

# Loss of Skill During Unemployment and TFP Differences Across Countries

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## Abstract

In an economy with search and matching frictions in which workers lose human capital during unemployment, TFP becomes endogenous and depends on workers' unemployment history. Using available estimates of labor market flows for a sample of OECD countries, this paper quantifies the amount of TFP differences due to skill losses during unemployment among developed countries. Continental European countries, with their low job finding rates, exhibit the lowest TFPs. Nordic countries display the highest levels of TFP due to their high job finding rate relative to the separation rate. TFP in Anglo-Saxon countries stands in-between the two groups. The paper further studies the effect of hiring subsidies on TFP and the labor market. Because TFP changes depend on the vacancy posting decision of firms, countries with the lowest TFP do not necessarily experience the largest productivity improvements from the policy implementation.

*JEL Classification:* E24.

*Keywords:* Search and matching; unemployment; endogenous TFP; loss of skills; unemployment history.

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# 1. Introduction

There is abundant evidence in the labor literature on the negative effects of unemployment on workers' wages. Workers separated from their jobs suffer large productivity losses compared to non-separated workers.<sup>1</sup> At the aggregate level this implies that, other things equal, an economy in which workers experience long and frequent unemployment spells is less productive than an economy in which workers' unemployment spells are shorter and less frequent. Since the number and duration of unemployment spells are determined by how quickly workers find and lose jobs, an economy's productivity is partly determined by its labor market flows. Using empirical evidence on labor market flows for a sample of developed countries, this paper investigates to what extent observed TFP differences can be accounted for by search frictions in the labor market and the associated skill losses during unemployment. Alternatively, the paper asks the question: if labor market flows in a rigid market such as Spain, were instead similar to labor market flows in a more dynamic economy such as the US, how much would its productivity improve?

The paper develops a Diamond-Mortensen-Pissarides (DMP henceforth) search and matching framework in which workers lose some human capital during unemployment.<sup>2</sup> In the model TFP is endogenous and depends on overall efficiency in the economy and the average human capital. In a dynamic labor market workers find jobs very quickly and lose them infrequently, so workers experience short unemployment durations and small human capital losses due to unemployment. As a result, human capital depends on workers' unemployment history—the cumulative duration of their unemployment spells. Since workers' unemployment history is determined by how quickly they find jobs and how frequently jobs are destroyed, the endogenous TFP is lower in economies with low job finding rates and high separation rates, other things equal.

The paper shows how the economy's average human capital and endogenous TFP depend on labor market flows and the amount of human capital depreciation during unemployment. Many of the countries considered in the paper have different labor market distortions, such as income taxes, firing taxes and subsidies, and may have different matching efficiencies and vacancy costs. However, TFP in the model depends uniquely on labor market flows and the rate at which skills depreciate, regardless of the exact mechanism behind labor market flows. Therefore, the endogenous TFP has a “sufficient” statistic property, in the sense that one can measure TFP differences among countries by looking at observed labor market flows, without having to model or calibrate the underlying distortions or frictions in detail.<sup>3</sup>

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<sup>1</sup>Fallick (1996) and Kletzer (1998) review some of the findings in the early job displacement literature. See the references in Couch and Placzek (2010) for more recent results. An incomplete list of this big literature includes: Couch and Placzek (2010), Davis and von Wachter (2011), Jacobson, LaLonde, and Sullivan (1993), Jarosch (2015), von Wachter, Song, and Manchester (2009), which use administrative data; Ruhm (1991), Stevens (1997), which use the Panel Study of Income Dynamics (PSID); Addison and Portugal (1989), Carrington (1993), Farber (1997), Neal (1995) and Topel (1990) which use the Displaced Worker Survey (DWS) supplement of the Current Population Survey (CPS). Relatedly, Edin and Gustavsson (2008) use Swedish data on test scores that assess respondents' quantitative and analytical skills, and find that one full year of non-employment is associated with a loss of the equivalent of 0.7 years of schooling—even though most of the respondents are low skill workers.

<sup>2</sup>See Pissarides (2000) for a textbook treatment of the DMP framework.

<sup>3</sup>This is similar to Hornstein, Krusell, and Violante (2011), where wage dispersion is measured directly by looking at labor market flows, independently of the exact mechanism that generates the wage distribution. The model of TFP in Lagos (2006) exhibits a similar property, the reservation productivity uniquely determines TFP.

In order to quantify TFP differences due to human capital depreciation, I focus on a sample of OECD countries for which empirical estimates of labor market flows exist. The paper draws from the empirical findings in Elsby, Hobijn, and Şahin (2013), who use a similar approach to Shimer (2005) and Shimer (2012) to estimate the job finding and separation rates in Australia, Canada, France, Germany, Ireland, Italy, New Zealand, Norway, Portugal, Spain, Sweden, United Kingdom and United States. Although this group consists of developed countries that may seem homogenous along a number of measures, as Elsby et al. (2013) show, the unemployment rate and labor market flows vary considerably among these countries. Anglo-Saxon and Nordic countries have high job finding and separation rates, whereas in continental Europe both rates are much lower. To calibrate the human capital depreciation rate during unemployment, the paper uses estimates from the Panel Study of Income Dynamics (PSID) in Ortego-Martí (2016b). The PSID estimation shows that an additional month of unemployment history is associated with a 1.22% wage loss, which is comparable to other estimates from the job displacement literature.<sup>4</sup>

To measure the amount of TFP variation due to unemployment history the paper considers the following two exercises. First, assuming the same overall efficiency level across countries and that countries differ only in their labor market flows, I calculate the implied endogenous TFP. There is substantial variation across countries, and as in Elsby et al. (2013) there is a natural partition between continental European, Anglo-Saxon and Nordic countries. The highest TFP corresponds to Norway, with a value that is 5.1% larger than in the US. Although Norway does not have the highest job finding rate (which would reduce unemployment duration and lower human capital losses), its separation rate is extremely low, meaning that workers experience very few unemployment spells. At the other end of the spectrum Spain has the lowest TFP, which is not surprising given its high unemployment rate and sclerotic labor market. Spain's endogenous TFP is around 12% lower than in the US. To get a sense of how big these TFP differences are, as in Caselli (2005) I compare the variance of the model's endogenous TFPs to the variance of observed TFPs, using TFP measures from the Penn World Table (PWT) 9.0.<sup>5</sup> Around 17% of the variance in TFP can be explained by differences in human capital due to skill losses.<sup>6</sup>

Secondly, using observed TFP from the PWT 9.0, the paper asks the question: how much would each country's TFP change if labor market flows were the same as in the US? Not surprisingly, continental European countries have the largest predicted productivity gains, ranging from a 4.8% increase in Portugal to 13.5% in Spain. Anglo-Saxon countries would see smaller gains, with an average gain of 3.8%. On the other hand, Nordic countries would see productivity losses. Even though the job finding rate is higher in the US, the separation rate in Nordic countries is relatively much smaller. The losses range from 4.5% in Sweden to 5.1% in Norway.

Finally, the paper analyzes the impact of a hiring subsidy on TFP. This policy has a positive impact on the labor market and stimulates job creation. Even though the country that would benefit the most from this policy is Spain, the analysis shows that it is not always true that countries with the lowest TFPs benefit the most from the policy. This happens because the impact of a hiring subsidy depends on several factors: the separation rate, the job finding rate,

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<sup>4</sup>Addison and Portugal (1989) find a monthly depreciation rate of 1.44% and Neal (1995) finds a monthly rate of 1.59%.

<sup>5</sup>See Feenstra, Inklaar, and Timmer (2015) for details on the PWT 9.0.

<sup>6</sup>Other measures give larger values. The model explains around 45% of the observed mean absolute deviation and 89% of the observed 90-10 percentile ratio.

the ratio of the two—which determines the distribution of human capital—and the effect on labor market tightness—which determines the increase in the job finding rate and captures firms’ vacancy posting decision. Countries that have a bigger change in the job finding-separation rates ratio experience the highest TFP gains after the policy implementation.

**Related literature.** This paper is most closely related to Lagos (2006) and Petrosky-Nadeau (2013). Lagos (2006) introduces a model of TFP in a frictional labor market à la Mortensen and Pissarides (1994) and studies the effect of labor market policies on TFP. Petrosky-Nadeau (2013) studies TFP in a model with frictional labor and credit markets to explain the surge of TFP during the Great Recession despite a sharp decline in output and employment. As in these papers, I adopt a search and matching approach to the labor market which leads to an endogenous TFP. However, this paper focuses on the loss of skill during unemployment and provides a quantitative cross-country comparison. The paper is also broadly related to the vast literature on development accounting that aims to explain TFP variation across countries, especially to those studies that use the calibration approach. The literature is summarized in Caselli (2005), and includes among others Bils and Klenow (2000), Hall and Jones (1999), Klenow and Rodriguez-Clare (1997a) and (1997b), Lagakos (2016), Prescott (1998) and Restuccia, Yang, and Zhu (2008). However, none of these papers look at a frictional labor market or human capital losses due to unemployment.<sup>7</sup>

There is substantial empirical evidence on the effects of unemployment on workers’ wages. The job displacement literature finds large and very persistent earning losses among displaced workers.<sup>8</sup> To estimate the causal effect of job displacement on wages, this literature deals with the endogeneity of separations by focusing on plant closing and mass-layoffs. Papers in this literature focus on a subset of workers who are very attached to their job or sector—for example, they only consider worker with a minimum tenure at a job. With the exception of Addison and Portugal (1989) and Neal (1995), most papers in this literature do not have information on unemployment duration and therefore can not provide an estimate of how wage losses depend on duration, which is key for the model. Therefore, this paper draws from the empirical evidence in Ortego-Martí (2016b) on the effects of unemployment history on workers’ wages in the PSID.<sup>9</sup>

This paper is also related to a literature that combines search frictions with human capital depreciation during unemployment. Two important references in this literature are Ljungqvist and Sargent (1998) and Pissarides (1992). In Pissarides (1992) unemployment becomes more persistent when unemployed workers lose skills during unemployment. Ljungqvist and Sargent

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<sup>7</sup>Similar to Lagos (2006), this paper focuses on developed countries, which are more homogenous, and does not aim to explain TFP differences among all countries in the world. TFP differences are extremely large among all countries—some countries are 30 times less productive than others. Although productivity differences are smaller among developed countries, they are still present and significant.

<sup>8</sup>See footnote 1 for a list of references in the job displacement literature.

<sup>9</sup>See section 3.2 and footnote 1 for a list of references in the job displacement literature. Starting with Mincer and Polachek (1974) and Mincer and Ofek (1982), the literature on the effects of motherhood on women’s earnings also find evidence of human capital depreciation during employment breaks. See Beblo, Bender, and Wolf (2008) and Gangl and Ziefle (2009) and the references therein for more recent results. Further evidence on human capital decay due to breaks in production are found in the provision of health services—David and Brachet (2011), Hockenberry, Lien, and Chou (2008) and Hockenberry and Helmchen (2014)—, and even in jobs involving routine tasks such as data entry—Globerson, Levin, and Shtub (1989)—, mechanical assembly—Bailey (1989)—and car radio production—Shafer, Nembhard, and Uzumeri (2001). This literature also finds that worker productivity depreciation increases with the temporal distance between tasks.

(1998) offer an explanation for the high levels of unemployment in Europe compared to the US.<sup>10</sup> However, papers in this literature do not quantify the fraction of TFP differences due to loss of skills during unemployment.

## 2. A model of endogenous TFP

Consider the following labor market with search and matching frictions. Time is continuous. There are two agents in the economy, workers and firms. They are infinitely-lived and discount future income at a rate  $r > 0$ . For simplicity, normalize the population size to one. It takes time for workers to find jobs and for firms to find applicants. To attract workers, firms post vacancies at a flow cost  $c$ . The number of matches formed is given by a matching function  $m(u, v)$ , where  $u$  and  $v$  denote the number of unemployed and employed workers. Assume that the matching function is concave, increasing in both its arguments and displays constant returns to scale. Given these assumptions, workers find jobs at a Poisson rate  $f(\theta) = m(1, \theta)$  and firms fill their vacancies at a Poisson rate  $q(\theta) = m(\theta^{-1}, 1)$ , where  $\theta$  denotes labor market tightness and is equal to the vacancy-unemployment ratio  $v/u$ . The properties of the matching function imply that  $f(\theta) = \theta q(\theta)$ . The job finding rate is increasing in  $\theta$ , i.e.  $f'(\theta) > 0$ , since higher market tightness implies vacancies are more abundant relative to job seekers, so workers find jobs more quickly. Because of frictions in the labor market, some jobs are destroyed. Assume that separations occur exogenously at a Poisson rate  $s$ .

Given the focus of the paper on TFP differences due to loss of skills during unemployment, human capital in the model is net of other determinants of human capital such as education. As a result, human capital in the model is determined by workers' unemployment history.<sup>11</sup> Workers lose human capital during unemployment at a constant rate  $\delta$ . Longer unemployment spells lead to larger human capital losses, so a worker's human capital depends on her complete history of unemployment spells. Let  $\gamma$  denote unemployment history, i.e. the cumulative duration of a worker's unemployment spells. For a given unemployment history  $\gamma$ , human capital is given by  $h(\gamma)$ . Normalizing  $h(0) = 1$ , a constant human capital depreciation rate during unemployment implies that  $h(\gamma) = e^{-\delta\gamma}$ . The empirical evidence from the PSID in section 3 shows that the assumption that human capital depends on workers' unemployment history and that human capital losses are persistent are well supported by data. Pissarides (1992), Ljungqvist and Sargent (1998), Pavoni and Violante (2007) and Pavoni (2011), among others, make similar assumptions.<sup>12</sup>

The baseline model in this section does not include human capital accumulation during employment. However, the appendix includes an extension of this model with returns to experience, and shows that the results are essentially the same as in the model with unemployment history alone. The intuition is the following. With two employment states, employment and unemployment, workers either accumulate unemployment history or employment history. As

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<sup>10</sup>See also den Haan, Ramey, and Watson (2000), den Haan, Haefke, and Ramey (2005), and Ljungqvist and Sargent (2007) and (2008). Ortego-Martí (2016a) shows that skill losses matter for labor market fluctuations and that fluctuations are larger when workers lose skills during unemployment.

<sup>11</sup>See Caselli (2005) and the references therein for studies that focus on TFP differences due to the quality of human capital and other determinants of human capital, such as years of schooling. These sources of TFP differences are important, but not the focus of the paper.

<sup>12</sup>This model does not consider the life-cycle. As the empirical section 3 shows, human capital losses are similar across age groups, so the quantitative results from the model would be unchanged if one introduced the life-cycle. This is consistent with evidence from the job displacement literature. See section 3 for details.

a result, whenever unemployment history is high, employment history is low. For given labor market flows  $f(\theta)$  and  $s$ , unemployment and employment histories are the same with or without returns to experience (they are determined by labor market flows). In both models TFP differences come from the fact that unemployed workers have different human capital dynamics than employed workers. Whether the difference between the human capital of an unemployed and an employed worker is due to loss of skills alone, or the fact that the employed worker is also accumulating skills, does not affect the results—so long as the *effective* depreciation rate is the same in both models, which must be the case to be consistent with the empirical evidence. See the appendix for details.

There is an overall labor efficiency to all matches in the economy, which I denote  $p$ . Labor productivity is further determined by workers' human capital. The productivity of a match is denoted  $y$  and is given by the product of the economy's overall efficiency  $p$  and the worker's human capital  $h(\gamma)$ , i.e.

$$y = h(\gamma)p. \quad (1)$$

Employed workers earn wages  $w(\gamma)$  and unemployed workers receive flow payments  $b$ , where  $b$  is the value of non-market activities and includes unemployment benefits, home production and leisure.

Workers are identical when they join the labor market for the first time and their unemployment history  $\gamma$  is 0. However, due to search frictions they find and lose jobs at random and as a result they accumulate different unemployment histories. Let  $G^E(\gamma)$  and  $G^U(\gamma)$  denote the endogenous distribution of unemployment histories among employed and unemployed workers. To ensure stationarity of these distributions, assume that workers leave the labor force—or “die”—at a Poisson rate  $\psi$ . When workers leave the labor force they are replaced by new entrants with zero unemployment history.

Let  $U(\gamma)$  and  $W(\gamma)$  denote the value functions of an unemployed and employed worker with unemployment history  $\gamma$ . The Bellman equations for workers are given by

$$(r + \psi)U(\gamma) = b + f(\theta) [\max\{W(\gamma), U(\gamma)\} - U(\gamma)] + \frac{\partial U(\gamma)}{\partial \gamma}, \quad (2)$$

$$(r + \psi)W(\gamma) = w(\gamma) - s[W(\gamma) - U(\gamma)]. \quad (3)$$

The Bellman equations satisfy that the return from the assets  $U(\gamma)$  and  $W(\gamma)$  must equal the payment flows plus any change in the capital value of the assets, where the effective discount rate  $r + \psi$  takes into account that workers “die” at a rate  $\psi$ . The right-hand side of (2) captures that unemployed workers are paid income flow  $b$ . At a rate  $f(\theta)$  they receive a job offer, which yields a net capital gain of  $W(\gamma) - U(\gamma)$  if the offer is profitable (i.e. if  $W(\gamma) \geq U(\gamma)$ ). Finally, the last term accounts for the depreciation of the asset value  $U(\gamma)$  due to skill loss. Similarly, equation (3) captures that employed workers are paid wages  $w(\gamma)$  and that at a rate  $s$  they lose their jobs, which carries out a net loss of  $W(\gamma) - U(\gamma)$ .

Following Lagos (2006) and Pissarides (2000), assume that firms receive a subsidy from the government at the time a job is created and that the size of the subsidy is proportional to the job's productivity, i.e. firms receive a payment of  $\tau_h h(\gamma)p$ , with  $\tau_h$  constant.<sup>13</sup> The

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<sup>13</sup>Unemployment history is fully observed, so the productivity of a match is common knowledge. The assumption that the job creation subsidy is proportional to the productivity of the match is the same as in Lagos

appendix shows that the measure of endogenous TFP is the same when there is a richer set of distortionary policies—income taxes, employment subsidies and firing taxes—given observed labor market flows, as long as firing taxes are not too high.<sup>14</sup> For simplicity of exposition, I present the simpler case where a hiring subsidy is the only labor market policy. Let  $J(\gamma)$  and  $V$  denote the value functions of a filled job and an open vacancy. They satisfy the following Bellman equations

$$(r + \psi)J(\gamma) = h(\gamma)p - w(\gamma) - sJ(\gamma), \quad (4)$$

$$rV = -c + q(\theta) \int_0^\infty [\max\{J(\Gamma) + \tau_h h(\Gamma)p, V\} - V] dG^U(\Gamma). \quad (5)$$

The intuition is similar. From (4), a firm with a filled position receives a profit flow  $h(\gamma)p - w(\gamma)$  and at a rate  $s$  the job is destroyed, which implies a net capital loss of  $J(\gamma)$ . Similarly, the right-hand side of (5) includes the flow costs  $c$  of posting a vacancy and that at a rate  $q(\theta)$  the firm draws a worker from the pool of unemployed workers, taking into account that the distribution of job seekers' unemployment history is  $G^U(\gamma)$ . If the match is profitable the firm hires the worker and receives the hiring subsidy, which carries a net capital gain of  $J(\gamma) + \tau_h h(\Gamma)p - V$ . Assume that there is free entry in the market for vacancies, so firm entry drives the value of a vacancy to  $V = 0$ .<sup>15</sup>

Due to search frictions, matches generate rents that must be split between the firm and the worker. Assume that wages are determined by Nash Bargaining, as in Nash (1950), where  $\beta$  denotes workers' bargaining strength. Since the subsidy only applies at the time of hiring, similar to Lagos (2006) and Pissarides (2000) there are two wages: the wage  $w_0(\gamma)$  that is negotiated at the time of hiring and the continuing wage  $w(\gamma)$  that prevails after the worker is taken on.<sup>16</sup> As in Pissarides (2000), the wage  $w_0$  maximizes the Nash product

$$w_0(\gamma) = \arg \max_{w_0(\gamma)} (W_0(\gamma) - U(\gamma))^\beta (J_0(\gamma) + \tau_h h(\gamma)p - V)^{1-\beta}, \quad (6)$$

where  $W_0(\gamma)$  and  $J_0(\gamma)$  denote the value functions at the time of hiring. The above bargaining problem takes into account that at the time of signing the contract, the firm's payoff is  $J_0(\gamma)$  plus the amount of the subsidy  $\tau_h p h(\gamma)$ . Once the worker is taken on and production begins,

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(2006) and Pissarides (2000). As Pissarides (2000) points out, this would arise if the subsidy is tied to the wage. Assuming that subsidies are proportional to wages would give similar results. The reason a proportional subsidy is appealing is that it removes scale effects. If the subsidy was constant, a 1% increase in the subsidy would be a relatively larger policy in a country with lower productivity. The interpretation of the effect of the policy change across countries would thus be less clear.

<sup>14</sup>As in Pissarides (2000) and Lagos (2006), if firing taxes are too high matches are not formed. As in Lagos (2006) and Pissarides (2000), for simplicity I ignore the government's financing constraint. One can achieve a balanced budget by introducing a tax on wages and benefits while still getting an effect of subsidies on market tightness.

<sup>15</sup>One could assume that when the job is destroyed the firm recovers the value of the vacancy. In this case (4) would be given by  $(r + \psi)J(\gamma) = h(\gamma)p - w(\gamma) - s(J(\gamma) - V)$ . Given the assumption of free entry and no fixed costs, both assumptions give the same results.

<sup>16</sup>In Pissarides (2000),  $w_0$  and  $w$  are called "outside" and "inside" wages.

the continuing wage  $w(\gamma)$  solves the following bargaining problem

$$w(\gamma) = \arg \max_{w(\gamma)} (W(\gamma) - U(\gamma))^\beta (J(\gamma) - V)^{1-\beta}. \quad (7)$$

Using the free entry condition  $V = 0$ , the solution to  $w_0(\gamma)$  is given by

$$(1 - \beta)(W_0(\gamma) - U(\gamma)) = \beta(J_0(\gamma) + \tau_h h(\gamma)p). \quad (8)$$

Similarly, bargaining over the continuing wage  $w(\gamma)$  gives

$$(1 - \beta)(W(\gamma) - U(\gamma)) = \beta J(\gamma). \quad (9)$$

Let  $S_0(\gamma)$  and  $S(\gamma)$  denote the surplus at the time of job creation and the surplus once the worker is hired, i.e.  $S_0(\gamma) \equiv W_0(\gamma) - U(\gamma) + J_0(\gamma) + \tau_h h(\gamma)p - V$  and  $S(\gamma) \equiv W(\gamma) - U(\gamma) + J(\gamma) - V$ . Nash Bargaining implies that the worker is assigned a share  $\beta$  of the surplus from the match and the firm the remaining share  $1 - \beta$ , i.e.  $W_0(\gamma) - U(\gamma) = \beta S_0(\gamma)$  and  $J_0(\gamma) + \tau_h h(\gamma)p - V = (1 - \beta)S_0(\gamma)$ , and similarly  $W(\gamma) - U(\gamma) = \beta S(\gamma)$  and  $J(\gamma) - V = (1 - \beta)S(\gamma)$ .

Due to human capital decay, a match's surplus becomes zero if workers accumulate too much unemployment history. At that point, the worker collects all the output as a wage and is indifferent between market and non-market activities. The following proposition shows this result formally.

**Proposition 1.** *There exists a unique  $\bar{\gamma}$  such that*

$$(r + \psi)U(\bar{\gamma}) = b, \quad \text{and} \\ h(\bar{\gamma})p = w(\bar{\gamma})$$

The proof is included in the appendix, but the intuition is the following. Under the Nash Bargaining assumption, the firm must compensate the worker for her outside option, in this case  $U(\gamma)$ . This outside option includes the constant value of non-market time  $b$ . Because the value of output declines with unemployment history, output will be unable to cover for payments  $b$  to the worker if unemployment history is too large. When unemployment history reaches a certain level  $\bar{\gamma}$ , the value of the surplus is zero, and from (4) workers collect all the output in the form of wages, i.e.  $w(\bar{\gamma}) = h(\bar{\gamma})p$ . It follows from this result that  $J(\bar{\gamma}) = S(\bar{\gamma}) = 0$ .

Proposition 1 implies that

$$h(\bar{\gamma})p = b. \quad (10)$$

Once workers reach the terminal level  $\bar{\gamma}$ , output is used to compensate them for the value of non-market activities. In particular,  $\bar{\gamma}$  is determined by

$$\bar{\gamma} = -\frac{\log(b/p)}{\delta}. \quad (11)$$

I assume that when workers accumulate unemployment history beyond  $\bar{\gamma}$ , firms can assign them to a zero surplus position. This is similar to Pavoni and Violante (2007) and Pavoni, Setty, and Violante (2012), where workers can always be assigned to a low skill job that is not subject to human capital decay. This assumption is equivalent to assuming a lower bound for



human capital and that workers who reach this lower bound are indifferent between market and non-market activities, which is reasonable and consistent with previous studies. Given this assumption, the Bellman equation for unemployment (2) becomes

$$\begin{aligned} (r + \psi)U(\gamma) &= b + f(\theta)(W_0(\gamma) - U(\gamma)) + \frac{\partial U(\gamma)}{\partial \gamma}, \quad \forall \gamma \leq \bar{\gamma} \\ (r + \psi)U(\gamma) &= b, \quad \forall \gamma > \bar{\gamma}. \end{aligned} \quad (12)$$

Similarly, the Bellman equation for vacancies (5) becomes

$$rV = -c + q(\theta) \int_0^{\bar{\gamma}} (J_0(\Gamma) + \tau_h h(\Gamma)p) dG^U(\Gamma) + \int_{\bar{\gamma}}^{\infty} \tau_h h(\bar{\gamma})p dG^U(\Gamma), \quad (13)$$

where the last term of (13) captures that matches beyond  $\bar{\gamma}$  yield a zero surplus, so firms only collect the hiring subsidy.

## 2.1. Endogenous unemployment history distributions

This section derives the stationary distributions  $G^E(\gamma)$  and  $G^U(\gamma)$  by looking at flows in the labor market. First, consider the group of unemployed workers with unemployment history lower than a given  $\gamma$ . In steady-state the flows in and out of this group must be equal to ensure stationarity, which implies the following flow equation

$$g^U(\gamma)u + (f(\theta) + \psi)G^U(\gamma)u = sG^E(\gamma)(1 - u) + \psi. \quad (14)$$

Consider now the overall group of unemployed workers. Flows out and into this group must be equal, which gives the following flow equation

$$(f(\theta) + \psi)u = s(1 - u) + \psi, \quad (15)$$

where the left-hand side captures the flows out and the right-hand side the flows into the unemployment pool. The above equation implies that the unemployment rate  $u$  is given by

$$u = \frac{s + \psi}{s + \psi + f(\theta)}. \quad (16)$$

Finally, consider the group of employed workers with unemployment history lower than a given  $\gamma$ . The following flow equation holds

$$f(\theta)G^U(\gamma)u = (s + \psi)G^E(\gamma)(1 - u). \quad (17)$$

Substituting (16) into the above flow equation gives that  $G^U(\gamma) = G^E(\gamma)$ .<sup>17</sup> Combining this result with (14) and (16) implies the differential equation

$$g^U(\gamma) + \frac{\psi(f(\theta) + s + \psi)}{s + \psi} G^U(\gamma) = \frac{\psi(f(\theta) + s + \psi)}{s + \psi}. \quad (18)$$

The solution gives the endogenous distribution

$$G^U(\gamma) = 1 - e^{-\alpha\gamma}, \quad (19)$$

where  $\alpha \equiv \psi(f(\theta) + s + \psi)/(s + \psi) = \psi/u$ , i.e. the distribution is exponential with parameter  $\alpha$ . Using the PSID and its panel structure, one can construct workers' unemployment history, as is done in the empirical section 3, to compare the empirical distribution to the one generated by the model. Numerical simulations show that the above distribution matches very well the distribution of unemployment history in the PSID.

The distribution of unemployment history depends on the size of labor market flows  $f(\theta)$  and  $s$ , which vary across countries. When  $f(\theta)$  is high, workers find jobs quickly and do not accumulate long unemployment histories. Similarly, a high  $s$  implies that workers lose their jobs more frequently and thus accumulate longer unemployment histories. Because average human capital is determined by this distribution, the economy's productivity depends on labor market flows. In particular, just as with the unemployment rate in the DMP framework, countries with the same ratio of job finding to separation rate—and therefore the same unemployment rate—will also have the same unemployment history distribution.<sup>18</sup>

## 2.2. Equilibrium

Using the Bellman equations and the Nash Bargaining rule (8) gives wages as a function of  $U(\gamma)$

$$w_0(\gamma) = (1 - \beta)(r + \psi)U(\gamma) + \beta[1 + \tau_h(r + \psi + s)]h(\gamma)p. \quad (20)$$

Combining the Bellman equations gives the surplus

$$S_0(\gamma) = \frac{h(\gamma)p[1 + \tau_h(r + \psi + s)] - (r + \psi)U(\gamma)}{r + \psi + s} \quad (21)$$

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<sup>17</sup>That the distributions  $G^U(\gamma)$  and  $G^E(\gamma)$  are equal makes the model tractable, but empirically the two distributions are likely to be different. One can break the feature that  $G^U(\gamma) = G^E(\gamma)$  by assuming a match specific productivity, as in Ortego-Martí (2016b).

<sup>18</sup>This result is not surprising. In the DMP model, two countries with different flows will have the same unemployment rate as long as the ratio of the job finding to separation rate is the same. The same applies to the distribution of unemployment history. Intuitively, what determines how many workers are unemployed—and how long they are unemployed—is the relative “speed” of leaving and joining unemployment.

Substitute (8) and (21) into (2) and solve the differential equation to get  $U(\gamma)$

$$(r + \psi)U(\gamma) = \left[ e^{-\rho(\bar{\gamma}-\gamma)} \left( \frac{r + \psi + s - \beta f(\theta)T + \delta(\frac{r+\psi+s}{r+\psi})}{r + \psi + s + \beta f(\theta) + \delta(\frac{r+\psi+s}{r+\psi})} \right) + \frac{(r + \psi + s)(1 - e^{-\rho(\bar{\gamma}-\gamma)})}{r + \psi + s + \beta f(\theta)} \right] b \\ + \left[ \frac{\beta f(\theta)(1 + T)}{r + \psi + s + \beta f(\theta) + \delta(\frac{r+\psi+s}{r+\psi})} \right] h(\gamma)p, \quad (22)$$

where  $T$  and  $\rho$  are defined as  $T \equiv \tau_h(r + \psi + s)$  and  $\rho = r + \psi + \beta f(\theta)(r + \psi)/(r + \psi + s)$  to simplify the notation.

The Nash Bargaining rule (8), together with free entry, gives the job creation condition

$$\frac{c}{q(\theta)} = \left( \frac{1 - \beta}{r + \psi + s} \right) \Phi(f(\theta)) + \tau_h b e^{-\alpha\bar{\gamma}}, \quad (23)$$

where  $\Phi(f(\theta)) = \int_0^\infty [h(\Gamma)p(1 + T) - (r + \psi)U(\Gamma)]dG^U(\Gamma)$ . Substituting  $U(\gamma)$  from (22) and integrating yields

$$\Phi(f(\theta)) = \left( \frac{r + \psi + s + \delta(\frac{r+\psi+s}{r+\psi})}{r + \psi + s + \beta f(\theta) + \delta(\frac{r+\psi+s}{r+\psi})} \right) \left( \frac{\alpha}{\alpha + \delta} \right) (1 - e^{-(\delta+\alpha)\bar{\gamma}})p(1 + T) \\ - \left( \frac{r + \psi + s - \beta f(\theta)T + \delta(\frac{r+\psi+s}{r+\psi})}{r + \psi + s + \beta f(\theta) + \delta(\frac{r+\psi+s}{r+\psi})} \right) \left( \frac{\alpha}{\rho - \alpha} \right) (e^{-\alpha\bar{\gamma}} - e^{-\rho\bar{\gamma}})b \\ - \left( \frac{r + \psi + s}{r + \psi + s + \beta f(\theta)} \right) \left[ 1 - e^{-\alpha\bar{\gamma}} - \left( \frac{\alpha}{\rho - \alpha} \right) (e^{-\alpha\bar{\gamma}} - e^{-\rho\bar{\gamma}}) \right] b. \quad (24)$$

The job creation condition has some intuitive interpretation. Firms post vacancies until the expected cost—the left-hand side, which corresponds to the flow cost  $c$  times the expected vacancy duration  $1/q(\theta)$ —equals expected future profits from hiring a worker. The job creation condition (23) gives the equilibrium labor market tightness  $\theta$ . Although it is somewhat cumbersome, it can be easily solved numerically. In particular, a convenient feature is that the right-hand side depends on  $\theta$  only through the job finding rate  $f(\theta)$ .

### 2.3. Total Factor Productivity

The economy's TFP is endogenous and depends on the average human capital. When  $\gamma \leq \bar{\gamma}$  a worker's productivity is given by  $y = h(\gamma)p$ , i.e. the product of her human capital  $h(\gamma)$  and the overall efficiency in the economy  $p$ . Given the assumption of a lower bound for human capital, labor productivity satisfies  $h(\gamma)p = h(\bar{\gamma})p = b$  when  $\gamma > \bar{\gamma}$ . Let  $\bar{y}$  denote the economy's TFP. Using the distribution  $G^U(\gamma)$  derived in section 2.1 and integrating,  $\bar{y}$  is given by

$$\bar{y} = p \left( \frac{\alpha}{\alpha + \delta} \right) [1 - e^{-(\alpha+\delta)\bar{\gamma}}] + b e^{-\alpha\bar{\gamma}}. \quad (25)$$

Clearly, TFP depends on labor market transition rates, as they determine the distribution of unemployment history among workers and the economy's average human capital. A higher job finding rate  $f(\theta)$ —whether this comes from an increase in  $\theta$  or an increase in matching

efficiency—leads to a higher average human capital and raises TFP. Similarly, an increase in  $s$  implies that workers lose their jobs more frequently and accumulate more unemployment history, so the economy’s average human capital depreciates.

Many of the countries considered in the paper have different labor market policies. For example, continental European countries are known to have more distortionary policies, with higher firing taxes, income taxes or subsidies. As (25) shows, TFP is uniquely determined by labor market flows, regardless of the mechanism behind them—labor market institutions, matching efficiency or vacancy costs.<sup>19</sup> In this sense, the endogenous TFP in the model has a “sufficient” statistic property. This is similar to Hornstein et al. (2011), where wage dispersion can be measured using observed labor market flows. In Lagos (2006), TFP has a similar “sufficient” statistic property, TFP is determined by the equilibrium reservation productivity. As in Hornstein et al. (2011), the advantage with the measure of TFP in (25) is that labor market flows are directly observable in the data. This is an important contribution of the paper, as one can measure TFP differences without having to model or calibrate the underlying labor market policies or frictions in detail.<sup>20</sup>

This paper assumes exogenous separations. In a model with endogenous separations and loss of skill, the distribution of unemployment histories becomes a state variable. What makes the analysis complicated is that the reservation productivities depend on unemployment history, its distribution and the reservation productivity for all values of unemployment history. In terms of the differences in human capital, the results would follow through, as what matters is the actual value of the separation rate, not whether it is endogenous. Endogenous separations are a source of further TFP differences, which can be interpreted as accounting for some of the differences in overall efficiency  $p$  in the model. With endogenous separations the overall efficiency  $p$  becomes endogenous and depends on the reservation productivity, as in Lagos (2006). However, TFP differences from reservation productivities go in the same direction as differences in human capital. With endogenous separations, a drop in the matching efficiency lowers separation rates and reservation productivities, which lowers TFP further. As a result, this mechanism would amplify TFP differences.<sup>21</sup>

Next, using evidence on labor market transition rates, I quantify what fraction of TFP differences can be explained by the effect of unemployment history on the economy’s human capital.

### 3. Empirical Evidence

This section presents the empirical evidence used to calibrate the model and quantify TFP differences. Given the sufficient statistic property of TFP in the model, quantifying TFP differences only requires empirical estimates of the rate at which human capital depreciates during unemployment, labor market flows and observed TFP differences across the sample of

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<sup>19</sup>The appendix shows that the measure of TFP given by (25) is the same in an economy with a richer set of labor market policies, namely income taxes, employment subsidies, firing taxes and hiring subsidies.

<sup>20</sup>However, the quantitative response to a change in a labor market policy does depend on the source of differences in the job finding rates. In section 5, I quantify the response of TFP to a change in a hiring subsidy and assume that differences in job finding rates across countries come from differences in matching efficiency, based on the evidence in Jung and Kuhn (2014).

<sup>21</sup>A more rigorous study of TFP with both endogenous separations and loss of skills is left for future research. I thank an anonymous referee for useful comments and suggestions on the sufficient statistic properties and TFP with endogenous separations.

countries.

### 3.1. Loss of skills during unemployment

To calibrate the human capital depreciation rate during unemployment, the paper uses estimates in Ortego-Martí (2016b) based on the 1968-1997 waves of the PSID, a large panel of US workers. Using a panel structure for the estimation is important for a number of reasons. First, there may be some unobserved characteristics that make some workers more productive than others. If less productive workers are more likely to be unemployed, the estimation may be biased. Second, when a worker joins the sample previous unemployment history is unknown. However, when a worker joins the sample, prior unemployment history remains constant in later observations. By controlling for workers' constant unobserved characteristics, fixed effects estimation solves these two problems. Finally, a panel structure allows us to estimate how wage losses depend on unemployment duration, which is needed in the calibration.

Although the calibration uses the estimates based on the PSID, estimated losses are similar for the other OECD countries in the sample, given that this is a fairly homogenous group of countries. For example, Burda and Mertens (2001), Eliason and Storrie (2006) and Schmieder, von Wachter, and Bender (2010) find similar effects in Germany and Sweden. In particular, Jarosch (2015) finds remarkably similar results to Davis and von Wachter (2011) for Germany using administrative data and following the same estimation procedure than Davis and von Wachter (2011). This assumption follows the approach in many papers in the development accounting literature, which exploit differences in the quantity of human capital (as measured for example by years of schooling), assuming the same quality of human capital across countries. Although some papers find that differences in human capital quality play an important role, they mostly explain productivity differences between developed and developing countries, or among developing countries.

The PSID asks workers how many weeks they were unemployed in the previous year. Using the answers to this question, Ortego-Martí (2016b) constructs the variable  $Unhis$ , which contains each worker's unemployment history in months, and regresses the log of wages on  $Unhis$  and other covariates  $X$  standard in Mincerian regressions. To avoid labor supply decisions that are not in the model, the regression model is run for men only. The regression model is given by

$$\log w_{it} = \alpha_i - \delta Unhis_{it} + \beta X_{it} + \varepsilon_{it}. \quad (26)$$

Fixed effects regression controls for all constant characteristics, so  $X$  includes potential experience (cubic), regional dummies, and one-digit occupational dummies. The estimation results are included in table 1, column (1). The regression gives an estimate for  $\delta$  of 0.0122, which is the value used in the rest of the paper. Part of the skills loss due to unemployment may include the fact that workers take worse occupations once their skill level depreciates too much. In this sense, the estimate in (26) with occupation controls may underestimate the loss of skills. For this reason, the regression model (26) is also run without occupation controls. Column (2) in table 1 shows the results for the regression model (26) without occupation controls. The estimate for  $\delta$  is higher and equal to 1.24%.

TABLE 1. AROUND HERE

As Ortego-Martí (2016b) shows, wage losses due to unemployment history are very persistent. Consider a modification of the above regression model. The log of wages are now regressed on unemployment history in the previous 5 years—denote it by  $Unhis^{\leq 5}$ — and on unemployment history accumulated more than 5 years prior to the survey year—denote it by  $Unhis^{>5}$ .<sup>22</sup> The modified regression model is

$$\log w_{it} = \alpha_i - \delta^{\leq 5} Unhis_{it}^{\leq 5} - \delta^{>5} Unhis_{it}^{>5} + \beta X_{it} + \varepsilon_{it}. \quad (27)$$

The results are included in Table 1, column (3). Recent unemployment history has a very strong effect on wages. The estimated coefficient on  $Unhis^{\leq 5}$  is 0.0161, meaning that unemployment history accumulated in the past 5 years is associated with a 1.61% wage loss. These wage losses are persistent. Unemployment history more than 5 years old also has a strong effect on wages. The estimated coefficient on  $Unhis^{>5}$  is 0.0104, compared to 0.0122 in the baseline regression model. A month of unemployment history that was experienced more than 5 years ago is associated with a 1.04% wage loss. This supports the model’s assumption of long-lasting effects of unemployment history and that human capital depends on the accumulated length of unemployment spells.

The evidence further suggests that wage losses depend on unemployment duration and are not simply sunk at the time of separation. Consider a modification of the regression model (26), which adds a dummy variable that equals one if a worker experienced at least one unemployment spell in the previous year. If losses are sunk and unemployment duration has no effect, most of wage losses will be captured by the dummy variable instead of unemployment history. The estimate for  $\delta$  in this modified regression model is 1.16%, which is very close to the estimate in the baseline regression. This evidence supports that there is indeed duration dependence.<sup>23</sup>

Finally, life-cycle considerations do not affect the predictions from the model. To show this, I consider the regression model in (26), and add a dummy variable for each age group and its interaction with unemployment history.<sup>24</sup> The estimate for the human capital depreciation rate is similar across age groups, and range between -0.94% and -1.31%. In particular, an F-test cannot reject the hypothesis that the coefficients of the interaction between age group and unemployment history are equal. This shows that the quantitative predictions of the model are unaffected by life-cycle considerations, and that even young workers suffer large human capital losses due to unemployment. This is consistent with evidence from the job displacement literature, who find similar earnings losses for young workers, see for example Kletzer and Fairlie (2003).

### 3.2. Comparison with findings from the job displacement literature

The job displacement literature finds large and very persistent earnings losses due to unemployment. Most estimates from the literature are not directly comparable because they lack information on unemployment duration, but broadly speaking the literature finds similar or larger estimates than those presented in this paper.

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<sup>22</sup>The results are similar when the regression uses 3 years or 7 years instead of 5 as a cutoff.

<sup>23</sup>Similar to Elsby et al. (2013) and Shimer (2012), the separation rate is extremely low relative to the job finding rate. Therefore, the probability of multiple spells during a period is very low, so the estimates are unaffected.

<sup>24</sup>The dummy variables correspond to less than 25 years of age, between 25 and 35, 35 and 45 and so on. The results are similar with different cut-offs.

The job displacement literature exploits the exogeneity of plant closings to solve the endogeneity of job separations and estimate the causal effect of job loss on wages. Overall, studies in this literature use either survey data (usually the DWS or the PSID) or administrative data. Among those using survey data, Addison and Portugal (1989) and Neal (1995) provide the most comparable estimates and find similar results. Neal (1995) Table 3, reports that an additional week of unemployment is associated with a 0.37% wage loss, which implies a monthly depreciation rate of 1.59%. Addison and Portugal (1989) find a similar monthly value of 1.44%. These estimates are larger compared to 1.22% from the above regression, but they are otherwise similar. These papers generally find larger values because they focus on displaced workers, a subset of the unemployed that are likely to suffer larger losses.<sup>25</sup> However, given that displaced workers tend to have lower earnings than non-displaced workers, estimates that do not control for workers' unobserved characteristics might be biased.

Jacobson et al. (1993) use administrative data from the state of Pennsylvania and plant closings to estimate the earnings losses of displaced workers. They find large losses of 50% at the time of separation. These losses are very persistent and remain 30% below the earnings of non-separated workers 5 years after separation. Similarly, Couch and Placzek (2010), Ruhm (1991), Stevens (1997) and Sullivan and Von Wachter (2009) find that earnings losses are large and persist five to ten years after the job loss. An issue with these estimates is that data availability limits how long these studies can follow workers after job separation.<sup>26</sup> More recently, Davis and von Wachter (2011), Jarosch (2015), and von Wachter et al. (2009) use administrative data and follow workers for more than 20 years. Davis and von Wachter (2011) use longitudinal Social Security records of US workers, which covers almost the entire universe of US workers, from 1974 to 2008. They focus on mass-layoffs and find average losses of around 30% upon separation. While there is some recovery, after 20 years earnings remain at around 15 to 20% below the control group, with losses flattening after 10 years. Jarosch (2015) finds similar results for all workers, not just for workers separated at mass-layoffs. Earnings drop by 35% upon separation and are still around 10% lower 20 years after separation, with some flattening in wage losses after 10 years. Wages follow a similar pattern, they drop by 20% after separation and are still around 10% lower 20 years later. Further, the results barely change when he considers only workers separated at mass-layoffs.<sup>27</sup> By comparison, these losses are much larger than the ones presented in the previous section based on the PSID. A full year of unemployment would result in a 13.7% wage loss, lower than most of these estimates. Taking into account that very few workers are unemployed for a full year, it is clear that the estimate used in the paper is a lower bound.<sup>28</sup> Overall, using the values from the job displacement literature would yield larger differences in TFP due to loss of skills, so the results in this paper can be thought of as a lower bound on TFP differences.

All the above studies find large losses at the time of separation. Although losses persist,

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<sup>25</sup>Pavoni and Violante (2007) use a monthly depreciation rate of 1.5% partly based on the evidence in Addison and Portugal (1989) and Neal (1995).

<sup>26</sup>Further, most studies based on US administrative data cover some regions only.

<sup>27</sup>Workers fired at mass-layoff tend to see a bit more recovery in wages than workers fired for cause, likely due to signaling effects—see for example Michaud (2016). However, Jarosch (2015) shows that the difference in earnings losses between all separators and workers separated at mass-layoffs is very small 20 years after separation, and similarly for wages.

<sup>28</sup>The average unemployment history among those with positive unemployment history is around 6 months. The average unemployment duration in a period for those who experience some unemployment is slightly above 2 months.

there is some recovery over time. Therefore, there might be a concern that the effects of unemployment on wages may not be linear after separation. This is confirmed by the results from the regression estimation in (27). Recent unemployment history has a larger effect on wages than unemployment history that happened a long time ago. For example, a month of unemployment history accumulated in the previous 5 years has a negative effect of around 1.61%, whereas a month accumulated prior to the previous 5 years has a negative effect of 1.04%. Running the regression model in (27), but with 10 years instead of 5 years as the threshold gives similar results, which are reported in table 1, column (4). Although this evidence confirms that the losses are not linear and that there is some recovery, the long-term losses are very similar to the baseline estimate of a 1.22% monthly depreciation. Compared to Davis and von Wachter (2011) and Jarosch (2015), long-run losses in their studies are still larger than the estimate of 1.22% used in the baseline, even 20 years after separation—they remain between 10% and 20% below the control group, compared to 13.7% for a *full* year of unemployment implied the baseline estimation. Further, wage losses seem to flatten in the US after 10 years, and similarly for Germany, although less so than in the US.

Finally, a model with non-linear losses is likely to give similar results. Even though there is some recovery, losses are much larger in the years following the separation. Overall, results are unlikely to change, as the large short run losses compensate for the relatively smaller long run losses, so on average losses are similar.<sup>29</sup>

### 3.3. Labor Market Flows

The paper draws from the findings in Elsby et al. (2013). The authors generalize the methodology in Shimer (2005) and Shimer (2012) to estimate the job finding and separation rates for a sample of thirteen European and Anglo-Saxon countries that are members of the OECD, namely Australia, Canada, France, Germany, Ireland, Italy, New Zealand, Norway, Portugal, Spain, Sweden, United Kingdom and the United States.<sup>30</sup> Table 2 reproduces their estimates of the monthly flow rates and the unemployment rate for the sample of countries, see table 2 in Elsby et al. (2013). The rates differ significantly, but one can see that Anglo-Saxon and Nordic countries tend to have very high job finding and separation rates compared to continental Europe. The last column of table 2 also reports the ratio of the job finding rate to the separation rate, given that this is an important value in the textbook DMP model and this paper’s model.

TABLE 2. AROUND HERE

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<sup>29</sup>Incorporating a non-linear path for losses after separation complicates the model significantly, as it requires keeping track of the distribution of time of separation. However, the case of a quadratic rate of human capital depreciation illustrates why results are unlikely to change much with non-linear losses. Assume that human capital is given by  $h(\gamma) = e^{-\delta_1\gamma + \delta_2\gamma^2}$ , so low values of unemployment history  $\gamma$  have large effects, but large values have an increasingly smaller effect. Ortego-Martí (2016b) finds estimates for  $\delta_1$  and  $\delta_2$ . Using *Mathematica*, the endogenous TFP is 2% lower than in the baseline model with a constant depreciation rate. Intuitively, even though large unemployment histories are associated with a relatively smaller loss, the large losses incurred at short unemployment duration more than compensate for them—in fact, they lead to even larger losses. I thank an anonymous referee for helpful suggestions and comments on this empirical section.

<sup>30</sup>The sample is selected based on available data and comparability across countries. See Table 1 in Elsby et al. (2013) for more details on the data sources for each country. See also Hobijn and Şahin (2009) and Petrongolo and Pissarides (2008) for alternative estimates for a group of OECD countries using different estimation techniques.



### 3.4. Observed TFP differences

Evidence on observed TFP differences comes from the Penn World Table 9.0 (PWT 9.0). Feenstra et al. (2015) provide detailed information on the construction of the PWT 9.0 and on how TFP is estimated. Their findings are reported in table 3. The PWT 9.0 provides countries' TFP relative to the US, so TFP equals 1 in the US. To be consistent with the estimates for the job finding and separation rates in Elsbly et al. (2013), TFP covers the same period between 1986 and 2014.

## 4. TFP differences due to loss of skills

One can use the model without subsidies ( $\tau_h = 0$ ) to quantify the amount of productivity differences due to skill decay during unemployment. Without hiring subsidies, the quantitative analysis only requires the calibration of parameters  $\{\delta, f, s, \psi, b\}$ .<sup>31</sup> The calibration of  $f$ ,  $s$  and  $\delta$  uses the empirical evidence in the previous section.<sup>32</sup> The rate at which workers leave the labor force  $\psi$  is chosen to match an average working life of 40 years, which implies a monthly value of 0.0021. Finally, the value for  $b$  is taken from Hall and Milgrom (2008) based on data on UI replacement ratios and the empirical Frisch elasticity of labor supply. In particular, the target for  $b$  is a replacement ratio  $b/\bar{y}$  of 0.73. Given that countries have different TFPs, I choose  $b$  for the country with the highest TFP (Norway), since lower values of  $b$  would amplify TFP differences. This calibration thus provides a lower bound on the effects of unemployment history.<sup>33</sup>

The economy's TFP is determined by  $\bar{y}$  in (25) and depends on: (1) the overall efficiency  $p$ , which plays the role of the parameter  $A$  in a Cobb-Douglas production function  $y = Ak^\alpha l^{1-\alpha}$ ; and (2), the average human capital in the economy, which is determined by labor market flows and workers' average unemployment history. Similar to Caselli (2005), suppose that overall efficiency  $p$  is the same across countries. I then compute the model's endogenous TFP using countries' labor market flows and compare the resulting differences to the observed variation in TFP. In other words, this exercise answers the question: how does the predicted distribution of productivities in the model with unemployment history compare to the distribution we observe in the data? Or alternatively, how much of the observed TFP differences can be explained by the model with unemployment history and loss of skills?

The results are reported in table 3. Similar to Elsbly et al. (2013), one can see a natural partition between Anglo-Saxon, Nordic and continental European countries. Continental European countries, not surprisingly, exhibit the lowest levels of TFP. Separation rates are much lower compared to the US in France, Germany, Italy and Portugal, with an average 0.005 at

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<sup>31</sup>TFP is uniquely determined by observed labor market flows. In particular, TFP differences are independent of what is the source of differences in labor market flows—labor market institutions, matching efficiency or vacancy costs. In this sense, the endogenous TFP in the model has a “sufficient” statistic property. This is similar to Hornstein et al. (2011), where wage dispersion can be measured using observed labor market flows. However, the quantitative response to a hiring subsidy depends on the source of differences in job finding rates. I assume that differences in job finding rates across countries come from differences in matching efficiency, which is consistent with evidence in Jung and Kuhn (2014).

<sup>32</sup>The semielasticity of wages with respect to unemployment history is not exactly  $\delta$ . However,  $\delta$  would be slightly higher if one were to calibrate  $\delta$  to match the observed estimate in the empirical section. In this sense, the results in this section can be thought of as a lower bound on TFP differences.

<sup>33</sup>Results are similar if one chooses average TFP instead.

monthly frequencies. The separation rate is thus around 7 times higher in the US. However, the job finding rate is so much higher in the US (it is more than 9 times the average for these countries) that US workers accumulate less unemployment history and suffer fewer human capital losses. Overall TFP for these countries is on average 7% lower than in the US. The same intuition applies to Anglo-Saxon countries, although their predicted TFP is only 3.9% lower than in the US. As one would expect given its sclerotic labor market, Spain is the country with the lowest endogenous TFP. Although its job finding rate is similar to other continental European countries, its separation rate is twice as large. As a result, Spain’s predicted TFP is around 12% lower than in the US. By contrast, the endogenous TFP in Nordic countries is on average 4.9% higher than in the US, as workers experience unemployment less often. In Nordic countries the job finding rate is around half of the value in the US, but the job separation rate is more than 3 times as large in the US. The country with the highest TFP is Norway, due to its very low job separation rate combined with a relatively high job finding rate.

TABLE 3. AROUND HERE

This section assumes that overall efficiency  $p$  is the same across countries, whereas the observed TFP is likely affected by other factors. This approach allows us to quantify the productivity differences arising from the fact that Norway’s workers spend less time in unemployment and suffer fewer human capital losses than US workers. That Norway’s endogenous TFP is 1.051 implies that avoiding the skill losses from unemployment give Norway a productivity advantage of 5.1% over the US. Consider the other end of the spectrum. Given Spain’s labor market flows, its endogenous TFP is 0.881. This captures that because Spain’s workers sit in unemployment for so long, Spain suffers a productivity loss of around 12% due to human capital depreciation compared to the US.<sup>34</sup>

#### 4.1. Productivity dispersion

Similar to Caselli (2005), one can measure the fraction of the variance of observed TFPs that can be explained by the variance of the endogenous TFP  $\bar{y}$ . In other words, I calculate the following measure  $\Delta_{var}$

$$\Delta_{var} = \frac{\text{var}(\bar{y})}{\text{var}(y^{emp})}, \tag{28}$$

where  $y^{emp}$  denotes observed TFP. The results are reported in table 4. First, with common overall efficiency  $p$  the correlation between the model’s TFP and the observed TFP is positive, with a value of 0.198. The value for  $\Delta_{var}$  is 0.167, meaning that the model explains around 17% of the observed variance in TFP.<sup>35</sup> This suggests that the skills loss occurring during unemployment plays an important role in explaining cross-country productivities. The

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<sup>34</sup>Section 4.2 calibrates  $p$  so that the endogenous TFP matches its empirical counterpart.

<sup>35</sup>To get a sense of how big this fraction is, Caselli (2005) reports that a factor-only model with capital can explain around 39% of the observed variation in productivity, including developing countries. Productivity differences among all countries are much larger than productivity differences among developed countries, which are the focus of this paper. Nevertheless, productivity differences are still present and significant among developed countries.

ratio of the variance of log TFPs  $\tilde{\Delta}_{var} = \text{var}[\log(\bar{y})]/\text{var}[\log(y^{emp})]$  is similar and equal to 15%.<sup>36</sup>

TABLE 4. AROUND HERE

## 4.2. TFP with different overall efficiency

The previous sections assumed the same overall efficiency  $p$  across countries. However, overall efficiency  $p$  differs across countries due to other factors. To gain a further understanding of the magnitude of productivity differences due to skills loss, consider the following alternative exercise. Suppose now that overall efficiency  $p$  is different across countries and calibrate  $p$  so that the endogenous TFP  $\bar{y}$  matches its empirical value. I then ask the question: how would TFP change for each country if labor market flows were the same as in the US? This exercise tells us how much productivity would increase in, say, Spain if we could somehow reform the labor market so that flows are the same as in the US, taking into account initial differences in overall efficiency.

The results are reported in table 3, last column. This exercise gives a similar picture. Continental European countries would see the biggest productivity improvements. On average, productivity gains for this group would be around 8.5% (7.2% excluding Spain). Spain would see the highest improvement with an increase of 13.5%. In Anglo-Saxon countries productivity would increase by an average 4.1%. By contrast, Nordic countries would see an average loss of 4.7%. With US labor market flows their workers would accumulate more unemployment history and experience more human capital losses.

## 5. Effect of hiring subsidies

Hiring subsidies are a policy that stimulates job creation and thus improves human capital. This section quantifies the effect of this policy on TFP. In particular, this section answers the question: do countries that suffer the largest human capital losses from unemployment benefit the most from the policy?

Without subsidies, TFP can be quantified with knowledge of  $\{\delta, f, s, \psi, b\}$  alone. In particular, equilibrium market tightness  $\theta$  is not required because TFP depends on  $\theta$  only through the job finding rate  $f(\theta)$ . Since there are empirical estimates for the job finding rate, it can be

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<sup>36</sup>One can alternatively measure TFP differences using the mean absolute deviation instead of the variance

$$\Delta_{dev} = \frac{\sum |\bar{y} - \psi_{\bar{y}}|}{\sum |y^{emp} - \psi_{y^{emp}}|},$$

where  $\psi_{\bar{y}}$  denotes the mean of  $\bar{y}$  and  $\psi_{y^{emp}}$  is defined similarly. This measure delivers larger TFP differences, with  $\Delta_{dev}$  equal to 45%—the ratio is 43% if the log of TFP is used instead. However, this may be due to the fact that the mean absolute deviation is more sensitive to outliers—the mean absolute value is an  $L^1$  measure, whereas the variance is  $L^2$ . Caselli (2005) suggests an alternative measure  $\Delta_{90/10}$  that uses the 90-10 percentile ratio

$$\Delta_{90/10} = \frac{\bar{y}^{90}/\bar{y}^{10}}{y_{emp}^{90}/y_{emp}^{10}},$$

where  $\bar{y}^i$  and  $y_{emp}^i$  are the  $i$ -percentiles of  $\bar{y}$  and  $y^{emp}$ . The measure  $\Delta_{90/10}$  is 0.89, i.e. skills losses explain up to 89% of the 90-10 percentile ratio of observed TFPs.

treated as a parameter. However, this is no longer true with hiring subsidies and some additional parameters must be calibrated. Assume that the job finding rate takes the form  $m_0\theta^{1-\eta}$ , which implies that  $q(\theta) = m_0\theta^{-\eta}$ , where  $m_0$  is matching efficiency and  $1 - \eta$  is the elasticity of the job finding rate with respect to market tightness. The calibration requires additional parameter values for  $\{m_0, c, \eta, \beta\}$ . Following Pissarides (2009), set  $\eta$  equal to 0.5, which is within the range of plausible estimates given by Petrongolo and Pissarides (2001).<sup>37</sup> As is standard in the literature, assume  $\beta = \eta$  to satisfy the Hosios-Mortensen-Pissarides condition.<sup>38</sup>

The two targets used to calibrate  $m_0$  and  $c$  are: (1) the job finding rate  $m_0\theta^{1-\eta}$  must match the observed job finding rate; (2) the job creation condition (23) must hold. However, as in Shimer (2005) one can normalize either  $m_0$  or  $c$ . This can easily be seen by looking at (23). Let  $\tilde{\Phi}(f(\theta))$  denote the right-hand side of (23), which depends on  $\theta$  only through  $f(\theta)$ . Rearranging, this implies that  $\theta = \{c/[\tilde{\Phi}(f(\theta))m_0]\}^{-1/\eta}$ . Given that  $f(\theta)$  must match its empirical value,  $\theta$  depends on the ratio  $c/m_0$ , not the individual values for  $c$  and  $m_0$ . Based on this observation, let  $c = 0.5$ , which is similar to the value used in Hagedorn and Manovskii (2008) and Silva and Toledo (2009). Using this value and the empirical job finding rate gives equilibrium  $\theta$ .<sup>39</sup>

Once the required parameters are calibrated, I solve for the equilibrium market tightness with a positive hiring subsidy. In particular, assume  $\tau_h$  equals 0.5, meaning that the government gives a one-off payment at the time of job creation that equals half the match's output. Equilibrium tightness is determined by the job creation condition (23) (now with  $\tau_h = 0.5$ ), which can be easily solved numerically by iteration. Equilibrium market tightness then determines the new job finding rate after the policy is implemented, and thus the average human capital and the economy's TFP.

Table 5 reports the ratio of TFP with a hiring subsidy to TFP in the model without the subsidy. As expected, hiring subsidies have a positive effect on the labor market and encourage job creation. This leads to lower average unemployment history and an overall improvement in average human capital and TFP. However, a similar partition of countries between Anglo-Saxon, Nordic and continental European is less clear now. Continental European countries, excluding Spain, together with Australia, Ireland, New Zealand and the UK would see middle range productivity gains, with an average gain of 1.06%. Nordic countries would see the lowest gains with an average of 0.52%. Canada, Spain and the US would see the largest gains with an average of 1.83%.

TABLE 5. AROUND HERE

This pattern of productivity gains is slightly different from the conclusions in section 4 because the effect of a hiring subsidy on TFP depends on a number of factors: the job finding

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<sup>37</sup>One could use a different value for each country. However, as Petrongolo and Pissarides (2001) show, the elasticity is similar among OECD countries.

<sup>38</sup>As Laureys (2014) shows, there is an additional composition externality in the DMP model with loss of skills because firms' do not take into account how their hiring decisions affect the average human capital. Posting more vacancies reduces unemployment duration and improves productivity for other firms, but firms do not internalize this positive externality when deciding whether to post a vacancy. As a result, the model is not efficient, even when the Hosios-Mortensen-Pissarides condition  $\eta = \beta$  holds.

<sup>39</sup>One can alternatively choose a value for  $\theta$  (as in Pissarides (2009)) or normalize  $\theta = 1$  (as in Shimer (2005)), or calibrate the value for  $m_0$  and find the other remaining parameters similarly by matching the empirical job finding rate and ensuring that the job creation condition holds. All these alternatives give the exact same results for the reasons exposed in the text.

and the separation rates separately, the ratio of the two rates and the size of the market tightness response, which depends on how many vacancies firms choose to post. One can see this by looking at the change in TFP for a given change in the subsidy rate  $\tau_h$

$$\frac{d\bar{y}}{d\tau_h} = \frac{\partial \bar{y}}{\partial f(\theta)} (1 - \eta) f(\theta) \frac{d\theta/d\tau_h}{\theta}, \quad (29)$$

where

$$\frac{\partial \bar{y}}{\partial f(\theta)} = p \left[ \frac{\delta}{(\alpha + \delta)^2} \frac{\psi}{s + \psi} (1 - e^{-(\alpha + \delta)\bar{\gamma}}) + \bar{\gamma} \frac{\alpha}{\alpha + \delta} \frac{\psi}{s + \psi} e^{-(\alpha + \delta)\bar{\gamma}} \right] - b\bar{\gamma} \frac{\psi}{s + \psi} e^{-\alpha\bar{\gamma}}. \quad (30)$$

The ratio of the job finding to the separation rate determines the shape of the distribution of human capital, so in general the change in this ratio predicts very well the policy's impact on TFP. Quantitatively, Spain, Canada and the US see the largest increase in the ratio following the policy, with an average increase of 17.75% (Spain has the highest increase, with a 24% increase). By contrast, countries with mid-range gains experience an average increase of 9% in this ratio, and Nordic countries see an increase of only 3%. These results suggest that one should be cautious about the relative effectiveness of hiring subsidies, since countries with the highest levels of unemployment history are not necessarily the ones to benefit the most from these policies.

## 6. Conclusion

If workers lose some human capital during unemployment, how fast workers find jobs and how long they hold on to them affects the economy's productivity and TFP. The paper develops a search and matching model of the labor market in which workers lose skills during periods of unemployment. The model shows that TFP is endogenous and depends on labor market flows and workers' unemployment history, since these affect the economy's average human capital. Using available estimates in the literature for labor market flows in a sample of OECD countries, the paper quantifies TFP differences due to loss of skills during unemployment. One can partition the sample among Anglo-Saxon countries, Nordic countries and continental European countries. Continental European countries exhibit the lowest TFPs due to their more sclerotic labor markets. With high job finding rates but also relatively high separation rates, Anglo-Saxon countries exhibit mid-range TFPs. By contrast, Nordic countries exhibit the largest TFPs. The paper also analyzes the effect of hiring subsidies. Hiring subsidies stimulate job creation and increase TFP, as they raise the job finding rate and lower average unemployment histories. However, because the effect on productivity depends on how firms respond to the policy and their vacancy posting decision, countries with the lowest levels of TFP may not benefit the most from the policy.

A few extensions are worth pursuing. In the model there is no participation margin. However, it is reasonable to think that in reality some workers do not participate in the labor market due to very low skills. This selection effect is likely to amplify the effect of labor market policies such as hiring subsidies. For simplicity, separations are exogenous in the model. Endogenous separations seem likely to amplify the role of skills losses. These extensions, though important, are left for future work.

# Appendix

## A1. Proof of Proposition 1

Let  $S(\gamma)$  denote the match surplus after hiring, i.e.  $S(\gamma) \equiv J(\gamma) + W(\gamma) - U(\gamma)$  (since there are no firing costs). Nash Bargaining implies that

$$W(\gamma) - U(\gamma) = \beta S(\gamma), \quad (\text{A1})$$

$$J(\gamma) = (1 - \beta)S(\gamma). \quad (\text{A2})$$

Using (3) and (4) in the main text gives

$$(r + \psi + s)(W(\gamma) - U(\gamma)) = w(\gamma) - (r + \psi)U(\gamma), \quad (\text{A3})$$

$$(r + \psi + s)J(\gamma) = h(\gamma)p - w(\gamma). \quad (\text{A4})$$

Combining the above equations with the Nash Bargaining condition and solving for wages gives

$$S(\gamma) = \frac{h(\gamma)p - (r + \psi)U}{r + \psi + s}. \quad (\text{A5})$$

Given that an unemployed worker can always choose to keep the value of non-market time  $b$ , clearly  $(r + \psi)U(\gamma) \geq b$ . Therefore

$$S(\gamma) \leq \frac{h(\gamma)p - b}{r + \psi + s}. \quad (\text{A6})$$

As  $\gamma$  tends to infinity, productivity  $h(\gamma)p$  tends to zero, so there exists a  $\bar{\gamma}$  such that  $S(\bar{\gamma}) = 0$ . As a result,  $J(\bar{\gamma}) = 0$  and  $W(\bar{\gamma}) = U(\bar{\gamma})$ . In particular, using (2) and (4) it follows that

$$h(\bar{\gamma})p = w(\bar{\gamma}), \quad (\text{A7})$$

$$(r + \psi)U(\bar{\gamma}) = b. \quad (\text{A8})$$

■

## A2. TFP with several labor market policies

This section shows that the measure of TFP given by (25) is the same in an economy with a more complex set of labor market policies, as long as the process for human capital is the same as in the baseline model—that is, human capital depreciates at a rate  $\delta$  and has a lower bound equal to  $b$ . As a result, TFP measured by (25) keeps its sufficient statistic property, in the sense that it is uniquely determined by labor market flows, regardless of whether differences in labor market flows come from labor market policies, matching efficiency or vacancy costs.

The assumptions are the same as in section 2, except that now we also have the following policies. Income is taxed at a rate  $\tau_w$  for both unemployed and employed workers.<sup>40</sup> Firms receive a hiring subsidy  $\tau_h h(\gamma)p$  at the time a job is created and an employment subsidy  $\tau_e h(\gamma)p$  throughout the duration of the match, both of which are proportional to the job's productivity.

<sup>40</sup>As in Pissarides (2000) Chapter 9, I assume that both unemployment income and wages are taxed, as this makes the exposition simpler. However, the results are the same if only wages are taxed.

At the time of separation, firms must pay a firing tax proportional to the match's productivity  $\tau_f h(\gamma)p$ . All rates  $\tau_w$ ,  $\tau_h$ ,  $\tau_e$  and  $\tau_f$  are constant. The Bellman equations for workers are given by

$$(r + \psi)U(\gamma) = (1 - \tau_w)b + f(\theta) [\max\{W_0(\gamma), U(\gamma)\} - U(\gamma)] + \frac{\partial U(\gamma)}{\partial \gamma}, \quad (\text{A9})$$

$$(r + \psi)W(\gamma) = (1 - \tau_w)w(\gamma) - s[W(\gamma) - U(\gamma)], \quad (\text{A10})$$

where  $W_0(\gamma)$  denotes the value functions at the time of hiring. Compared to the baseline model of section 2, the above Bellman equations capture that unemployed workers are paid income flow  $(1 - \tau_w)b$  and that workers take-home pay is  $(1 - \tau_w)w(\gamma)$ . Firms' value functions satisfy the following Bellman equations

$$(r + \psi)J(\gamma) = h(\gamma)p + \tau_e h(\gamma)p - w(\gamma) - s[J(\gamma) + \tau_f h(\gamma)p - V], \quad (\text{A11})$$

$$rV = -c + q(\theta) \int_0^\infty [\max\{J_0(\Gamma) + \tau_h h(\Gamma)p, V\} - V] dG^U(\Gamma), \quad (\text{A12})$$

where  $J_0(\gamma)$  denote the value functions at the time of hiring.

Wages are determined by Nash Bargaining, as in Nash (1950), where  $\beta$  denotes workers' bargaining strength. Since the subsidy only applies at the time of hiring, as in the baseline model there are two wages: the wage  $w_0(\gamma)$  that is negotiated at the time of hiring and the continuing wage  $w(\gamma)$  that prevails after the worker is taken on. The wage  $w_0$  maximizes the Nash product

$$w_0(\gamma) = \arg \max_{w_0(\gamma)} (W_0(\gamma) - U(\gamma))^\beta (J_0(\gamma) + \tau_h h(\gamma)p - V)^{1-\beta}. \quad (\text{A13})$$

The above bargaining problem takes into account that at the time of signing the contract, the firm's payoff is  $J_0(\gamma)$  plus the amount of the subsidy  $\tau_h p h(\gamma)$ . Once the worker is taken on and production begins, the continuing wage  $w(\gamma)$  solves the following bargaining problem

$$w(\gamma) = \arg \max_{w(\gamma)} (W(\gamma) - U(\gamma))^\beta (J(\gamma) + \tau_f h(\gamma)p - V)^{1-\beta}. \quad (\text{A14})$$

The above problem captures that if negotiations fail and the match were to break up, the firm must pay the firing tax.

The solution to  $w_0(\gamma)$  and  $w(\gamma)$  are given by

$$(1 - \beta)(W_0(\gamma) - U(\gamma)) = \beta(1 - \tau_w)(J_0(\gamma) + \tau_h h(\gamma)p), \quad (\text{A15})$$

$$(1 - \beta)(W(\gamma) - U(\gamma)) = \beta(1 - \tau_w)(J(\gamma) + \tau_f h(\gamma)p). \quad (\text{A16})$$

Let  $S_0(\gamma)$  and  $S(\gamma)$  denote the surplus at the time of job creation and the surplus once the worker is hired, i.e.  $S_0(\gamma) \equiv W_0(\gamma) - U(\gamma) + J_0(\gamma) + \tau_h h(\gamma)p - V$  and  $S(\gamma) \equiv W(\gamma) - U(\gamma) + J(\gamma) + \tau_f h(\gamma)p - V$ . Because of the labor income tax, the worker's share of the surplus is no longer  $\beta$ , as in the baseline DMP model. Instead, the worker receives a share  $\beta(1 - \tau_w)/(1 - \beta\tau_w)$ , and the firm a share  $(1 - \beta)/(1 - \beta\tau_w)$ .<sup>41</sup> Using the Bellman equations and the Nash Bargaining

<sup>41</sup>This result is the same as in the baseline DMP model with exogenous separations, see Pissarides (2000),

rules (A15) and (A16) gives wages as a function of  $U(\gamma)$

$$w_0(\gamma) = (1 - \beta) \frac{(r + \psi)U(\gamma)}{1 - \tau_w} + \beta[1 + \tau_e - s\tau_f + (r + \psi + s)\tau_h]h(\gamma)p, \quad (\text{A17})$$

$$w(\gamma) = (1 - \beta) \frac{(r + \psi)U(\gamma)}{1 - \tau_w} + \beta[1 + \tau_e + (r + \psi)\tau_f]h(\gamma)p. \quad (\text{A18})$$

I assume the same process for human capital as in the baseline model of section 2, namely that human capital depreciates at a constant rate  $\delta$  during unemployment, and that there is a lower bound on human capital such that  $h(\gamma)p \geq b$ . Similar to Lagos (2006), assume that the firing tax  $\tau_f$  exceeds the hiring subsidy  $\tau_h$  whenever the continuation surplus  $S(\gamma)$  is negative, i.e.  $\tau_f \geq \tau_h$  if  $S(\gamma) < 0$ . This ensures that firms do not create a match just to collect the hiring subsidy and then destroy the job. The following proposition shows that all matches yield positive surplus.

**Proposition 2.** *Assume that  $T \equiv \tau_e + (r + \psi + s)\tau_h - \tau_f \geq 0$ , and let  $\bar{\gamma}$  be defined by  $h(\bar{\gamma})p = b$ . Then  $S_0(\bar{\gamma})$  is positive. In particular,  $S_0(\gamma)$  and  $S(\gamma)$  are positive for all  $\gamma$ .*

*Proof:* Intuitively, without a lower bound on human capital the surplus  $S_0(\bar{\gamma})$  becomes 0 at a  $\tilde{\gamma}$  larger than  $\bar{\gamma}$ , as long as  $T$  is positive, i.e. firing taxes are not too large.<sup>42</sup> First,  $S_0(\gamma) \leq \frac{h(\gamma)p(1+T) - b(1-\tau_w)}{r + \mu + s}$ , and without a lower bound the right-hand side of the inequality tends to something negative as  $\gamma$  tends to infinity. So there exists a  $\tilde{\gamma}$  such that  $S_0(\tilde{\gamma}) = 0$ . Using the Bellman equations,  $S_0(\tilde{\gamma}) = 0$  implies that  $J_0(\tilde{\gamma}) = -\tau_h h(\tilde{\gamma})p$  and  $w_0(\tilde{\gamma}) = b$ , which gives that  $h(\tilde{\gamma})p = b/(1 + T)$ . The assumption that  $T \geq 0$  implies that  $\tilde{\gamma} \geq \bar{\gamma}$ . Given that  $S_0(\gamma) > 0$  for all  $\gamma < \tilde{\gamma}$ , with a lower bound on human capital satisfying  $h(\gamma)p \geq h(\bar{\gamma})p = b$ , all matches yield positive surplus.

More formally, using (A17) and the Bellman equations, and given that  $h(\gamma)p = b$  for all  $\gamma \geq \bar{\gamma}$ , the following holds

$$(r + \psi)U(\gamma) = \frac{r + \psi + s + \beta f(\theta)(1 + T)}{r + \psi + s + \beta f(\theta)}(1 - \tau_w)b, \quad \forall \gamma \geq \bar{\gamma}$$

$$w_0(\gamma) = \left[ (1 - \beta) \frac{r + \psi + s + \beta f(\theta)(1 + T)}{r + \psi + s + \beta f(\theta)} + \beta(1 + T) \right] b, \quad \forall \gamma \geq \bar{\gamma}.$$

The surplus in initial matches is given by  $(r + \psi + s)S_0(\gamma) = h(\gamma)p(1 + T) - (r + \psi)U(\gamma) - \tau_w w_0(\gamma)$ , for all  $\gamma$ . Substitute the above equations and  $h(\gamma)p = b$  for all  $\gamma \geq \bar{\gamma}$  into  $S_0(\gamma)$  to get

$$S_0(\gamma) = \frac{(1 - \beta\tau_w)T}{r + \psi + s + \beta f(\theta)}b \geq 0, \quad \forall \gamma \geq \bar{\gamma}.$$

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chapter 9. The labor income tax reduces both the size of the surplus and the worker's share of the surplus. When the firm gives up a unit of wages to the worker, a fraction  $\tau_w$  is "lost" due to the income tax. During bargaining, a way to reduce this loss is by lowering wages, or equivalently giving workers a lower share.

<sup>42</sup>As in the textbook model, matches are not formed if firing taxes are too large relative to the other subsidies. Pissarides (2000) and Lagos (2006) have a similar assumption, i.e. firing taxes must not be too large so that matches are formed in equilibrium. For all  $\gamma \geq \bar{\gamma}$ , the surplus is proportional to  $T$ . Therefore, assuming that  $T \geq 0$  is equivalent to assuming that matches with  $\gamma \geq \bar{\gamma}$  have positive surplus, as in the baseline model with no policy.



The above is positive given the assumption of  $T \geq 0$ .

Finally, let us prove that  $S(\gamma)$  is also positive for all  $\gamma$ . Similar to Lagos (2006), by assumption the government sets  $\tau_f \geq \tau_h$  whenever  $S(\gamma) < 0$ —this prevents firms from creating a job and immediately destroying it to capture the hiring subsidy. Using (A17), (A18) and the Bellman equations, the surplus in continuing matches  $S(\gamma)$  is greater than  $S_0(\gamma)$  if and only if  $\tau_f \geq \tau_h$ . It is easy to prove by contradiction that  $S(\gamma) \geq 0$  for all  $\gamma$ . Assume that  $S(\gamma) < 0$ . Then  $\tau_f \geq \tau_h$  and  $S(\gamma) \geq S_0(\gamma) \geq 0$ , which is a contradiction.<sup>43</sup>

■

Given proposition 2, the Bellman equation for unemployed workers becomes

$$\begin{aligned} (r + \psi)U(\gamma) &= (1 - \tau_w)b + f(\theta)(W_0(\gamma) - U(\gamma)) + \frac{\partial U(\gamma)}{\partial \gamma}, \quad \forall \gamma < \bar{\gamma} \\ (r + \psi)U(\gamma) &= (1 - \tau_w)b + f(\theta)(W_0(\gamma) - U(\gamma)), \quad \forall \gamma \geq \bar{\gamma}, \end{aligned} \quad (\text{A19})$$

where (A19) captures that human capital stays the same when  $\gamma$  is greater than  $\bar{\gamma}$ .

### A2.1. Equilibrium

The labor market flow equations are the same as in section 2, so the distribution of employment and unemployment history are

$$G^U(\gamma) = G^E(\gamma) = 1 - e^{-\alpha\gamma}, \quad (\text{A20})$$

where  $\alpha \equiv \psi(f(\theta) + s + \psi)/(s + \psi) = \psi/u$ , i.e. the distribution is exponential with parameter  $\alpha$ .

Combining the Bellman equations for workers gives

$$W_0(\gamma) - U(\gamma) = \frac{\beta[(1 - \tau_w)(1 + T)h(\gamma)p - (r + \mu)U(\gamma)]}{r + \psi + s}, \quad (\text{A21})$$

where  $T$  is defined in proposition 2. Substitute (A21) into (A19) and solve the differential equation to get  $U(\gamma)$  for  $\gamma \leq \bar{\gamma}$

$$U(\gamma) = e^{-\rho(\bar{\gamma}-\gamma)}U(\bar{\gamma}) + \int_{\gamma}^{\bar{\gamma}} e^{-\rho(\Gamma-\gamma)} \left[ (1 - \tau_w)b + \beta \frac{f(\theta)(1 - \tau_w)(1 + T)h(\Gamma)p}{r + \psi + s} \right] d\Gamma, \quad \forall \gamma \leq \bar{\gamma} \quad (\text{A22})$$

where as in the baseline model of section 2,  $\rho = (r + \psi + s + \beta f(\theta))(r + \psi)/(r + \psi + s)$ . Use the Bellman equations for workers and that  $h(\gamma)p = b$  for all  $\gamma \geq \bar{\gamma}$  to derive  $U(\gamma)$  for  $\gamma > \bar{\gamma}$

$$(r + \psi)U(\gamma) = \frac{r + \psi + s + \beta f(\theta)(1 + T)}{r + \psi + s + \beta f(\theta)}(1 - \tau_w)b, \quad \forall \gamma > \bar{\gamma}. \quad (\text{A23})$$

<sup>43</sup>Alternatively, evaluating (A18) for  $\gamma \geq \bar{\gamma}$  and using the above equations gives that  $S(\gamma) = b(1 - \beta\tau_w)[\tau_e + (r + \psi)\tau_f + \beta f(\theta)(\tau_f - \tau_h)]/[r + \psi + s + \beta f(\theta)]$  for all  $\gamma \geq \bar{\gamma}$ . Clearly,  $\tau_f \geq \tau_h$  implies  $S(\gamma) > 0$ .

Use the above equation to replace  $U(\bar{\gamma})$  in (A22) and integrate to get

$$\begin{aligned}
(r + \psi)U(\gamma) = & \\
e^{-\rho(\bar{\gamma}-\gamma)} & \left[ \frac{r + \psi + s + \beta f(\theta)(1 + T)}{r + \psi + s + \beta f(\theta)} - \frac{\beta f(\theta)(1 + T)}{r + \psi + s + \beta f(\theta) + \delta(\frac{r+\psi+s}{r+\psi})} \right] (1 - \tau_w)b \\
& + \left[ \frac{r + \psi + s}{r + \psi + s + \beta f(\theta)} (1 - e^{-\rho(\bar{\gamma}-\gamma)}) \right] (1 - \tau_w)b \\
& + \left[ \frac{\beta f(\theta)(1 + T)}{r + \psi + s + \beta f(\theta) + \delta(\frac{r+\psi+s}{r+\psi})} \right] (1 - \tau_w)h(\gamma)p, \quad \forall \gamma \leq \bar{\gamma}. \tag{A24}
\end{aligned}$$

The Nash Bargaining rule (A15) together with the Bellman equations imply

$$J_0(\gamma) + \tau_h h(\gamma)p = (1 - \beta) \left[ (1 + T)h(\gamma)p - \frac{(r + \psi)U(\gamma)}{1 - \tau_w} \right], \quad \forall \gamma. \tag{A25}$$

In particular, for  $\gamma$  greater than  $\bar{\gamma}$

$$J_0(\gamma) + \tau_h h(\gamma)p = \frac{(1 - \beta)T}{r + \psi + s + \beta f(\theta)} b, \quad \forall \gamma \geq \bar{\gamma}. \tag{A26}$$

Combing the above expressions for  $J_0(\gamma) + \tau_h h(\gamma)p$  with the Bellman equation for vacancies and free entry gives the job creation condition

$$\frac{c}{q(\theta)} = \left( \frac{1 - \beta}{r + \psi + s} \right) \Phi(f(\theta)) + \frac{(1 - \beta)T}{r + \psi + s + \beta f(\theta)} e^{-\alpha \bar{\gamma}} b, \tag{A27}$$

where  $\Phi(f(\theta)) = \int_0^{\bar{\gamma}} [(1 + T)h(\Gamma)p - (r + \psi)U(\Gamma)/(1 - \tau_w)] dG^U(\Gamma)$ . Substituting  $U(\gamma)$  from (A24) and integrating gives

$$\begin{aligned}
\Phi(f(\theta)) = & \left[ \frac{r + \psi + s + \delta(\frac{r+\psi+s}{r+\psi})}{r + \psi + s + \beta f(\theta) + \delta(\frac{r+\psi+s}{r+\psi})} \right] \left( \frac{\alpha}{\alpha + \delta} \right) (1 - e^{-(\delta+\alpha)\bar{\gamma}})(1 + T)p \\
& - \left[ \frac{r + \psi + s + \beta f(\theta)(1 + T)}{r + \psi + s + \beta f(\theta)} - \frac{\beta f(\theta)(1 + T)}{r + \psi + s + \beta f(\theta) + \delta(\frac{r+\psi+s}{r+\psi})} \right] \left( \frac{\alpha}{\alpha - \rho} \right) (e^{-\rho \bar{\gamma}} - e^{-\alpha \bar{\gamma}})b \\
& - \left( \frac{r + \psi + s}{r + \psi + s + \beta f(\theta)} \right) \left[ 1 - e^{-\alpha \bar{\gamma}} - \left( \frac{\alpha}{\alpha - \rho} \right) (e^{-\rho \bar{\gamma}} - e^{-\alpha \bar{\gamma}}) \right]. \tag{A28}
\end{aligned}$$

Combining (A27) and (A28) gives the job creation condition and the equilibrium  $\theta$ . Firms post vacancies until the expected cost—the left-hand side, which corresponds to the flow cost  $c$  times the expected vacancy duration  $1/q(\theta)$ —equals expected future profits from hiring a worker.

## A2.2. Total Factor Productivity

Let  $\bar{y}$  denote the economy's TFP. Using the distribution  $G^U(\gamma)$  and integrating gives the same expression for the endogenous TFP  $\bar{y}$  as in the baseline model in section 2

$$\bar{y} = p \left( \frac{\alpha}{\alpha + \delta} \right) [1 - e^{-(\alpha+\delta)\bar{\gamma}}] + b e^{-\alpha\bar{\gamma}}. \quad (\text{A29})$$

This shows the sufficient statistic property of the model's TFP, in the sense that TFP is determined by labor market flows, which are observed in the data, regardless of the exact mechanism or labor market policies that generate the flows.

## A3. TFP with unemployment history and human capital accumulation

This section extends the model in section 2 to include human capital accumulation, and shows that the results of the paper barely change. The assumptions are the same as in section 2, except that now workers accumulate human capital at a rate  $\delta_e$  when they are employed. Let  $\delta_u$  denote the rate at which human capital depreciates during unemployment. When a worker is unemployed, human capital losses include both the depreciation of skills due to unemployment and the foregone human capital accumulation (if the worker were employed, she would be accumulating skills at a rate  $\delta_e$ ). Since  $\delta$  in the main text captures the human capital depreciation of an unemployed worker relative to an employed worker,  $\delta_u$  and  $\delta_e$  must satisfy that  $\delta = \delta_u + \delta_e$ .<sup>44</sup> There are now two state variables: employment history  $\gamma_e$  and unemployment history  $\gamma_u$ . Given these assumptions, and normalizing  $h(0, 0) = 1$ , human capital  $h(\gamma_e, \gamma_u)$  is given by  $h(\gamma_e, \gamma_u) = e^{\delta_e \gamma_e - \delta_u \gamma_u}$ .<sup>45</sup> As is standard in models with returns to experience,  $\delta_e$  must be lower than the effective discount rate  $r + \psi$ .

As before, when workers' human capital is such that labor productivity equals  $b$ , workers are assigned to a zero surplus job (or equivalently, there is a lower bound on human capital depreciation). The Bellman equations are given by

$$(r + \psi)U(\gamma) = b + f(\theta)[W(\gamma) - U(\gamma)] + \frac{\partial U(\gamma)}{\partial \gamma_u} \quad (\text{A30})$$

$$(r + \psi)W(\gamma) = w(\gamma) - s[W(\gamma) - U(\gamma)] + \frac{\partial W(\gamma)}{\partial \gamma_e} \quad (\text{A31})$$

$$(r + \psi)J(\gamma) = h(\gamma)p - w(\gamma) - sJ(\gamma) + \frac{\partial J(\gamma)}{\partial \gamma_e} \quad (\text{A32})$$

$$rV = -k + q(\theta) \int \max\{J(\Gamma) - V, 0\} dG(\Gamma) \quad (\text{A33})$$

where  $\gamma \equiv (\gamma_e, \gamma_u)$  and  $G(\cdot)$  is the distribution of  $\gamma$ .

Worker flows are described by the following. Unemployed workers find jobs at a rate  $f(\theta)$ . Employed workers lose their jobs at a rate  $s$ . Unemployed workers accumulate unemployment history  $\gamma_u$  and employed workers accumulate employment history  $\gamma_e$ . All workers die at a rate

<sup>44</sup>Without this restriction TFP differences would be even larger.

<sup>45</sup>The results are essentially the same if one assumes instead that labor productivity is initially  $b$ , i.e.  $h(0, 0)p = b$ .

$\psi$ . Let  $G^e(\gamma_u)$  and  $G^u(\gamma_u)$  denote the distribution of unemployment history among employed and unemployed workers, and let  $H^e(\gamma_e)$  and  $H^u(\gamma_e)$  denote the distribution of employment history among employed and unemployed workers. Consider the pool of unemployed workers with unemployment history lower than  $\gamma_u$ . As in section 2, in steady state the flows in and out of this pool must be equal, so the following flow equation holds

$$g^u(\gamma_u)u + [f(\theta) + \psi]G^u(\gamma_u)u = sG^e(\gamma_u)(1 - u) + \psi, \quad (\text{A34})$$

where  $g^u(\cdot)$  is the pdf of the distribution  $G^u(\gamma_u)$ . Similarly, the flows in and out of the pool of employed workers with unemployment history lower than  $\gamma_u$  must be equal, so the following flow equation is satisfied

$$(s + \psi)G^e(\gamma_u)(1 - u) = f(\theta)G^u(\gamma_u)u. \quad (\text{A35})$$

Following the same approach for the pools of employed and unemployed workers with employment history lower than  $\gamma_e$ , the following flow equations hold

$$h^e(\gamma_e)(1 - u) + (s + \psi)H^e(\gamma_e)(1 - u) = f(\theta)H^u(\gamma_e)u, \quad (\text{A36})$$

$$(f(\theta) + \psi)H^u(\gamma_e)u = sH^e(\gamma_e)(1 - u) + \psi. \quad (\text{A37})$$

Using the above flow equations and solving the differential equations gives the equilibrium distributions

$$G^u(\gamma_u) = 1 - e^{-\alpha_1 \gamma_u}, \quad (\text{A38})$$

$$H^e(\gamma_e) = 1 - e^{-\alpha_2 \gamma_e}, \quad (\text{A39})$$

where  $\alpha_1 \equiv \psi \left( \frac{s+\psi+f(\theta)}{s+\psi} \right) = \psi/u$  and  $\alpha_2 \equiv \psi \left( \frac{s+\psi+f(\theta)}{\psi+f(\theta)} \right)$ . Average employment history increases with  $f(\theta)$  and decreases with  $s$ . Further, combining the flow equations gives that  $G^u(\gamma_u) = G^e(\gamma_e)$ .

Similar to proposition 1, when workers accumulate too much unemployment history their labor productivity equals  $b$ , at which point they are assigned to a zero surplus job. For a given employment history  $\gamma_e$ , there exists a unique unemployment history  $\bar{\gamma}_u(\gamma_e)$  such that  $h(\bar{\gamma}_u(\gamma_e), \gamma_e)p = b$ . The difference with the model in section 2 is that this threshold now depends on  $\gamma_e$  and is given by  $\bar{\gamma}_u(\gamma_e) = \frac{1}{\delta_u}(\delta_e \gamma_e - \tilde{\gamma})$ , where  $\tilde{\gamma} \equiv \log(b/p)$ .

The Bellman equation for vacancies becomes

$$rV = -c + q(\theta) \int_0^\infty \left( \int_0^{\bar{\gamma}_u(\gamma_e)} J(\gamma_e, \gamma_u) dG^u(\gamma_u) \right) dH^e(\gamma_e). \quad (\text{A40})$$

The endogenous TFP  $\bar{y}$  is given by

$$\bar{y} = \int_0^\infty \left( \int_0^{\bar{\gamma}_u(\gamma_e)} h(\gamma_e, \gamma_u) p dG^u(\gamma_u) \right) dH^e(\gamma_e) + \int_0^\infty \left( \int_{\bar{\gamma}_u(\gamma_e)}^\infty b dG^u(\gamma_u) \right) dH^e(\gamma_e). \quad (\text{A41})$$

Integrating gives that

$$\bar{y} = p \frac{\alpha_1}{\alpha_1 + \delta_u} \left[ \frac{\alpha_2}{\alpha_2 - \delta_e} - \frac{\delta_u \alpha_2 e^{\frac{\delta_u + \alpha_1}{\delta_u} \bar{\gamma}}}{\delta_u (\alpha_2 - \delta_e) + \delta_e (\delta_u + \alpha_1)} \right] + b \frac{\delta_u \alpha_2 e^{\frac{\alpha_1}{\delta_u} \bar{\gamma}}}{\alpha_1 \delta_e + \alpha_2 \delta_u}. \quad (\text{A42})$$

The endogenous TFP  $\bar{y}$  is uniquely determined by labor market flows and model parameters.

The calibration strategy is the same as in section 4. Additionally,  $\delta_e$  is chosen to match the same ratio  $b/\bar{y}$  as in the baseline model of section 2, so that the two models are comparable.<sup>46</sup> Table 6 shows the results. Comparing tables 3 and 6 shows that the model with both unemployment history and returns to experience gives essentially the same results as the baseline model with unemployment history alone.

Intuitively, whenever unemployment history is high, employment history is low, given that with two employment states, employment and unemployment, workers either accumulate unemployment history or employment history. Unemployment and employment history are the same with or without returns to experience (they are determined by labor market flows). TFP differences come in both models from the fact that unemployed workers have different human capital dynamics than employed workers. Whether the difference between the human capital of unemployed and employed workers are due to loss of skills alone, or the fact that employed workers are also accumulating skills, makes no difference in the results.

## Acknowledgments

I am grateful to the Editor Ayşe İmrohoroğlu, an Associate Editor and two anonymous referees, Nicholas Bloom, William Branch, Gabriele Camera, Joel David, Jang-Ting Guo, Nir Jaimovich, Greg Kaplan, David Lagakos, Dave Malueg, Vincenzo Quadrini, Peter Rupert, Chris Tonetti, Etienne Wasmer, Pierre-Olivier Weill and Alwyn Young for their valuable comments and suggestions. I also thank seminar participants at the 1st California Macroeconomics Conference, Claremont McKenna, the 92nd WEAI Annual Conference, Chapman University ESI and UC Riverside for helpful discussions.

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<sup>46</sup>Otherwise the ratio  $b/\bar{y}$  would be much smaller in the model with returns to experience than in the baseline model.

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Table 1: EFFECTS OF UNEMPLOYMENT HISTORY ON WAGES

	(1)	(2)	(3)	(4)
<i>Unhis</i>	0.0122 (0.0004)	0.0124 (0.0004)		
<i>Unhis</i> <sup>≤5</sup>			0.0161 (0.0006)	
<i>Unhis</i> <sup>&gt;5</sup>			0.0104 (0.0005)	
<i>Unhis</i> <sup>≤10</sup>				0.0130 (0.0005)
<i>Unhis</i> <sup>&gt;10</sup>				0.0108 (0.0006)
Occupation	yes	yes	no	yes
<i>N</i>	34,542	34,542	34,542	34,542

*Note.* - *Unhis*, *Unhis*<sup>≤5</sup>, *Unhis*<sup>>5</sup>, *Unhis*<sup>≤10</sup> and *Unhis*<sup>>10</sup> contain unemployment history in months. Numbers in brackets indicate standard errors. *N* refers to the number of observations. Column (1) corresponds to the baseline regression model (26). Column (2) corresponds to the baseline regression without occupation controls. Column (3) corresponds to the regression model (27). Wages are regressed on unemployment history accumulated in the past 5 years (*Unhis*<sup>≤5</sup>) and on unemployment history accumulated more than 5 years prior (*Unhis*<sup>>5</sup>). Column (4) contains the same estimation as (3), but with 10 years instead of 5. All regression models include worker fixed effects and consider men only. See section 3 for details.

Table 2: LABOR MARKET FLOWS

Country	Unemployment rate	Job finding rate	Separation rate	Job finding to separation ratio
Australia	7.1%	22.8%	1.7%	13.4
Canada	8.5%	26.1%	2.4%	10.9
France	8.1%	7.7%	0.7%	11
Germany	8.3%	6.0%	0.5%	12
Ireland	10.8%	5.9%	0.6%	9.8
Italy	9.8%	4.3%	0.4%	10.8
New Zealand	6.4%	28.5%	1.7%	16.8
Norway	4.1%	38.5%	1.6%	24.1
Portugal	6.2%	6.3%	0.4%	15.8
Spain	15.4%	6.3%	1.1%	5.7
Sweden	4.3%	29.2%	1.2 %	24.3
UK	7.7%	13.9%	1.0%	13.9
US	6.1%	56.5%	3.6%	15.7

*Note.*- Rates are expressed monthly. The estimates are drawn from Table 2 in Elsby et al. (2013). See section 3 for details.

Table 3: TFP DIFFERENCES

Country	Observed TFP	Endogenous TFP	US flows
<b>Continent. European</b>			
France	1.026	0.932	7.32%
Germany	0.884	0.932	7.33%
Italy	0.905	0.913	9.48%
Portugal	0.699	0.954	4.79%
Spain	0.901	0.881	13.50%
<b>Anglo-Saxon</b>			
Australia	0.831	0.972	2.91%
Canada	0.861	0.950	5.24%
Ireland	1.050	0.916	9.11%
New Zealand	0.795	1.001	-0.09%
UK	0.852	0.967	3.42%
US	1	1	–
<b>Nordic</b>			
Norway	1.225	1.051	-4.82%
Sweden	0.886	1.047	-4.48%

*Note.*- Observed TFP is drawn from PWT 9.0 and reports TFP from 1986 to 2014. TFP is measured relative to the US, so US TFP=1 both in the model and the data. The last column captures productivity changes if labor market flows were the same as in the US. See section 4 for details.

Table 4: OBSERVED TFP VS MODEL TFP

Correlation	.198
Variance, model	.003
Variance, data	.016
Fraction explained by model $\Delta_{var}$	16.7%

*Note.*- Observed TFP is taken from PWT 9.0 and is measured relative to US TFP (US TFP=1). The correlation measures the correlation between the model's endogenous TFP and observed TFP.  $\Delta_{var}$  is the ratio of the variance of the model's TFP to the variance of observed TFP. See section 4 for details.

Table 5: IMPACT OF HIRING SUBSIDY ON TFP

Country	TFP ratio $\frac{\bar{y}^{\tau_h > 0}}{\bar{y}^{\tau_h = 0}}$
Australia	1.0128
Canada	1.0191
France	1.0114
Germany	1.0101
Ireland	1.0121
Italy	1.0108
New Zealand	1.0097
Norway	1.0055
Portugal	1.0077
Spain	1.0196
Sweden	1.0048
UK	1.0099
US	1.0161

*Note.*- Table 5 gives the ratio of TFP with a hiring subsidy  $\tau_h = 0.5$  ( $\bar{y}^{\tau_h > 0}$ ) to TFP in the model with no subsidy ( $\bar{y}^{\tau_h = 0}$ ).

Table 6: TFP DIFFERENCES WITH LOSS OF SKILLS AND RETURNS TO EXPERIENCE

Country	Endogenous TFP
<b>Continent. European</b>	
France	0.9347
Germany	0.9367
Italy	0.9183
Portugal	0.9620
Spain	0.8745
<b>Anglo-Saxon</b>	
Australia	0.9731
Canada	0.9500
Ireland	0.9189
New Zealand	1.0022
UK	0.9701
US	0.9701
<b>Nordic</b>	
Norway	1.2174
Sweden	1.0464

*Note.*- Endogenous TFP is relative to US (US=1), and provides TFP in the model with both unemployment history and human capital accumulation during employment. See appendix for details.