivity and job creation would be, respectively, by 13.45% and 7.19% higher, and unemployment would be lower by 0.35 percentage points.

popular but highly controversial hypotheses that generous unemployment benefits are the main reason for high unemployment in Europe. The analysis reveals that even in welfare-state economies that provide generous benefits, low rates of unemployment can be achieved by keeping the frequency of technology updates sufficiently high. This results suggests that after a shock to embodied technical change economies that are lagging behind in the adoption and implementation of new technologies experience a significant deterioration in their labor market performance irrespective of the generosity of the benefit system. There is an evident policy implication coming out of this conclusion. Rather than thinking about cutting back unemployment benefits - which might create large losses in welfare - policymakers should rather create conditions that prevent the emergence of a technology deficit. The evidence presented in Section 2 hinted strongly toward a negative correlation between the strictness of product market regulations and investment in new technologies. Therefore, the removal or the relaxation of burdensome regulatory practices appears to be a natural measure to stimulate rapid diffusion of new technologies by lowering adoption costs. Equally important would be subsidizing the training of unemployed people, for instance, by providing state-financed unemployment training. This measure would certainly prevent the obsolescence of unemployed workers production knowledge. Hence it would facilitates their re-integration into the labor market since it makes it less costly for firms to hire (and train) workers<sup>39</sup>.

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<sup>39</sup>If, however, state-financed training is a substitute for the training provided by firms it could potentially create moral hazard on the firm's side.

## References

- [1] Argotte, L. and Epple, D., Learning curves in manufacturing, *Science* 247, pp. 920-924.
- [2] Bahk, B.-H. and Gort, M., 1993, Decomposing Learnings by Doing in New Plants, *Journal of Political Economy*, 101 (4), pp. 561 - 583.
- [3] Baily, M.N., Hulten, C. and Campbell, D., 1992, The Distribution of Productivity in Manufacturing Plants, *Brookings Papers: Microeconomics*.
- [4] Bartelsman, E. and Drymes, P., 1998, Productivity Dynamics: U.S. manufacturing plants 1972-1986, *Journal of Productivity Analysis* 1, 5-33.
- [5] Bessen, J., 2002, Technology Adoption Costs and Productivity Growth: The Transition to Information Technology, *Review of Economic Dynamics*, Vol. 5(2), pp. 443-469.
- [6] Blanchard, O. and Wolfers, J., 2000, The Role of Shocks and Institutions in the Rise of European Unemployment: The Aggregate Evidence, *Economic Journal*, 110.
- [7] Blanchard, O., 2005, European Unemployment: The Evolution of Facts and Ideas, *NBER Working Paper* 11750.
- [8] Bentolila, S. and Bertola, G., 1990, Firing Costs and Labour Demand: How Bad Is Eurosclerosis?, *Review of Economic Studies*, Vol. 57(3), pp. 381-402.
- [9] Cochran, E.B., 1960, New concepts of the learning curve, *J. Industrial Eng.*, 11, pp. 317 - 327.
- [10] Colecchia, A. and Schreyer, P., 2002, The Contribution of Information and Communication Technologies to Economic Growth in Nine OECD countries, *OECD Economic Studies*.
- [11] Cummins, J.G. and Violante, G.L., 2002, Investment-specific technical change in the U.S. (1947-2000): measurement and macroeconomic consequences, *Review of Economic Dynamics*, 5, pp. 243 - 284.
- [12] Daveri, F., 2002, The New Economy in Europe (1992-2001), *Gasparini Institute for Economic Research Working Paper* No. 213.
- [13] den Haan, W., Haefke, C. and Ramey, G., 2005, Turbulence And Unemployment In A Job Matching Model, *Journal of the European Economic Association*, 3(6), pp. 1360-1385.

- [14] Dunne, T., 1994, Plant Age and Technology Use in U.S. Manufacturing Industries, *The Rand Journal of Economics* 25(3), 488-499.
- [15] Farber, H.S. The Incidence and Costs of Job Loss: 1982-1991, 1993, *Brookings Papers on Economic Activity: Microeconomics*.
- [16] Farber, H. S., 1999, Mobility and Stability: The Dynamics of Job Change in Labor Markets, in Ashenfelter, O. and Card, D, (eds), *Handbook of Labor Economics*, Vol.3, pp. 2439-2483
- [17] Felbermayr, G. and Pratt, J., 2007, Product Market Regulation, Firm Selection and Unemployment, University of Vienna, Working Paper.
- [18] Garg, A. and Milliman, P., 1961, The aircraft progress curve - Modified for design changes, *J Industrial Eng.*, 12, pp. 23-27.
- [19] Gordon, R.J., 1990, *The Measurement of Durable Good Prices*, NBER Monograph Series, University of Chicago Press.
- [20] Greenwood, J. and Yorukoglu, M., 1997, 1974, *Carnegie-Rochester Conference Series on Public Policy* 46, pp. 49-95.
- [21] Greenwood, J., Hercowitz, Z. and Krusell, P., 1997, Long-Run Implications of Investment-Specific Technological Change, *American Economic Review*, 87(3), pp. 342-62.
- [22] Gust, C. J. and Marquez, J., 2002, *International Comparisons of Productivity Growth: The Role of Information Technology and Regulatory Practices*, FRB International Finance Discussion Paper No. 727.
- [23] Hornstein, A. and Krusell, P., 1996, Can Technology Improvements Cause Productivity Slowdowns?, *NBER Macroeconomics Annual 1996*, Cambridge MA: MIT Press (1996), 209-59.
- [24] Hornstein, A., Krusell, P and Violante, G., 2007, Technology-Policy Interaction in Frictional Labor-Markets, *Review of Economic Studies*, 74(4), pp. 1089-1124.
- [25] Jacobson, L., LaLonde, R. and Sullivan, D., 1993, Earnings Losses of Displaced Workers, *American Economic Review*, 83, pp. 685 - 709.
- [26] Jensen, J.B., McGuckin, R.H. and Stiroh, K.J., 2001, The Impact of Vintage and Survival on Productivity: Evidence from Cohorts of U.S. Manufacturing Plants, *The Review of Economics and Statistics*, 83 (2), pp. 323-332

- [27] Jerzmanowski, M., 2007, TFP difference: Appropriate Technology vs. Efficiency, *European Economic Review*, forthcoming.
- [28] Jorgenson, D. W. and Stiroh, K. J., 2000, Raising the Speed Limit: U.S. Economic Growth in the Information Age, *OECD Economics Department Working Papers* 261.
- [29] Jovanovic, B. and Nyarko, Y., 1995, A Bayesian learning model fitted to a variety of empirical learning curves, *Brooking Papers on Economic Activity: Microeconomics*, pp. 247 - 305.
- [30] Klenow, P. J., 1998, Learning Curves and the Cyclical Behavior of Manufacturing Industries, *Review of Economic Dynamics* Vol. 1(2), pp. 531-550.
- [31] Ljungqvist, L. and Sargent, T.J., 1998, The European Unemployment Dilemma, *Journal of Political Economy* 106(3).
- [32] Ljungqvist, L. and Sargent, T.J., 2002, The European Employment Experience, *CEPR Discussion Paper No. 3543*.
- [33] Ljungqvist, L. and Sargent, T.J., 2007, Understanding European unemployment with matching and search-island models, *Journal of Monetary Economics*, 54 (8), pp. 2139-2179.
- [34] Machin, S. and Manning, A., 1999, The Causes and Consequences of Longterm Unemployment in Europe, *Handbook of Labor Economics* (ed. Ashenfelter, O. and Card, D.), Vol 3, ch. 47.
- [35] McGuckin, R.H. and van Ark, B., 2001, Making the Most of the Information Age: Productivity and Structural Reform in the New Economy, *Perspectives on a Global Economy*, Report, 1301-01-RR.
- [36] McGuckin, R.H., Spiegelman, M. and van Ark, B., 2005, The Retail Revolution: Can Europe Match the U.S. Productivity Performance?, *Perspectives on a Global Economy*, The Conference Board: New York.
- [37] Marimon, R. and Zilibotti, F., 1999, Unemployment versus Mismatch of Talents: Reconsidering Unemployment Benefits, *Economic Journal*, 109, pp. 266-91.
- [38] Mortensen, D. and Pissarides, C., 1998, Technological Progress, Job Creation and Job Destruction, *Review of Economic Dynamics*, 1(4), pp. 733-53.
- [39] Mortensen, D. and Pissarides, C., 1999, Unemployment Responses to Skill-Biased Technology Shocks: The Role of Labor Market Policy, *Economic Journal*, 109(455), pp. 242-65.

- [40] Nickell, S., Nunziata, L. and Ochel, W., 2005, Unemployment in the OECD since the 1960s. What do we know?, *The Economic Journal*, 115, pp. 1-27.
- [41] Nickell, S., 2003, Labour Market Institutions and Unemployment in OECD Countries, DICE Report 1, CESifo Summer, 13-26.
- [42] Nicoletti G., Scarpetta S. and Boylaud G., 1999, Summary Indicators of Product Market Regulation with an Extension to Employment Protection Legislation, OECD Working Paper 226.
- [43] Nicoletti G. and Scarpetta S., 2003, Regulation, productivity and growth: OECD evidence, *Economic Policy* 18(36), pp. 9-72.
- [44] Oliner, S. D. and Sichel, D. E., 2000, The resurgence of growth in the late 1990s: is information technology the story?, Federal Reserve Bank of San Francisco.
- [45] Oswald, A., 1997, The missing piece of the unemployment puzzle, Inaugural Lecture, University of Warwick, November.
- [46] Pakko, M. R., 2002, The high-tech investment boom and economic growth in the 1990s: accounting for quality, Federal Reserve Bank of St. Louis, issue Mar., pages 3-18.
- [47] Pegels, C.C., 1969, On startup or learning curves: An expanded view, *AIIE Trans. Eng. Manag.*, 1, pp. 216-223.
- [48] Russell, J.H., 1968, Progress function models and their deviations. *J. Industrial Eng.*, 19, pp. 5-11.
- [49] Scarpetta, S., Bassanini, A., Pilat, D. and Schreyer, P., 2000, Economic Growth in the OECD Area: Recent Trends and the Aggregate and Sectoral Level, OECD Economics Department Working Papers, No. 248.
- [50] Schreyer, P., 2000, The Contribution of Information and Communication Technology to Output Growth: A Study of the G7 Countries, STI Working Paper, 2000/2.
- [51] Timmer, M., Ypma, G. and van Ark, B., 2003, IT in the European Union: Driving Productivity Divergence?, Groningen Growth and Development Centre, Research Memorandum GD-67.
- [52] van Ark, B., Inklaar, R. and McGuckin, R., 2002, Groningen Growth and Development Centre, Research Memorandum GD-60.



- [53] van Ours, J. and Ridder, G., 1992, Vacancies and the Recruitment of New Employees, *Journal of Labor Economics*, Vol. 10(2), pp. 138-55.
- [54] Yelle, L.E., 1979, The learning curve: Historical review and comprehensive survey, *Decision Sci.*, 10, pp. 302-328.
- [55] Yorukoglu, M., 1998, The Information Technology Productivity Paradox, *Review of Economic Dynamics*, Vol. 1(2), pp. 551-592.