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Essays on the Macroeconomics of Labor Markets

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A la memoria de mi abuelo.
A las "pequeñas personitas" de mi vida.
Porque estar lejos es siempre difícil.

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Abstract

This thesis sheds light on several macroeconomic aspects of labor markets. The first chapter focuses on the impact of dual labor markets on human capital investment. Using a large dataset of the Spanish Social Security the wage losses of permanent and fixed term workers after displacement are analyzed. Results indicate that workers under permanent contracts accumulate a higher share of firm specific human capital than workers under fixed term contracts. The impact on aggregate productivity is analyzed using a calibrated model à la Mortensen and Pissarides (1994) with endogenous investment in human capital and dual labor markets. The second chapter develops a model in order to explain cross countries differences in the cyclical fluctuations of informal employment for developing countries. The explanation can be found in institutional differences between the formal and informal sector. The third chapter proposes a model that uses the flows into and out of unemployment to forecast the unemployment rate. It shows why this model should outperform standard time series models, and quantifies empirically this contribution for several OECD countries.

Resumen

Esta tesis arroja luz sobre varios aspectos macroeconómicos de los mercados laborales. El primer capítulo se centra en el impacto de los mercados duales de trabajo sobre la inversión en capital humano. Usando una base de datos de la Seguridad Social española, se analizan las pérdidas salariales de los trabajadores permanentes y a plazo fijo tras cambiar de empleo. Los resultados indican que los trabajadores con contratos permanentes acumulan una mayor proporción de capital humano específico a la firma, que los trabajadores con contratos de duración determinada. El impacto sobre la productividad es analizado calibrando un modelo à la Mortensen y Pissarides (1994) con invesión endógena en capital humano y mercado de trabajo dual. El segundo capítulo desarrolla un modelo para explicar las diferencias en las fluctuaciones cíclicas del empleo informal en los países en desarrollo. La explicación se basa en diferencias institucionales entre el sector formal e informal. En el tercer capítulo se propone un modelo que utiliza flujos de entrada y salida del desempleo para pronosticar la tasa de desempleo. Se analizan cuáles son las condiciones bajo las cuales este modelo tiene una performance superior a los modelos estándar de series de tiempo, y cuantifica empíricamente esta contribución para varios países de la OCDE.

Foreword

This dissertation consists in three self-contained chapters that deal with different aspects of the macroeconomic analysis of the labor markets. The first chapter is concerned about the impact of dual labor market institutions on the investment of human capital and on productivity. The second chapter deals with the cyclical fluctuations of informal employment in developing countries. Finally, the last chapter analyzes the performance of a novel model that uses the flows into and out of unemployment to forecast the unemployment rate in OECD countries.

The objective of the first chapter is to evaluate the impact of dual labor market institutions on the investment in firm specific human capital and productivity. Empirically this is done by estimating the impact of mass-layoffs on subsequent wages in Spain, differentiating between workers holding permanent and fixed term contracts at the time of displacement. The main empirical finding is that permanent contract (PC) workers suffer larger and more persistent wage losses than their fixed term contract (FTC) counterparts. Wage losses for PC workers stem mainly from the loss of pre-displacement firm tenure, while this source is not important for FTC workers. This is taken as evidence of the difference in the accumulation of job specific human capital between the two type of contracts. The wage loss gap due to the difference of investment in firm specific human capital is estimated to be 6% after the first quarter of displacement. A search and matching model à la Mortensen and Pissarides allowing for endogenous accumulation of firm specific human capital and the existence of the two type of contracts is developed. The model shows that firms always offer fixed term contracts if they are allowed to do so. The employee's decision of investment in human capital depends on the expected duration of the contracts, and hence on the expiration rate of FTC and firing costs. Calibrated to the Spanish economy the model predicts that only PC workers invest in firm specific human capital, while FTC workes do not. This implies that PC workers are on average 12% more productive than FTC. The model suggests that aggregate labor productivity would increase due to the investment in firm specific human capital of FTC workers if the employment protection law for FTC workers was more stringent (i.e. lower maximum duration of this type of contract).

The goal of the second chapter is to understand the cyclical fluctuations of informal employment in developing countries. Developing countries, as developed ones, are characterized by procyclical employment rates, countercyclical unemployment rates. While informal employment as *a share* of total employment is countercyclical, the cyclical behavior of informal employment in *absolute terms* (as a percentage of working age population) differs across countries. While in Mexico informal employment in *absolute terms* is countercyclical, in Brazil it has a procyclical behavior. This chapter analyzes whether institutional differences between the formal and informal sector are important to explain the different cyclical fluctuations of informal employment across countries. In the model, the informal sector arises because of the possibility of evading the payment of a fixed cost that formal firms pay to the government. On the other hand, being informal requires bearing the risk of being monitored by the government with the consequence of destroying the match, and suffer from lower productivity. Results show that this very simple model can replicate the correlation of informal employment and unemployment with output in the case of Mexico and Brazil. The calibration exercise predicts that informal employment as a *share* of total employment is countercyclical as in the data. While informal employment *in absolute terms* is countercyclical in Mexico, it is procyclical in Brazil. This different cyclical fluctuations of informal employment are driven by a higher productivity gap and higher fixed cost of the formal sector compared to the informal sector, in Mexico relative to Brazil.

The third and final chapter provides the theoretical and empirical foundations for a new approach to unemployment forecasting that can be applied to a wide range of countries. The approach builds on a convergence property of the unemployment rate, whereby the actual unemployment rate converges toward the rate implied by the labor force flows. The performance of the model over a range of OECD countries is evaluated, finding that the model yields dramatic improvements in forecast accuracy, with large reductions in the mean-squared errors of the best alternative models for forecasts as far as one- to two-year ahead. Improvements are especially large during recessions and turning points, when unemployment forecasts are most valuable.

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Chapter 1

WAGE LOSSES AFTER DISPLACEMENT IN DUAL LABOR MARKETS. THE ROLE OF FIRM SPECIFIC HUMAN CAPITAL.

1.1 Introduction

In the period 1996-2007, the Spanish economy experienced significantly weaker labor productivity growth than other OECD economies and failed to catch up with the most advanced economies. According to Mora Sanguinetti and Fuentes (2012), the key factor explaining this poor performance is the reduction of TFP growth during this period. This weakening productivity performance in Spain is not explained by specialization in industries with generally weaker productivity growth is several OECD countries; productivity growth in Spain was relatively weak in a wide range of sectors. The authors identify some characteristics of the Spanish institutional environment that have contributed to the low TFP growth.

One of the identified institutional arrangements affecting the Spanish productivity performance is the dualism in its labor market, governed by two different types of contracts: permanent contracts (PC) with high employment protection, and fixed term contracts (FTC) with very low or no employment protection[1]. These large differences in employment protection lead to a widespread use of fixed-term contracts, reducing training motivations for workers and firms, and discouraging investments in firm-specific human capital having detrimental effects on productivity (Damiani and Pompei (2010)).

The main objective of this chapter is to investigate the impact of dual labor market institutions on the accumulation of firm specific human capital (FSHC). Therefore, this chapter analyses wage losses after displacement distinguishing between workers holding fixed term and permanent contracts. After displacement, workers usually need to restart their career from scratch in a new job, where they need to acquire new skills or establish a new network inside the firm, with the subsequent wage losses. The acquisition of specific skills through, for example, learning-by-doing on the job and investments in specific training can yield substantial wage losses when starting a new job after displacement. Topel (1990) and Neal (1995), and more recently Davis and Wachter (2011), among others, argue that specific forms of human capital play a central role in determining the magnitude of earnings losses associated with job displacement.

The first contribution of the chapter is to develop a detailed picture of the displacement event in Spain, providing evidence on wage losses after displacement distinguishing between displacement from fixed term contracts and permanent contracts. Spain is, in fact, a good laboratory to analyze the sources of wage losses since it is an an extreme example of dual labor markets allowing us to analyze the sources of wage losses by type of contract. PC and FTC workers have very different expected job duration. The standard human capital theory of Becker (1964) has clear predictions on the type of human capital accumulated by workers hired under these two different contractual arrangements. PC workers are expected to accumulate more firm specific human capital relative to workers employed with FTC, due to the lower expected duration of the jobs of the latter. Hence, FTC workers wage losses upon displacement should be relatively lower than PC workers' losses, generating a *wage loss gap* between PC and FTC workers.

This study makes use of a novel data set that traces the labor market experiences of a large number of workers, and data from their employers in Spain from 1996 to 2008. The resulting data set contains quarterly earnings histories for a large number of displaced and non-displaced workers, and the type of contract they hold. Therefore, this chapter reveals a detailed decomposition of the wage losses into firm or sector specific human capital, and unemployment duration.

[1]Dual economies appeared in Europe in the mid-80s when policy makers introduced flexibility at the margin in order to tackle the very rigid labor markets and the low employment rates. These reforms affected the relative strictness of the employment protection legislation (EPL) on fixed-term and permanent contracts. The consequence was the rise of segmented labor markets with highly protected employees under permanent contracts, and weakly protected fixed term contracts, which are typically subject to low firing costs. Temporary contracts, however, are usually subject to restrictions such as limited renewals and maximum durations.

The methodology focuses on mass-layoffs in order to isolate the group of workers who would not have moved under normal business conditions, approximating an exogenous displacement. By doing so, the selection bias problem due to low qualified workers being laid off is reduced. The methodology used is a differences-in-differences approach. Assuming that selection into mass-layoffs is done based on observable pre-displacement characteristics and fixed effects, results show the causal effect of a mass-layoff on wages. The control group is defined by workers not suffering mass-layoffs in the entire period.

The results show that workers under PCs suffer larger and more persistent wage losses after displacement than their fixed term counterparts. In the first quarter after displacement PC workers suffer a sharp drop in wages amounting to 20% relative to the control group, consisting of employees not suffereing mass-layoffs in the entire period. While the estimated wage loss for FTC workers, one quarter after displacement, is 8%. In the fourth year following displacement, substantial recovery occurs and the wage loss is estimated 11% average for PC workers and 1% for FTC workers. Results are robust for workers with less than three years of firm tenure. Even if the point estimates are lower for PC workers, there is still a statistcally significant wage loss gap.

In a second step, a decomposition of these wage losses into its sources is done. Results indicate that changing industry has a negative impact on post-displacement wages for both worker types, being the impact of similar size. On the other side, unemployment duration is important to explain wage losses, and is more important for PC workers. Finally, while pre-displacement tenure is the most important source explaining wage losses for PC, it is not important for FTC workers. This is taken as evidence of lower accumulation of FSHC under fixed term contracts. The wage loss gap due to the difference in investment in FSHC is 6% in the first quarter after displacement.

The second contribution of the chapter is the development of a search and matching model to understand how investment in firm specific human capital depends on the type of contract arrangement. A search and matching model à la Mortensen and Pissarides (1994) with two type of contracts, permanent and fixed term, and endogenous accumulation of firm specific human capital is developed. Firms decide which type of contract to offer to a worker when first matched; whether to offer a permanent contract or lay-off the worker when a fixed term contract expires; and when to separate endogenously. Workers decide whether to invest in firm specific human capital when first matched to a firm, and when offered a conversion to a permanent contract. They correctly anticipate the type of contract they are offered and the result of the wage bargaining. The investment entails a cost, which has to be paid at the beginning of the period, and the workers becomes instantaneously more productive if she decides to invest. The cost of investment is sunk before reaching the wage bargain. Due to the nature of these specific investments, training or the effort to become more productive can neither be contracted nor enforced. Hence, this investment can be thought of as the workers effort, not observable by firms.

In the model, it can be shown that firms always offer FTCs when first matched to workers if legally allowed to do so. Hence workers always begin a match with a FTC. Some of them are going to be converted to a PC, while others will be laid-off. The decision of acquiring human capital will depend on two parameters that determine the duality of the economy: firing costs of PC and the expiration rate of fixed term contracts. Under fixed term contracts there is little incentive to invest in firm specific human capital, since the expected duration of these jobs is not enough to reap the benefits from the investment.

Calibrated to the Spanish economy, the model predicts that only PC workers invest in FSHC, while workers holding FTC do not. In fact, FTC workers invest only if the maximum duration allowed for these contracts is shorter, i.e. stringent law employment protection of FTC workers. This is because with shorter duration of FTCs firms rely less on FTC, converting them more to PC, because laying-off a worker and hiring another one is also costly. The 6% wage loss gap due to the difference in the investment in firm specific human capital found in the data, translates into a 12% gap in productivity between the two types of workers. Lastly, the model is used to measure the labor productivity loss due to the use of fixed term contracts with lower investment in firm specific human capital. The model predicts an increase of 16% in aggregate labor productivity if the law on FTC was more stringent, i.e if the maximum duration of FTC goes from two years and a half to two years.

The chapter is organized as follows. The next section revises the related literature. Section 3 presents the empirical analysis, showing the data, and methodology used, while section 4 presents the empirical results. Section 5 presents the theoretical model, and section 6 discusses the results from the model. At the end, conclusions are drawn.

1.2 Related literature

This study is related to three different strands of literature. First, the literature that revises the effects of firing costs, or more general employment protection, on the economy. Second, the empirical literature documenting earning losses after displacement. And third, search and matching models introducing flexibility at the margin.

According to the literature regarding firing costs, or more generally of employment protection legislation (EPL), EPL has uncertain effects on the unemployment rate, although it reduces the labor market dynamics, and its speed of reallocation (Bentolila and Bertola (1990)). It has also been shown that it can decrease productivity (Hopenhayn and Rogerson (1993), Bertola and Caballero (1994)) through the inefficient lower reallocation of workers. On the other side, Belot et al. (2007) shows that EPL could have improving welfare effects by increasing investment in firm specific skills. These papers analyze employment protection when applied uniformly to all workers in the economy. Studies analyzing the effects of the introduction of flexibility at the margin, i.e. duality, have found that it has created inefficient labor turnover (Boeri (2011))) although the effect on unemployment is mixed, it has increased the volatility of unemployment (Costain et al. (2010), Sala et al. (2011),Bentolila et al. (2010)).

Finally, this research is very related to studies that analyze the effects of dual labor markets on productivity. Damiani and Pompei (2010) look at how employment contacts (permanent and temporary) affect cross-national and sectoral differences in multifactor productivity growth in sixteen European countries from 1995 to 2005. The authors show that fixed-term contracts, may discourage investment in skills and have detrimental effects on multifactor productivity increases, and that employment protection reforms which slacken the rules of fixed-term contracts cause potential drawbacks in terms of low productivity gains. Dolado et al. (2012) show that duality institutions have a negative effect on TFP development at the firm level. With a simple model they show that a larger firing cost gap has negative effects on firms' TFP, by lowering the exerted effort of temporary workers and the training they receive from employers. The authors test this implication by using a longitudinal firm-level dataset. They evaluate the impact of changes in the firing-cost gap on firms' TFP using as natural experiments several labor market reforms entailing changes in EPL in 1994, 1997 and 2002. They found that firms with larger share of FTC workers before the reforms, show higher conversion rates and higher TFP after the reforms. This chapter looks to the same issue from a different angle. First, shows empirically the different content of firm specific human capital between the two type of contract arrangements. Then, shows how this translates to lower labor productivity using a search and matching model with endogenous firm specific human capital investment.

The empirical evidence on earning losses is vast for US. The evidence suggests that the average earnings losses of displaced workers are large and persistent in US (see Ruhm (1991), Farber (1997) Stevens (1997), Couch and Placzek (2010) and Jacobson et al. (1993)). Perhaps the most cited work is the latter. It introduced the use of program evaluation techniques into the job displacement literature. In this study, the authors use administrative data on Pennsylvanian workers to compare pre and post-displacement earnings of high-tenure (more than six years) displaced workers relative to a control group of non-displaced workers. The Pennsylvania data span the years 1974 to 1986. By focusing on workers that remained attached to the labor market after massive layoffs, they find that high tenure workers suffer substantial earning losses when they leave their jobs. The authors provide the largest estimates of lost earnings in the literature, 45 percent the year of displacement. The paper has been criticized for focusing only in very high tenured workers, possibly biasing upwards the average earning losses. Davis and Wachter (2011) present evidence of wage losses after displacement for more than three years tenured workers, obtaining very similar results to Couch and Placzek (2010) and Jacobson et al. (1993).

The empirical evidence for Europe is relatively sparse. Studies by Lefranc (2003) for France, Carneiro and Portugal (2006) for Portugal, Eliason and Storrie (2006) for Sweden find the long-term losses to be large and concordant with the earlier studies for the US. Other results for Germany, confirm these findings. Burda and Mertens (2001) and Schmieder et al. (2010) found wage losses to be around 4 and 14%, respectively. For the British economy, Arulampalam (2001) reaches similar conclusions. The author also stress the importance of the source of unemployment and report significant scarring not only after dismissals and layoffs, but also after non renewal of temporary contracts and among workers from declining industries. More recently, Garcia Perez and Rebollo Sanz (2005) and Arranz et al. (2010) using the European Community Household Panel (ECHP) data analyze the effects of job mobility on wages, and particularly the effects of a spell of unemployment and inactivity on reemployment wages. The results found confirm that workers experience important changes in their real wages as a consequence of involuntary job mobility. According to Garcia Perez and Rebollo Sanz (2005), German workers tend to experience larger wage losses compared to the rest of countries (Spain, France and Portugal). When compared to stayers, German workers have much larger wage penalties, around 22%, followed by French, Spanish and Portuguese workers, who suffer wage losses of 10%, 9% and 8% relative to stayers, respectively. At the same time Arranz et al. (2010) found that spells of both, unemployment and inactivity, scar future wages. These scars are deeper in France if individuals move between jobs due to inactivity. Unemployment (but not inactivity) also brings about wage losses in Germany, Italy, Spain and Portugal. This study focuses on wage losses after a mass-layoff using a unique dataset from social security records distinguishing between workers holding permanent and fixed term contracts.

Finally, this chapter is related to search and matching models allowing for flexibility at the margin. Papers developed recently have focus on business cycle fluctuations in dual labor markets. In particular they explore whether flexibility at the margin is the reason why labor markets with a relatively high degree of employment protection may display similar volatility as fully flexible ones. Costain et al. (2010), Bentolila et al. (2010), and Sala et al. (2011) allow for two different type of contracts: permanent contracts with high severance payments, and fixed term contracts with very low or no severance payments. All the three papers focus on the interactions between aggregate productivity shocks and employment protection legislation, including the regulation of fixed term jobs. The model in this chapter is very similar to Sala et al. (2011) adding endogenous accumulation of firm specific human capital.

In the theoretical search and matching literature there are few attempts to reconcile the empirical evidence on earnings losses with the evidence on worker flows. The work of Davis and Wachter (2011) is a notable exception. They study search and matching models without worker heterogeneity and conclude that simple versions of the model are not able to reproduce the empirical earnings losses. This chapter contributes to this literature by developing a model with endogenous investment of firm specific human capital. The larger the accumulation of FSHC the larger the wage losses after displacement a worker suffers.

1.3 Data and empirical methodology

1.3.1 Data: Continuous Sample of Job Histories

The data used is a unique administrative dataset with Social Security records called Continuous Sample of Job Histories (Muestra Continua de Vidas Laborales, MCVL) for the year 2008, which contains information on individual job histories from social security records and basic individual information from the census. Thus, we can work with detailed information of all job spells in a worker's history.

The MCVL consist of a random sample of 4% of all affiliated workers, working or not, and pensioners from the Social Security archives. The MCVL is very rich and detailed as regards job histories, which include labour market status and type of contract for each and every job spell. It includes information on age, gender, qualification level, reason for termination of the spell (voluntary/involuntary or retirement), province of residence of the worker.

The MCVL contains information about the amount for which employees have to contribute to the Social Security System, which is a good approximation of the wage for the majority of workers. Wages are computed from covered wages, hence are censored from bellow and above. The fact that are censored from bellow is not that important, because there are very few cases and also because the minimum wage is binding. With respect to the censoring from above, there is no reason why the presence of the top-code should affect displaced workers more than non-displaced workers, in fact, is vice versa, leading to understate the earning losses at job displacement. This issue affects mainly permanent contract workers. Hence, the results are a lower bound of wage losses for PC workers.[2]

The analysis uses a sample period from 1996 to 2008. We focus on men born between 1948 and 1971, that is between 25 and 48 years old in 1996. The sample is restricted to people that were employed during the period 1996-1998 at least one year and half, and have at least one year tenure in their firms. The final database contains

[2] To check the robustness of the estimation a correction by the top coding in the data has been performed, using the algorithm described in Boldrin et al. (2004) to recover actual wages. The estimation of actual wages relies on the assumption that the true distribution of the logarithm of earnings is a normal distribution where the mean is a linear function of observed individual and job characteristics (age, nationality, sector, type of contract, region and time dummies). The censored values are replaced by the estimated conditional mean of wages. Results are robust to this estimation, confirming that not using this correction, i am finding a lower bound of wage losses. Results are available upon request.

quarterly information of complete job histories of the workers, their wages, region, industry, and qualification. Appendix 1.8 contains detailed description of the sample and restrictions imposed to the data used in the analysis.

Following the academic literature, the definition of displacement is based on mass-layoffs. Due to the fact that this is a 4% random sample, there is no available data on total firm size for all the years of the sample, hence the mass-layoff is defined in sample, as the 30% reduction of the workforce in a given firm, a given year[3]. See Appendix 1.8 for detailed definition of displacement.

The primary purpose of looking at workers from firms where employment has declined by at least 30% is to reduce the likelihood that workers fired for cause are included in the sample, and hence reducing selection bias. In this sense, the mass-layoff measure reduces the selection bias for the two type of workers since is measuring the probability of getting displaced or not having the contract renewed because of exogenous reasons to the characteristics of the workers, and more related to the business conditions of the firms. This way we can substantially lessen the importance of the selectivity bias by restricting the analysis to workers who separate from firms that reduce a large part of their workforce. Such workers are unlikely to have left their jobs as a result of their own poor performance.

Hence, the treatment group is going to be defined as those going through mass-layoffs in some year between 1999 and 2004. The control group is defined by workers not suffering mass-layoffs in the entire period, from 1996 to 2008. They can make direct job-to-job transitions, or convert contracts within the same firm. This is a better choice than that of using only workers that additionally maintain their initial jobs for all the period, because the comparison group is aimed to be representative of the counterfactual situation of displacement for both types of workers.

1.3.2 A glance at the data

Tables 1.1 to 1.3 present sample characteristics of displaced workers during mass-layoffs. These tables show that there are important differences between displaced and non displaced, and under the two types of contracts. Table 1.1 shows differences in workers characteristics in 1997 (the beginning of the sample), that is pre-treatment period. First, displaced workers under PC tend to be younger than non-displaced PC workers, while for FTC workers the difference is not significant. On the other hand, displaced workers tend to have shorter firm tenure. Displaced from fixed term contracts tend show lower wages than the non-displaced counterpart, but for the PC workers this difference is not significant. These differences are also present between the two type of contract.

[3]We present here the results for the this definition of mass-layoff sample, but other cutoffs have been tried. The 40% and the 15% show very similar results. Also, using only plant-closing in the sample show very similar results. Results are available upon request.

That is, fixed term workers are younger, lowered tenured and earn lower wages, than their open-ended contracts counterparts.

As table 1.2 shows, displaced workers tend to be lowly educated and occupy positions that require lower qualification (second panel of the table). These differences are also present when comparing PC and FTC workers. Fixed term workers tend to be lower educated, and occupy lower qualification positions, than the PC counterparts. Finally, as the third panel of that table shows, PC workers suffer mass-layoff mainly from manufacturing and service sectors, while for FTC workers, the construction sector is also very important.

These pre-separation differences highlight the importance of controlling for observable and unobservable characteristics of the displaced workers when comparing them to a control group, something that is going to be address in the regression analysis.

Finally, table 1.3 shows differences in the displacement event between temporary and permanent workers. First, firm tenure at displacement is much shorter for fixed term workers[4]. Second, workers displaced from permanent contracts tend to experience longer unemployment spells. Third, more than 60% of workers holding indefinite contracts at displacement are re-employed with fixed term contracts[5]. This figure is larger for workers holding fixed term contracts at displacement (almost 90%). Hence, displaced workers enter a mobile market with high incidence of temporary contracts. After two years of being re-employed, PCs workers tend to have more probability of re-gaining a PC while most FTCs still mantain the temporary status. Finally, almost half of these workers change industry after displacement. The industries are measured at two digit level. The figures are similar between the two type of workers, showing that changing industry is not more probable for any of the two contract arrangements after a mass-layoff event.

Figures 1.1a and 1.1b show the daily real wage path of individuals who separate from employment in 2001 relative to the control group. Figure 1.1b shows the wage path including the periods of unemployment with zero wages, while figure 1.1a shows only pure wage effects, i.e. being missing observations when unemployed. It is notable that before separation wages trends are similar relative to each other, for both types of workers. Figure 1.1a is the most interesting for us, since the regression analysis will have as dependent variable the logarithm of wages. If anything, there appears to be a simple intercept difference in the starting point of the wage paths at the start of the sample period between displaced and non-displaced, and permanent and fixed term contracts. Thus, estimators such as the fixed-effects, which control for individual specific

[4]Most of fixed term contracts may not be extended after 3 years, although changing the nature of the job for hiring the same worker under subsequent temporary contracts has been a common practice among Spanish employers. This and the fact that "per task or service" contracts are easily extended, explains the high tenures of some fixed term employees.

[5]This makes sense since the majority all new hires are done using fixed term contracts (Güell and Petrongolo (2007))

intercepts would be expected to effectively equalize earnings prior to job separation. Additionally, the figures show that workers experienced substantial long-term wage losses. The earning losses in figure 1.1b are larger than in figure 1.1a, related to the zero income during unemployment. In figure 1.1a, where pure wage losses can be analyzed, we can already see that fixed term workers experience much lower wage losses, if any, than workers holding permanent workers at the time of displacement.

1.3.3 Methodology

A key lesson from the literature is that is not sufficient to measure wage losses as the difference between workers' earnings in some post-displacement period and their earnings in a period shortly before separation. Some reasons why this measure may not capture the full effect of displacement on workers' earnings are: it does not control for macroeconomic factors that cause changes in workers' earnings regardless of whether they are displaced; does not account for the earnings growth that would have occurred in the absence of job loss; and, firms' declining fortunes may adversely affect workers' earnings several years prior to their job loss, as Jacobson et al. (1993) argued. Thus, the displaced workers' wage losses are defined as the difference between their actual and counterfactual wage that would be prevalent if the events leading to separation had not occurred.

The idea is to compare wages of non displaced versus displaced workers. An augmented mincerian wage equation that captures the difference in earnings across displaced and non-displaced workers, can be estimated:

$$y_{it} = \alpha_i + \mu_t + \beta X_{it} + \sum_k \gamma_k D_{it}^k + \sum_k \delta_k D_{it}^k * PC_i^0 + \eta PC_{it} + \varepsilon_{it} \tag{1.1}$$

y_{it} is the logarithm of the real daily wage earnings for individual i at period t. Wages were deflated by the CPI (base: January 2008). The displacements episodes are represented trough a set dummy variables: D^k. These dummies are equal to one if individual *i* was displaced at $t - k$ (k can be negative, this means that are k quarters after sepatrion; or if k positive means k quarters before separation). I differentiate between the type of contracts, multiplying by a dummy that indicates if at the time of separation the worker holds a PC (PC^0). Hence, the coefficient γ_k reflects the differences in earnings between separated and non-separated workers holding FTC at period k before/after separation, while δ_k indicate the wage loss gap between PC and FTC workers. This allow us to see the different evolution in wage losses for displaced workers, distinguishing PC and FTC. The equation includes a matrix X_{it} with observable characteristics, including time varying individual characteristics, such as a quadratic form in age, regional dummies, sectoral and qualification dummies. The equation includes a control for the type of contract hold at every t PC_{it}, where η captures any premium in wages between permanent and fixed term workers, after controlling for observed and unobserved characteristics.

μ_t are time effects that capture the general time pattern of earnings in the economy. α_i summarizes permanent differences among workers in observed and unobserved characteristics. The error term ε_{it} is assumed to have constant variance, and to be uncorrelated across time and individuals.

This strategy is a form of the differences-in-differences (DiD) estimation method, which in this case is implemented by using a fixed-effects estimator. Much of the literature on displacement recognizes that the event is likely to be non-random. Non-random assignment is likely to be a problem, even for a mass-layoff or plant-closings sample. Employer selection suggests that those workers with lower productivity will be displaced in a mass-layoff, while employee selection suggests that those workers whose outside job prospects are better will choose to leave. In the case of firm closure, it may be that those workers who remain in the firm until closure are a non-random sample of all those in the firm at the point where closure become public knowledge.

If selection into the treatment and control groups is on the basis of permanent characteristics embodied in workers' fixed effects and the observable characteristics, then equation 1.1 will yield consistent estimates of the expected wage loss. Hence, the assumption for interpreting γ_k and δ_k as causal impact of job separation is that conditional on fixed effects and included observable characteristics, displaced workers are observationally equal to the workers in the control group. In any case, Appendix 1.9 shows a robustness checks including specific time trends.

Another comment we need to make at this point, is that estimations are only taking into account people that find jobs again. There can be a problem in selection since we only observe successful people that manage to be re-employed again. Since, the idea of the study is to analyze pure wage effects of job displacement in order to capture the implication of the human capital theory, we restrict to this case.

1.4 Empirical results

1.4.1 Wage losses after displacement

Figure 1.2a provides a graphical representation of the estimated wage losses, γ_k for FTC workers and $\gamma_k + \delta_k$ for PC, and their 95% confidence interval, for the fixed-effects estimator (equation 1.1). Figure 1.2b shows the wage loss gap between PC and FTC, that is, the estimation of δ_k. The first quarter after displacement workers from permanent contracts suffer a sharp drop in wages. The estimate of wage reductions for PC workers of the fixed-effects estimators the first quarter after separation is 21,9 percent relative to the control group. [6] In the fourth year following displacement, substantial recovery occurs and the estimated impact average 11,7 percent. The estimated wage losses for workers holding FTCs at the time of displacement are much lower. The first quarter after displacement suffer an 8,5 percent wage losses relative to the control group, while after four years of displacement, substantial recovery occurs and the estimated impacts average 1,3 percent, being not statiscally significant.

As shown in figure 1.2b the differences in the wage losses between displaced from permanent or fixed term contracts are always significant, indicating that permanent contract workers loss more wages after a mass-layoff than their fixed term counterparts. The gap is 15% in the first quarter after displacement, recovering slowly till 10% 6 years after.

One of the main reasons behind the differences in the wage losses after displacement between PC and FTC is the clear differences in firm tenure that arise from table 1.3. In order to see if these differences are still present when restricting by tenure, we are going to apply the same methodology but taking into account, both in the control and treatment group, workers with less than three years of tenure in the last quarter of 1998, i.e. the quarter before I allow for mass-layoffs to happen.

Figure 1.3a shows the graphical representation of the coefficients in equation 1.1 using only workers with less than three years tenure. Results are robust. The figure is very similar to figure 1.2a, but now the point estimates for PC workers are lower. This makes sense since we are restricting to people with lower tenure, and hence lower accumulation of specific human capital. The wage loss gap, in figure 1.3b, is 10% in the first quarter after displacement, and four years later still remains very high (7%).

Appendix 1.9 shows some robustness checks including specific time trends, and estimating the wage losses depending on the type of contract the worker has been able to obtain after two years of being re-hired.

1.4.2 Decomposition of wage losses

According to Becker's theory, if job tenure contributes to the accumulation of specific human capital or seniority rights, it should be positively associated with wage losses. On the other hand if, a component of wage gains are due to industry-specific capital, then displacement should affect future wages only in the event that workers switch industries. Finally, if deterioration of general human capital during unemployment happens, or an unemployment spell serves as a signal of low productivity, wage losses should increase with the duration of unemployment.

[6] Although these figures look big, they make sense, since unemployment benefits in Spain are 70% of the covarge wages in the fist 180 days, and 60% from the day 181. The duration of the benefits go from three months to two years depending on the period the worker was employed in the last six years.

This exercise shows the decomposition of the wage losses in different sources, using equation 1.1 :

1. loss that stems from the loss of job tenure $\rightarrow$ firm specific skills, or seniority
2. loss related to changing industry$\rightarrow$ loss of sector specific skills
3. loss associated with unemployment duration $\rightarrow$ depreciation of general human capital, or signal of low productivity

The idea is to include to the baseline equation, one by one possible determinants of the wage losses. Including these variables we are explaining the wage losses, hence the estimated losses are the wage losses that remain after controlling for these sources. Thus, we expect a decrease in the estimated coefficients (δ^k and γ^k).

First, I am going to compute how the wage losses change when including the possible determinants, i.e. the coefficients on the displacement dummies, at one year after displacement, $k = 4$. After including each determinant, we are going to impute the change in the wage losses (the estimated coefficients) to that variable (e.g. unemployment duration). Since the estimated coefficients are sensible to the order on how we include these determinants, I am also going to change the order how these variables are included, and calculate the maximum and minimum change of the wage losses. These are interpreted as the range of change of the wage losses due to the different determinants.

The possible determinants included are pre-displacement tenure (equal to the tenure in the firm where the worker suffered the mass-layoff), duration of unemployment (total duration of unemployment after the mass-layoff), and a dummy variable that is equal to one after the mass-layoff if changed industry at two digit level in the new job. These variables are equal to zero before displacement and for the control group. This is like multiplying a dummy equal to one after displacement, by unemployment duration, pre-displacement tenure or if change industry. At the same time, these variables are interacted with PC^0, the dummy that indicates if the worker had a PC at the time of displacement, in order to analyze the effects by type of contract.

First, the analysis of the coefficients on the determinants is performed. Table 1.4 shows the the regression estimates after including all the determinants explained above. On average, one quarter of duration of unemployment rises the losses in wages, relative to the control group, in 0.99 percentage points (p.p.) for workers displaced from FTC, while 1.77 p.p for PC workers. This difference is statically significant, showing that duration of unemployment has a larger negative impact on worker displaced from PC.

Changing industry, has also a negative impact increasing losses by 3.4 p.p. and 3.6 p.p for FTC and PC, respectively. The difference of the impact is not significant. The result indicates that accumulated sector-specific capital is important to explain wage losses, but the there is no difference in the accumulation between the two type of contracts, i.e. both contracts accumulate the same sectoral human capital.

Finally, dummies for pre-displacement job tenure have been included. Having less than three years of pre-displacement tenure has no significant effect on post-displacement wages of FTC. The impact is negative and significant for worker with more then three years tenure under FTC, increasing the losses in 4.6 p.p.. For permanent contract workers, pre-displacement tenure has negative impact on wage losses after displacement, and increases with pre-displacement tenure. For workers with a year or less of tenure in the displacement job wage losses increase by 6.3 p.p.. For workers with tenure between one and three year this reaches to 7.3 pp and for more then three years 11.4 pp. This differences with respect to FTC workers are significant. This is evidence of different accumulation of job specific capital human capital between the two type of contracts, supporting the prediction of the human capital theory.

We can now turn to analyze what happens with the displacement dummies for the two type of workers. After including the determinants, the estimated wage losses can be interpreted as if workers did not experience unemployment, did not change industry, and did not loss tenure. Table 1.5 shows the change in the coefficients on the displacement dummy after a year of displacement in the base line equation 1.1. Since, the estimated coefficients can be altered by the order of inclusion of these determinants, the table shows the maximum and minimum of the change in the wage losses depending on the order.

As shown in the table 1.5, pre-displacement tenure is the more important source for explaining wage losses of PC workers; between 25% and 50% of their losses are explained by the loss of pre-displacement firm tenure, while between -20 and 20% of FTC losses, showing that is not significant. Again, this is evidence of the difference in the investment of firm specific human capital between the two type of contracts, confirming the hypothesis of lower investment in FTC. Controlling for unemployment duration is important to explain FTC and PC wage losses. From 6 to 22%, and from 14 to 23% of the wage losses of FTC and PC, respectively, are explained by the time spent in unemployment. Finally, the losses from changing industry explain a lower share of the wage losses, even if it seems to be very sensitive to the order on how we include variables. In any case, this is evidence that even if the accumulation of industry specific capital is important, is not different between the two type of contract arrangements.

Finally, figure 1.4 shows how the wage loss gap, δ^k, after including if changing industry and unemployment duration. In fact, this wage loss gap can be interpreted as the difference in the investment of firm specific human capital between the two type of contracts. Including pre-displacement firm tenure vanishes the wage losses after displacement. This wage loss gap due to differences in the investment of firms specific human capital amounts to 6% the first quarter after displacement, reduding to 4% four years after.

1.5 A model of dual labor markets and firm specific human capital

This section presents the model, an extension of the canonical search and matching model with endogenous separations (Mortensen and Pissarides (1994)), that allows for the existence of permanent and fixed term contracts.

The economy consists of a continuum of risk-neutral, infinitely-lived workers and firms. We normalize the measure of workers to 1. Workers and firms discount future payoffs at a common rate β. Moreover, capital markets are perfect and time is discrete. Workers may be either unemployed or employed. Unemployed individuals enjoy an instantaneous utility b each period. Those who are employed can be so either under a fixed term or a permanent contract.

Firms decide which type of contract to offer when matched to the workers, and decide when to endogenously separate, or promote the worker to a permanent contract (PC). Separating endogenously from a worker holding a permanent contract entails an exogenous cost F, while separating from a fixed term contract (FTC) is costless. This way, F reflects the firing cost gap between the two type of contracts. Exogenous separations may also occur at no cost with probability δ for any type of worker. When the pair separates, endogenously or exogenously, the worker becomes unemployed.

Moreover, fixed term contracts expire each period with probability λ. This parameter can be interpreted as the inverse of the mean duration of this contracts. The higher λ, the lower duration of FTCs. This parameter reflects legal restrictions regarding the use of fixed-term contracts, such as the limited number of renewals and the maximum duration of the contracts. A higher λ, in this model, indicates stringer legal restrictions in the use of FTC. At expiration, the firm decides if separate from the worker, or keep the worker and promote her to a permanent contract. Thus, while the expiration rate is constant the conversion probability is an endogenous variable in the model.

The dual economy is going to be defined by two policy parameters: the firing costs gap in permanent contracts, F; and the expiration rate, λ. At expiration firms decide if promote the worker and give a PC, or lay-off the worker. Firing costs in this model are not severance payments. Severance payments are a transfer from the firm to the worker, do not entail any difference in these type of models; unless other rigidities are added, such as minimum wages. The firing costs, F, are paid by the firm in case of separation, and are consider a waste. They can be interpreted as red tape costs, costs of judge for laying off a worker, etc.

Workers decide if invest in firm specific human capital (FSHC)[7]. Investing in FSHC entails a cost, C, and instead the workers become immediately more productive by an

[7] As indicated by Wasmer (2006) *"The fact that workers pay human capital investments in terms of effort has no direct implication on the choice of skills: as shown in Becker (1964) and in a search context by Acemoglu and Pischke (1999a) and (1999b), wages partly or fully internalize the cost structure. The assumption is however important in that the firm cannot easily write a*

amount s. As a simplifying assumption, the investment is made at the moment of realization of the contract, and the worker becomes immediately more productive. Note that since the acquired human capital is firm-specific, it is completely lost upon displacement.

Each firm consists of only one job which is either filled or vacant, and uses only labor as input. If the vacancy is filled, it produces ε_t, the idiosyncratic productivity of the match, which has a cumulative distribution function $G(\varepsilon)$, independent and identically distributed across firms and time, and is assumed to be log-normal. Thus, shocks to this idiosyncratic productivity happen every period. No persistence is assumed in this model.

Unemployed and vacancies meet according to a standard matching function with constant returns to scale: $m(u, v) = \psi u^{v1-\alpha}$. Labor market tightness is defined, as standard in the literature, as the ratio $\theta = v/u$, and the probability that an unemployed worker meets a vacant job is defined as $p(\theta) = \frac{m(u,v)}{u}$, and the that a vacancy meets a worker is $q(\theta) = \frac{m(u,v)}{v}$. $p(\theta)$ is increasing in θ, while $p(\theta)$ is decreasing.

After a match is realized, a match specific productivity is drawn. If the match is profitable the firm hires the worker. Workers and firms bargain over wages according to standard Nash bargaining every period. Finally, there is free entry, i.e. firms open vacancies until the value of a vacancy is driven to zero.

The timing of the model is the following. At the beginning of each period unemployed workers and vacancies meet. At the same time, all existing matches (i.e., those who produced last period) learn whether they break exogenously with probability δ. Right after that, surviving temporary matches realize whether their contracts expire according to probability λ. Afterwards, each match (old and new) draws an idiosyncratic productivity ε.

Then, workers decide if invest, correctly anticipating the type of contract to be offered, duration of the job and the result from the wage bargaining. Firms decide the type of contract to offer, and bargain an entry wage, and after every productivity shock bargain again. PC contracts are protected from separation by firing costs, after the first period, which is paid by the firm in case of separation. At the same time, if FTC expired the firm decides if convert it to a PC or lay-off the worker.

Note that, the assumption is that investment is non-contractible or unenforceable. Due to the nature of specific investments, training or the effort to become more productive cannot be contracted. The cost of investment is sunk before reaching the wage bargaining. Hence, it can be interpreted as the effort workers need to do to be trained which is not observable by firms.

From now on, the steady state properties of the model will be analyzed. Hence, we can abstract from aggregate productivity shocks.

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contract to induce an efficient level of effort if effort is imperfectly observable."

1.5.1 Match surplus and wage bargaining

The firms' value of fixed term or temporary and permanent contracts is defined as $J^T(\varepsilon)$ and $J^P(\varepsilon)$, respectively. While, the workers' value of temporary and permanent jobs is defined as $W^T(\varepsilon)$ and $W^P(\varepsilon)$[8]. The values of unemployed and vacant jobs are U and V, respectively[9].

Since temporary contracts separate costlessly, the total surplus of a match will be

$$S^T(\varepsilon) = J^T(\varepsilon) - V + W^T(\varepsilon) - U$$

However, when a permanent match separates the firm has to pay the firing cost F, lowering its outside option to $V - F$. Therefore the total surplus is:

$$S^P(\varepsilon) = J^P(\varepsilon) - V + F + W^P(\varepsilon) - U$$

The first period of a permanent contract does not entail this firing cost, since if there is no agreement on the contract, the firm is not liable to pay the firing cost. The firms' and workers' value of permanent contracts in this initial period are defined as $J_0^P(\varepsilon)$ and $W_0^P(\varepsilon)$. Hence, the the surplus can be written as:

$$S_0^P(\varepsilon) = J_0^P(\varepsilon) - V + W_0^P(\varepsilon) - U$$

Wages are determined by Nash Bargaining between firms and workers every period, as a new draw from the idiosyncratic productivity arrives. Hence, the sharing equations hold every period. The workers' bargaining power is defined as ϕ, hence the surplus-sharing rules are:

$$S^T(\varepsilon) = (1-\phi)(J^T(\varepsilon) - V) = \phi(W^T(\varepsilon) - U) \tag{1.2}$$

$$S^P(\varepsilon) = (1-\phi)(J^P(\varepsilon) - V + F) = \phi(W^P(\varepsilon) - U) \tag{1.3}$$

$$S_0^P(\varepsilon) = (1-\phi)(J_0^P(\varepsilon) - V) = \phi(W_0^P(\varepsilon) - U) \tag{1.4}$$

And the wage functions: w^T, w^P, and w_0^P.

1.5.2 Job creation and job destruction

The value of a filled vacancy is showed in equation 1.5. Firms post vacancies with a cost flow of a. When matched to a worker decide which type of contract to give the worker,

[8]Remember here we abstract from aggregate productivity shocks, and here the firms and workers value only depend on the idiosyncratic productivity of the match

[9]As in the standard MP(1994) these value function do not depend on the idiosyncratic productivity

maximizing the value of a filled vacancy under the two type of contracts. We can discuss three cases, one in which workers invest in FSHC in both contracts, one in which only invest in FTC, and one in which only invest in PC.

$$V_t = -a + \beta[q(\theta_t) \int_0^\infty max \left\{ J^{Ti}_{t+1}(z), J^{Pi}_{0,t+1}(z), 0 \right\} dG(z) + (1 - q(\theta_t))V_{t+1}] \quad (1.5)$$

where $i = I, NI$.

The first case is if both contracts I (invest) or NI (not invest) in FSHC. Considering all future realizations of ε, the expected income flow from temporary and permanent contracts is the same every period until separation. The difference is that upon displacement the pair in a PC losses F, hence $W^P + J^P < W^T + J^T$. At the same time, offering a PC lowers the firms' threat point from 0 to $-F$. Hence, since offering a PC diminishes the joint payoff, and lowers the firms' threat point, a firm will always prefer to offer a FTC if legally allowed to do so.

Second, the case FTC workers invest in FSHC but PC do not. According to the recent argument, firms will always offer a FTC. Even more in this case, in which PC will have a lower income flow than FTC workers, and lower threat point and the firing costs in case of displacement.

In the third case, PC workers invest in FSHC, while FTCs do not. In this case, the expected income flow from permanent contracts is larger than for fixed term contracts, by s, the productivity gain of inventing in FSHC. But still at separation the pair losses F, and firms' threat is reduced from zero to $-F$. Hence, the decision is going to depend on the relative size of the productivity gain due to the investment, s, and the firing costs, F. If the productivity gain is not much larger than the separation costs, the firm will still offer a temporary contract when matched to a worker. In fact, this true for a wide range of parameters; even more when analyzing the Spanish economy where firing costs are large. Hence, I restrict to study this case[10].

Hence, if a firm is legally allowed to hire under fixed term contracts, it will always choose to offer the worker a fixed term contract over a permanent contract.

There is free entry of firms in the economy, hence firms post vacancies until the point the value of a vacancy is zero: $V = 0$. Job creation and separation will be determined by three productivity thresholds, above which production takes place or continues. The first is the threshold for hiring and firing temporary contracts: ε^T, such that any eligible job continues if $\varepsilon_t > \varepsilon^T$. This threshold is defined as the match productivity that makes the firms value equal to zero, where $i = I, NI$:

$$J^{Ti}(\varepsilon^{Ti}) = S^{Ti}(\varepsilon^{Ti}) = 0 \quad (1.6)$$

[10] Also because more than 90% of new hires start as FTC in Spain. In any case, this will be checked during the calibration exercise

Second, there is the promotion threshold, that is relevant when the FTC expires, ε_0^P, such that any job no more eligible from FTC is converted to a PC if $\varepsilon >_0^P$. At this point the firm is indifferent between converting to a permanent contract or separating costless. The threshold is determine by

$$J_0^{Pi}(\varepsilon_0^{Pi}) = 0 \Rightarrow S_0^{Pi}(\varepsilon_0^{Pi}) = 0 \tag{1.7}$$

Finally, the threshold for firing permanent contracts is ε^P, and is determined by:

$$J^{Pi}(\varepsilon^{Pi}) + F = 0 \Rightarrow S^{Pi}(\varepsilon^{Pi}) = 0 \tag{1.8}$$

From all above, it can establish an ordering of the thresholds from this economy. From equations 1.8 and 1.7 we can establish that $\varepsilon_0^{Pi} = \varepsilon^{Pi} + F$. On the other hand, as stated above firms always offer worker FTC instead of PC when matched to a worker. This implies that FTC is the preferred option for firms. At expiration, the firms choice set is shrank, eliminating the preferred choice, and this match is less valuable, which implies that the threshold for firing and hiring FTCs is above promotion threshold (which is the same as hiring threshold for PC): $\varepsilon^T < \varepsilon_0^P$. Finally, given the firing costs in PC, the threshold for firing PC lies bellow the one for FTC. We already now that firms prefer to offer a FTC than a PC: $W^P + J^P < W^T + J^T$, but PC matches do not separate unless the surplus goes bellow F. Therefore, $W^P + J^P + F > W^T + J^T$, implying that $\varepsilon^P < \varepsilon^T$. This means that matches under PC accept lower productivity just to avoid paying F. Thus, the firing threshold for PC lies below the firing threshold for FTC, which lies below the promotion threshold.

Hence,

$$\varepsilon^{Pi} < \varepsilon^{Ti} < \varepsilon_0^{Pi} \tag{1.9}$$

At the same time we know that if the worker invests the threshold is lower than if the worker does not invest. This reflects the fact that if the worker invests the separation rate is lower. Hence,

$$\varepsilon^{jI} < \varepsilon^{jNI} \tag{1.10}$$

where $j = T, P$

In the appendix 1.10 can be found the rest of the detailed surplus functions for temporary and permanent contracts, as well as the steady state equilibrium conditions and steady state employment and unemployment.

1.5.3 The workers' decision of investment in firm specific human capital

Workers decide if invest in FSHC taking θ as given, and perfectly predicting which type of contract are offered and the results of the Nash Bargaining. Workers maximize the workers' value of a job knowing that the investment entails a cost C, so that:

$$max\left\{W^{jI}(y)-C,W^{jNI}(y)\right\} \tag{1.11}$$

where $j=T,P$ temporary or permanent contract.

When matched to a firm, the workers know he is going to be offered a temporary contract. In the equation 1.12, the value of unemployment, the maximization problem can be seen. The value of unemployment is equal to the income flow of being unemployed, b, plus the discounted expected future income. The moment they get hired pay C if invest, lowering the value of unemployment, but become immediately more productive, by s.

$$U=b+\beta[p(\theta)\int_0^\infty max\left\{W^{TI}-C,W^{TNI},U\right\}+(1-p(\theta))U] \tag{1.12}$$

After some algebra we can write the condition under which FTC workers invest depending on the threshold of firing temporary workers in equation 1.13.

$$\phi(\underbrace{\varepsilon^{TNI}-\varepsilon^{TI}}_{>0})+\Delta U-C\geq 0 \tag{1.13}$$

This condition has three parts. The first, is the difference in the firing thresholds under temporary contracts. As shown is equation 1.10 this difference is positive reflecting the lower separation rates if workers invest in FSHC. The second part reflects the change in the unemployment value. This change is negative because investing lowers the value of unemployment. Finally, the cost of investment. Hence, the investment decision will depend on which of the these trade-offs domains. Note also, that the larger ϕ, the workers' bargaining power, the higher the likelihood of investment. While the lower cost of investment, C, the higher likelihood of investment.

The decision problem for PC workers is very similar. In this case, if the FTC expires workers decide if invest in FSHC under PC. Hence, they are going to maximize the value of employment under permanent contracts at the time of promotion. Equation 1.14 shows the value of employment for a temporary contract, where this decision is embedded .

$$\begin{aligned} W_t^{Ti} &= w_t^{Ti}+\beta\left\{(1-\delta)\left[(1-\lambda)\int_0 max\left[W_{t+1}^{Ti}(s),U_{t+1}\right]dG(s)+\right.\right. \\ &+ \lambda\int_0 max\left[W_{t+1,0}^{PI}(s)-C,W_{t+1,0}^{PNI}(s),U_{t+1}\right]dG(s) \quad + \quad \delta U_{t+1} \end{aligned} \tag{1.15}$$

The workers' value of a temporary job is equal to the income flow, i.e. the wage, plus the expected income. If not exogenously separated and the contract does not expire, the value for a worker of a temporary job provided that the new idiosyncratic shock is above the threshold. In the case of expiration of contract, provided that the idiosyncratic productivity is above the promotion threshold, the value for the worker of a permanent job. If the worker decides to invest need to pay the cost C.

This maximization problem can be re-written as:

$$\phi(\underbrace{\varepsilon^{PNI} - \varepsilon^{PI}}_{>0}) + \Delta U - C \geq 0 \tag{1.16}$$

As in the case for temporary contracts, this condition has three parts. The first is related to the fact that after investment the threshold for firing in permanent contracts is lower (also the threshold for promotion). And the second and third part are related to the fact they have to pay the cost C, which changes the workers' value of employment of a temporary worker, and hence the unemployment value. Again, the decision of investment depends on the relative size of these effects on the threshold and the cost of investment, C.

The conditions for investment in temporary contracts, equation 1.13, and permanent contracts, equation 1.16, depend on the parameters of the model. More specifically on policy parameters that determine the duality of the economy: F, and λ. The next step is calibrating the model to then show how these parameters affect the decision of workers.

1.5.4 Wage losses in the model

As shown in the empirical work, I found evidence of a gap in the invest in FSHC, in which PC workers invest more than FTC, that translates in to a wage loss gap of 6% in the first quarter after displacement. Hence the strategy is calibrating the model assuming that PC invest, but FTC does not invest. This way the gain in productivity, s, can be interpreted as the produtivity gap due to the investment gap in firm specific skills. To be more clear, the wage equations are described in the following equations in the case PC workers invest and FTC workers do not:

$$\begin{aligned} w^{PI} &= \phi(\varepsilon + s + F(1 - \beta(1-\delta) + a\theta)) + (1-\phi)b \\ w_0^{PI} &= \phi(\varepsilon + s - F(\beta(1-\delta) + a\theta)) + (1-\phi)b \\ w^{TNI} &= \phi(\varepsilon + a\theta) + (1-\phi)(b + \beta(1-\delta)\lambda C * (1 - G(\varepsilon_0^P))) \end{aligned}$$

The wage loss is defined with respect to the entry wages: w^T, hence FTC workers show zero wage losses.

$$\chi^T = E(w^{TNI}) - E(w^{TNI}) = 0$$

While PC workers are going to be displaced from PC, and re-hired under a FTC, hence losing all the investment in FSHC.

$$\begin{aligned}\chi^P = \quad & E(w^{PI}) - E(w^{TNI}) = \phi\left[E(\varepsilon/\varepsilon > \varepsilon^P) - E(\varepsilon/\varepsilon > \varepsilon^T) + \right. \\ & +s + F(1-\beta(1-\delta)) - (1-\phi)\beta(1-\delta)\lambda(1-G(\varepsilon_0^{PI}))C\end{aligned} \tag{1.18}$$

As argued in the empirical analysis, the gap found is due to the investment in FSHC, since we control for other premiums in wages, and other sources of wage losses. Hence, we can calibrate the wage loss gap found due to the difference in FSHC as:

$$\chi^P = \phi s \tag{1.19}$$

1.6 Calibration and results

1.6.1 Calibration

The calibration of the model is done at quarterly frequency in order to match four targets that characterize the Spanish economy. The baseline parametrization is summarized in Table 1.6.

The first three parameters in the table are taken from the standard literature of search and matching, setting the quarterly discount rate β to 0.99. Then I choose other parameters following literature for Spain. Petrongolo and Pissarides (2001) indicate that the elasticity of the matching function is in between 0.5 and 0.7. We set it at 0.5 as Costain et al. (2010) and Bentolila et al. (2010). As standard in the literature, it is assumed that workers' bargaining power is equal to the elasticity of the matching function $\phi = \eta$. As in Costain et al. (2010) the unemployment income flow, b, is set relative to the steady state equilibrium cross-sectional average worker productivity, $E\varepsilon$, and equal to 0.8. Usually, for US is used a parameter of 0.7, but since in Spain the unemployment benefits are higher, instead set b to a larger amount. The cost of posting vacancies, a, is set to 0.3 which the mid-point found in the literature[11]. Following also Costain et al. (2010) we set

[11] Shimer (2005) set it to 0.21, while Hall and Milgrom (2008) to 0.43.

the exogenous probability of separation to 0.00625, which implies a worker who does not experience endogenous separations, stays in the same job a mean for 40 years.

As standard in the literature, I normalize the mean of the underlying log productivity distribution $\mu = E(log(\varepsilon))$ to 0, while the standard deviation is chosen to match the share of temporary workers in the Spanish economy, i.e. $\frac{n^T}{n} = 0.3$. The expiration rate of FTC, a policy parameter, is set to last a mean of two years and a half, $\lambda = 1/(30/3)$[12].

The exercise has four targets, the share of temporary workers in the Spanish economy, the outflow rate from unemployment, the inflow rate from unemployment for permanent contracts, and the conversion rate from fixed term to permanent contracts. The job finding rate is taken from Elsby et al. (2013) who calculates monthly outflows and inflows rates from unemployment for OECD countries using data on duration of unemployment. The job separation rate of PC is calculated using data from Silva and Vázquez-Grenno (2012) who calculate quarterly transition probabilities in the Spanish labor market using the data from the Spanish Labor Force Survey (SLFS), taken into account that employment is divided between permanent contract jobs and temporary jobs. They calculate these rates from a three state set up (employment, unemployment and inactivity). Since in the model unemployment and inactivity are the same, we take both into account. The average rates are calculated over the period 1995 to 2007.

The separation rate from permanent contracts is used to set the firings costs F, while the job finding rate is targeted to calibrate the parameter of efficiency in the matching function. Finally, the conversion rate is used to obtain the cost of investment in FSHC for PC, C.

Finally, I match the gain in productivity to a 6% wage loss gap. According to equation 1.19 and the value for the workers' bargaining power, this implies a gain in productivity for PC workers of 12% due to the investment in firm specific human capital. This seem to be a resonable parametrization. Sala and Silva (2009) calibrate their model to Spain with a productivity gap between permanent and fixed term contracts of 20%. They base their estimates in Aguirregabiria and Alonso-Borrego (2004), who estimate the productivity of a temporary worker to be on average 80% of the productivity of a permanent worker. This model is implying a lower productivity gap.

1.6.2 The investment decision

In this subsection the conditions for investment in FSHC of FTC workers in equation 1.13, and of PC workers in equation 1.16 are analyzed. The first goal is to corroborate that PC workers want to invest, and FTC workers do not. The second goal is

[12]In the Spanish legislation most of fixed term contracts may not be extended after 3 years, although changing the nature of the job for hiring the same worker under subsequent temporary contracts has been a common practice among Spanish employers. In any case, we set as mean duration two years and a half.

to understand how these conditions depend on the policy parameters that determine the duality of the economy: F and λ.

The next figure shows how the conditions in equation 1.16 (above panel), and equation 1.13 (bellow panel) change with the policy parameters. The graph shows the conditions for investment when changing F by $\pm 5\%$, and $\frac{1}{\lambda}$ from to 4 quarters ($\lambda = 0.25$) to 3 years ($\lambda = 0.83$). The picture can be interpreted as the likelihood of investment. If it has positive sign workers want to invest in FSHC, while if negative worker will not invest. Note that in this simple model, the investment is done in a fixed amount, hence, the larger is this condition, the larger is the likelihood of investment, but not the larger investment.

First, we can see that PC workers always want to invest under this calibration, since this condition is positive for all the combination of parameters shown. As we can see from the graph this condition is increasing in F and λ. It can be shown that $\frac{\partial \varepsilon^P}{\partial F} < 0$, the higher the firing costs, the lower separation rates from PC, i.e. longer duration of the job. This cut-off increases more if PC workers have invested, increasing the likelihood of investing in PC. At the same time, $\frac{\partial \varepsilon^P}{\partial \lambda} < 0$, thus the higher the expiration rate (lower duration of contracts), the lower separation rates in PC, meaning that firms are less selective to convert into PC, and to layoff PCs. This cut-off decreases more if PC workers have invested, increasing the likelihood of investing in PC. This is because firms become less selective in PCs in general, and can rely less in FTC. Since FTCs expire faster, and firms have to look for other workers, which is costly, they becoming less selective.

On the other hand, the condition for investment for FTC workers in the baseline calibration is negative, and only becomes positive for higher values of λ. The condition is also sightly increasing in F. This suggests that FTC workers would only invest for high values of λ, and F. It can be shown that $\frac{\partial \varepsilon^T}{\partial \lambda} > 0$, the larger the expiration rate (lower duration of contracts), makes firms more selective to hire FTC, but less if FTC invests, increasing the likelihood of investment in this type of contract. Also, $\frac{\partial \varepsilon_0^P}{\partial \lambda} < 0$, meaning an increasing conversion rate with λ. It increases more if FTC invests in FSHC, increasing the likelihood of investing in FTC. Finally, $\frac{\partial \varepsilon^T}{\partial F} > 0$. The higher the firing costs, the higher separation rates from FTC. This is the other side of sclerosis in PC, increasing the churning for FTC. This cut-off increases less with F if FTC had invested, increasing the likelihood of investing in FTC. In any case, as the picture shows under this parametrization the condition of investing for FTC remains almost constant with F, not affecting FTC contracts.

Hence the model predicts that when firing costs F are sufficiently large (stringent EPL under PC), and λ sufficiently low (flexible legal restrictions in FTCs), only workers with PC will invest in FSHC, as in the Spanish economy.

1.6.3 Wage loss gap in the calibrated model and the data

As argued in the subsection 1.5.4 temporary workers show no wage losses at all in this model. Only PC workers suffer wage losses, because they are re-hired under FTC, and only when converted to PC, invest in FSHC again. For this reason, the wage loss gap in this model is the wage loss PC workers suffer. In order to replicate the graph obtained in the empirical analysis a treatment and control group is defined. The treatment group is defined by workers displaced from PC. The analysis considers both endogenously and exogenously displaced workers. In this model, the type of displacement does not make any difference in wages. The workers endogenously displaced have a shock of low idiosyncratic productivity the period they are displaced, and production does not take place. Since the idiosyncratic productivity is random and changes every period, this is not reflected in wages. The control group is formed by workers non-displaced in the entire period under consideration.

We simulate complete job histories for 100,000 workers for 200 periods, disregarding the first 148 periods. So we get a complete history of worker for 52 quarters, as in the data, and run an OLS regression of the logarithm of wages on the dummies representing the displacement event, as in the empirical analysis, for 8 quarters before and 32 after displacement. Figure 1.6 shows the wage loss gap in the model (or the wage losses for PC workers) together with the wage loss gap in the data due to difference in the investment in FSHC between the two type of workers[13].

This exercise imputes with zero, wages during unemployment, and since the dependent variable is the logarithm of wages, as in the empirical analysis, during unemployment wages are missing. The wage loss gap in the model is missing in the first quarter. This is due to the fact that in this very simple model when a worker is displaced goes through an unemployment spell for at least a quarter. After, workers loss 6% of their wages with respect to the control group, and show similar recovery pattern as in the data. In the model, the recovery happens because some workers see their temporary contracts expire and converted to permanent workers, while other workers remain under temporary contracts, and unemployment spells. Remember that in this simple model, workers cannot go from a temporary contracts to another as in the data, because when displaced, exogenously or endogenously, they go through at least one quarter unemployment. Hence, the speed of recovery of wages in the simulated model has depends on the conversion rate, and the share of workers converting from FTC to PC every period.

[13]The wage loss gap in the data is the one in the baseline equation 1.1, after adding the other two sources: if changing industry and unemployment duration.

1.6.4 The labor productivity loss

This exercise wants to measure the aggregate loss productivity because of FTC workers not investing in firm specific human capital. In the model total output is calculated as in equation 1.20, hence total productivity is $\frac{Y}{n^P+n^T}$. In the baseline calibration FTC workers decide not to invest in FSHC, and only when offered a PC invest. As shown in graph 1.5, for the parametrization under analysis, PC always invest, while FTC only when λ and F are high enough.

$$Y = \tilde{\varepsilon^P} * (1 - sep^P) * n^P + \tilde{\varepsilon_0^P} * conv * n^T + \tilde{\varepsilon^T} * [(1 - sep^T) * n^T + jfr * u] \quad (1.20)$$

Where $\tilde{\varepsilon^J} = E[\varepsilon | \varepsilon \geq \varepsilon^J]$ being $J = P, T$.

The graph 1.7 shows what happens to average productivity under this parameterization. Average productivity jumps when FTC workers also decide to invest. Workers invest two times in their life's when an FTC is offered and when converted to a PC. Since the investment in this model is fixed, we have this jump in productivity, which implies 16% increase in productivity taken F constant, but λ larger (equal to $\lambda = \frac{1}{8}$), i.e. the allowed duration of contracts is lower (8 quarters). This can be interpreted as stringent regulation on fixed term contracts.

1.7 Concluding remarks

The Spanish economy has experienced significantly weaker labor productivity growth than other OECD economies failing to catch up with the most advanced economies in the period 1996-2007. The key factor explaining this poor performance is the reduction of TFP growth during this period. One characteristic of the Spanish institutional environment has contributed to the low TFP growth: the dualism in its labor market, governed by two different type of contracts; permanent contracts (PC) with high employment protection, and fixed term contracts (FTC) with very low or no employment protection. This dualism causes lower investment in firm specific human capital under fixed term contracts, affecting the performance of labor productivity.

The main goal of the chapter is to analyze how dual labor market institutions affect the accumulation of firm specific human capital. For this purpose the chapter investigates the wage losses upon displacement during mass-layoffs in Spain, differentiating between workers holding permanent and fixed term contracts at the time of displacement. The duality of the Spanish labor market allow us to study one of the basic predictions of the standard human capital theory (Becker (1964)): permanent contract workers are expected to accumulate a relatively higher share of firm specific human capital with respect to workers employed under fixed term contracts. For this purpose, the Continuous Sample of Working Histories, a large data set of the Spanish Social Security, is used.

The findings suggest that workers holding permanent contracts at the time of displacement suffer larger and more persistent wage losses than fixed term workers. Results are robust when restricting to low tenured workers. The wage loss gap is still present indicating that wage losses of permanent workers are larger and more persistent than for fixed term workers with less than three years tenure.

The exercise shows that wage losses are due, mainly, to the loss of pre-displacement firm tenure for PC workers, while is not an important source for FTC workers. This gap is taken as evidence of the different content of firm specific investment in human capital among the two type of contracts. On the other hand, changing industry after unemployment seems to be the less important source explaining wage losses, and similar for the two type of workers. Finally, the time spent in unemployment is important for both type of contract arrangements. This allow us to conclude that while the accumulation of sector specific human capital is important, is not different between permanent and fixed term contracts. Instead, firm specific human capital seems to be a very important source of human capital accumulation for PC workers, while FTC workers have no incentives to invest on this type of human capital.

The chapter presents a search and matching model that extends Mortensen-Pissarides (1994) to allow for the distinction between fixed term and permanent jobs entailing different firing costs and restrictions to the use of these contracts. The model shows that the likelihood of investing in FSHC depends on the firing costs present in permanent contracts, and on the legal maximum duration of fixed term contracts. After calibrating the parameters of the model with data for Spain, it shows that only PC workers invest in FSHC, and the model is able to replicate the picture of the wage losses as in the data. Finally, the results suggest that stringent law on the use of fixed term contract, like reducing the duration of FTC, increases labor productivity in this model.

The policy implication derived from this study suggest that reducing duality, i.e. making more stringent the law on the use of FTC would increase aggregate labor productivity, by increasing the incentives of fixed term workers to invest in firm specific human capital.

Tables

Table 1.1: Sample characteristics

	Permanent			Fixed term		
	Displaced	Non disp	Diff	Displaced	Non disp	Diff
Age	36.9	38.1	-1.2 [0.228]**	34.5	34.3	0.2 [0.217]
Firm tenure	8.4	8.9	-0.5 [0.239]**	2.3	2.7	-0.6 [0.093]***
Real daily wages	93.59	93.1	0.5 [1.207]	61.04	65.7	-4.6 [0.954]***
N obs	1,161	28,997		1,943	13,720	

Source: Author's calculations with MCVL2008. Notes: Sample Characteristics in 1997. Displaced are defined as those suffering mass-layoffs in the period 1999-2004. Non disp=non-displaced, i.e. the control group of workers not suffering mass-layoffs in the entire period.

Table 1.2: Sample characteristics of displaced and non-displaced workers

	Displaced		Not displaced	
	Permanent	Fixed term	Permanent	Fixed term
	Qualification of the position (%)			
Medium high	0.14	0.05	0.17	0.06
Medium	0.16	0.10	0.19	0.12
Medium low	0.33	0.39	0.33	0.41
Low	0.24	0.40	0.18	0.30
	Education (%)			
Incomplete Primary education	0.19	0.31	0.20	0.23
Primary education	0.35	0.39	0.33	0.37
Secondary and Technical Education	0.40	0.27	0.42	0.34
University	0.06	0.03	0.05	0.06
	Sector (%)			
Manufacturing	0.51	0.27	0.35	0.23
Construction	0.05	0.27	0.06	0.25
Services	0.44	0.46	0.60	0.52

Source: Author's calculations with MCVL2008. Notes: Displaced are defined as those suffering mass-layoffs in the period 1999-2004. Non disp = non-displaced, i.e. the control group of workers not suffering mass-layoffs in the entire period.

Table 1.3: Differences among displaced workers depending on the type of contract

	Permanent	Fixed term
Firm tenure at displacement (%)		
1 year	0.12	0.56
Between 1 and 3	0.21	0.24
Between 3 and 6	0.22	0.12
More than 6	0.45	0.08
Unemployment duration (%)		
Between 0 and 1 quarter	0.38	0.55
Between 1 and 4 quarters	0.44	0.36
Between 5 and 12	0.13	0.07
More than 12	0.05	0.02
Contract mobility at first quarter of re-employment(%)		
To a PC	0.37	0.12
To a FTC	0.63	0.88
After two years (%)		
To a PC	0.63	0.30
To a FTC	0.37	0.70
Change industry (%)	0.54	0.51

Source: Author's calculations with MCVL2008. Notes: Displaced are defined as those suffering mass-layoffs in the period 1999-2004.

Table 1.4: Determinants of wage losses

	Displaced	Incremental effect for PC
Duration unemployment	-0.00994***	-0.00788*
	[0.00284]	[0.00417]
Change industry	-0.0341***	-0.0200
	[0.0126]	[0.0226]
Pre-displacement tenure dummies		
One year or less	-0.0141	-0.0631*
	[0.0114]	[0.0341]
Between one and three years	0.00668	-0.0732**
	[0.0148]	[0.0306]
More than three years	-0.0462***	-0.0675**
	[0.0147]	[0.0251]
Permanent	0.0690***	
	[0.00218]	
Age	0.0517***	
	[0.00302]	
Age^2	0.0530***	
	[0.000761]	
Constant	-0.000420***	
	[8.66e-06]	
Time dummies	yes	
Regional dummies	yes	
Qualif. dummies	yes	
Industry dummies	yes	
R-squared	0.25	
Observations	2,252,663	
Number of id	45,821	

Standard errors clustered at the individual level in brackets. *** p<0.01, ** p<0.05, * p<0.1

Regression includes all displacement dummies not shown

First column: sources are x = x∗dummy for after displacement

Second column: sources are x = x = x∗PC^0*dummy for after displacement

Table 1.5: Contribution of each determinant to the earning losses

	Permanent contract		Fixed term	
	max	min	max	min
Pre-displacement tenure	50.0%	25.6%	22.0%	-25.6%
Unemployment duration	23.2%	14.7%	22.0%	6.3%
Change Industry	28.5%	0.9%	29.8%	-0.3%

Calculated contribution of each variable adding one by one and changing order of the determinants at one year after displacement ($\Delta\gamma^{k=4}$ and $\Delta\delta^{k=4}$)

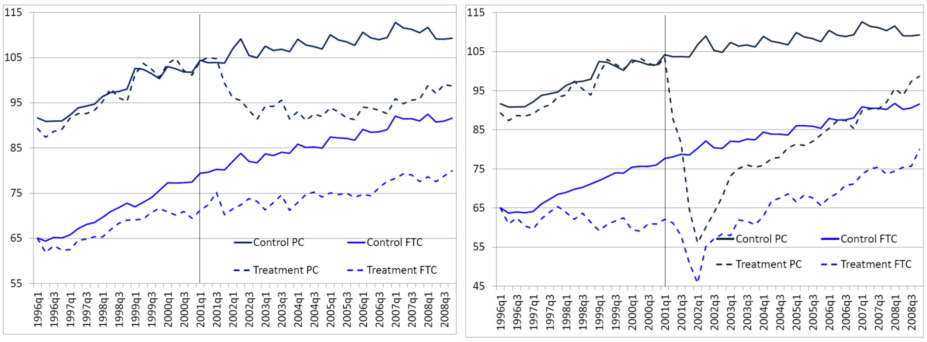
Table 1.6: Calibration

Interpretation	Param	Value	Source
Discount rate	β	0.99	Annual 4% interest rate
Workers' bargaining power	ϕ	0.5	$\phi = \eta$ Hosios condition
Elasticity of the matching function	η	0.5	Petrongolo and Pissarides (2001)
Employment opportunity cost	b	0.8 $E\varepsilon$	Costain et al. (2010)
Vacancy posting cost	a	0.30	Costain et al. (2010)
Exogenous separation probability	δ	0.00625	Costain et al. (2010)
Expected value $log(z)$	$E\varepsilon$	0	Normalization
Standard deviation $log(z)$	σ_ε	0.5	To match $\frac{n^T}{n}= 0.3$
Firing tax of permanent contracts	F	0.697	To match $s^P = 0.018$
Parameter of the matching function	ψ	0.745	To match $JFR = 0.2$
Cost of FSHC	C	0.12	To match 5% conversion rate
FSHC investment	s	0.12	To match wage loss gap of 6%
Expiration rate of FTC	λ	0.10	Duration 2 year and a half

Figures

Figure 1.1: Wage path of displaced workers in 2001

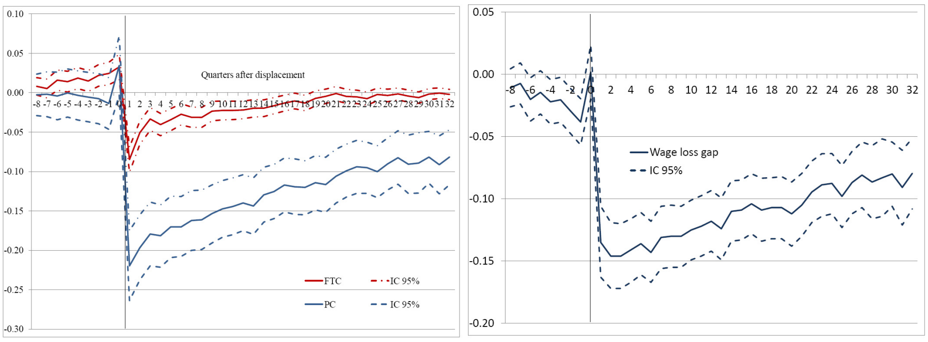
(a) Pure wages (b) Including zeros



Source: Author's calculations with MCVL2008. Notes: Earning paths are the raw wages, assuming (a) missing or (b) zero income during unemployment. Treatment group is defined according to the type of contract at the time of displacement in the year 2001. The control group of workers is classified according to the type of contract if not suffered mass-layoffs in the entire period.

Figure 1.2: Wage losses from separation by type of contract

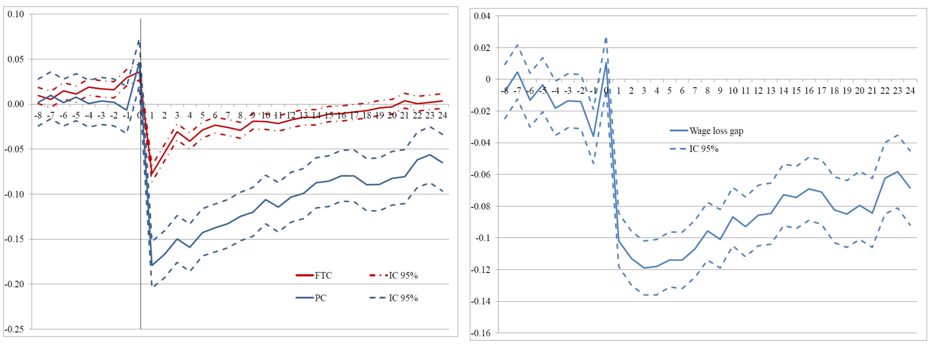
(a) Fixed effects estimator (b) Wage loss gap from separation δ^k.



Source: Author's calculations with MCVL2008. Notes: Dependant variable: log real daily wages. Standard errors clustered at the individual level. Regression with individual fixed effects. Other Controls: dummy for Permanent contract, age, and its squared, sectoral, regional and qualification dummies, and time dummies. Displaced workers from 1999 to 2004. (b) Graphical representation of δ^k, wage loss gap between PC and FTC.

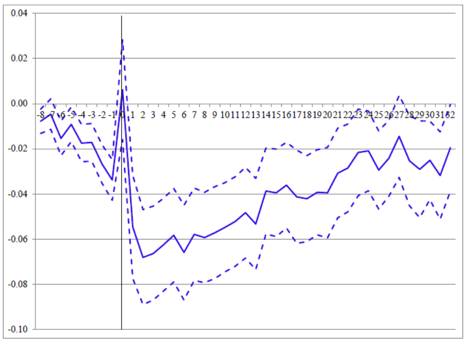
Figure 1.3: Wage losses from displacement for low tenured workers

(a) Wage losses by type of contract (b) Wage loss gap δ_k



Source: Author's calculations with MCVL2008. Notes: Dependant variable: log real daily wages. Standard errors clustered at the individual level. Regression with individual fixed effects. Other Controls: dummy for Permanent contract, age, and its squared, sectoral, regional and qualification dummies, and time dummies. Treatment and control groups include only workers with less than three years tenure in 1998. Displaced workers from 1999 to 2004.

Figure 1.4: Wage loss gap after controlling for changing industry and unemployment duration



Source: Author's calculations with MCVL2008. Notes: Representation of δ_k. Dependant variable: log real daily wages. Standard errors clustered at the individual level. Regression with individual fixed effects, adding determinants of the wage losses: changing industry and duration of unemployment. Other Controls: dummy for Permanent contract, age, and its squared, sectoral, regional and qualification dummies, time dummies. Displaced workers from 1999 to 2004.

Figure 1.5: Investment decision in the model

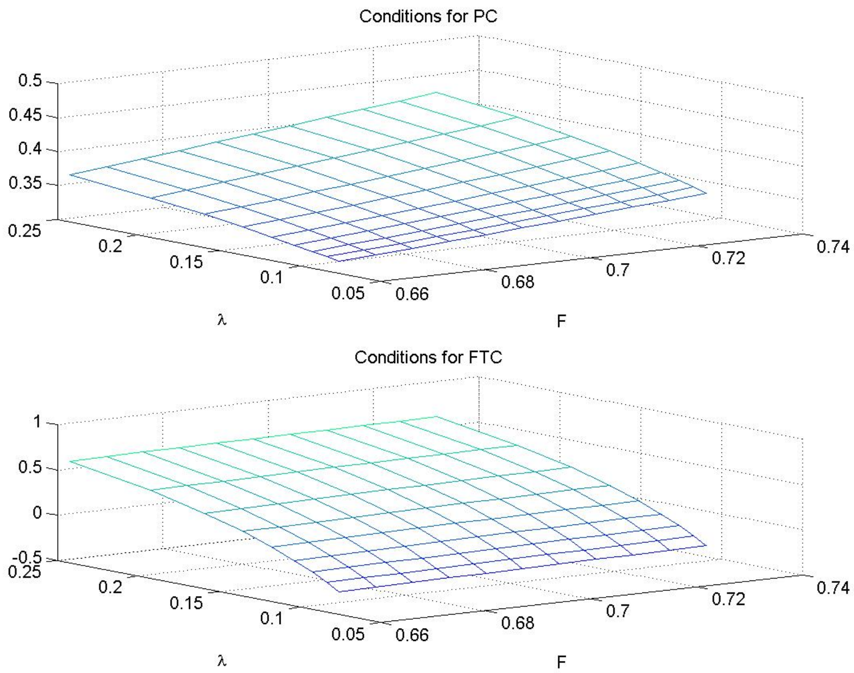
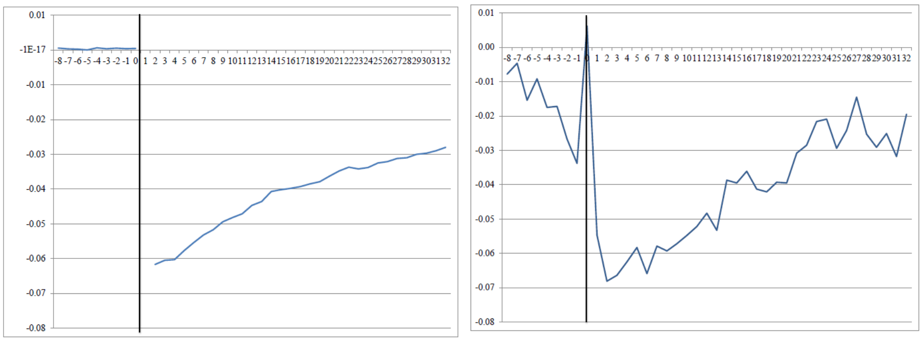


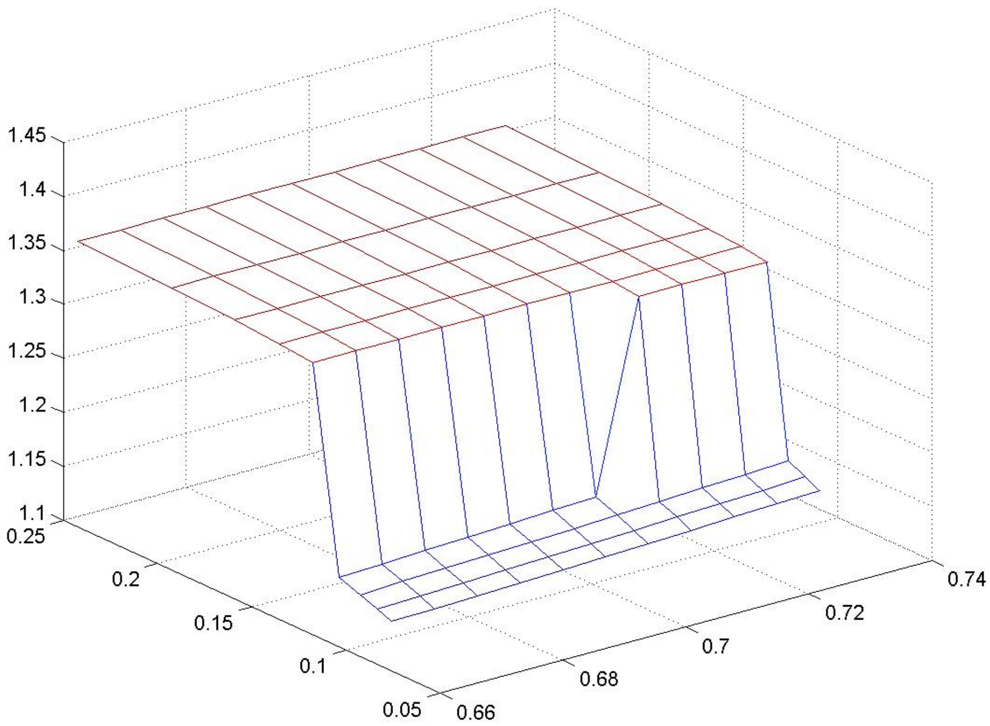
Figure 1.6: Wage loss gap in the calibrated model and data

(a) Wage loss gap in the calibrated model (b) Wage loss gap in the data



Notes: Wage losses due to lower investment in FSHC of FTC workers in the model and data. (a) Simulated model for 100,000 workers. Wage loss for PC workers displaced exogenously. Control group composed by non-displaced workers (b) Empirical representation of δ_k. Dependant variable: log real daily wages. Standard errors clustered at the individual level. Regression with individual fixed effects, adding determinants of the wage losses: changing industry and duration of unemployment. Other Controls: dummy for Permanent contract, age, and its squared, sectoral, regional and qualification dummies, and time dummies. Displaced workers from 1999 to 2004. Source: MCVL2008

Figure 1.7: Average productivity in the model



1.8 Appendix A: Sample selection and displacement definition

1.8.1 Sample selection

First, the sample period is from 1996 to 2008, because the type of contract is not reliable for the previous period. We focus on men born between 1948 and 1971, that is between 25 and 48 years old in 1996. This is because is better to avoid the behavior of wages when starting the job career, that could be different from older ages workers. Second, we only use job spells posterior to 1996, since prior to that year, information on type of contract is not reliable. Third, we consider workers who are in the "Regimen General" which includes 90 per cent of all workers; i.e. we exclude the self-employed, workers in Agriculture, Fishing and other minor special cases. Forth, the data is transformed to show as unit of observation a quarter. Because of this, more restrictions are added. Simultaneous employment spells are disregarded and, instead, use the information corresponding to the full time job or longer-lasting of these. We unify any two registers that present overlapping contracts, i.e., when one of the contracts begins before the previous one has ended. Incomplete or incorrect registers are dropped (for example, negative spells durations). The sample is also restricted to full-employment workers at the time of displacement. This, the wage in a given quarter will be mean daily wage observed in that quarter.

This database stores the entire labor history for each worker, for whom it provides information relating to the worker's age, gender, qualification of the job, and the exact duration of each unemployment/employment spell. Moreover, periods of no employment can represent either periods of unemployment with or without benefits or periods of inactivity. I use the term unemployment to denote all periods of inactivity with respect to work. All contracts have been re-codified to the new contracts, and codified as permanent, fixed term or unknown.

The sample is restricted to people that were employed during the period 1996-1998 at least one year and half, and have at least one year tenure in their firms. This is done in order to capture workers attached to the labor market. The control group is defined by people that do not suffer mass-layoff in the entire period, from 1996 to 2008. It is composed by workers making direct job-to-job transitions, or converting contracts within the same firm, or mantaining their initial job during the whole sample. This is a better choice than that of using only workers that additionally maintain their initial jobs for all the period, because the control group is aimed to represent the hypothetical (and not observed) outcomes of the same displaced workers if they simply did not experience the involuntary job loss, without additionally (and arbitrarily) ruling out that they would experience a job change (or non-employment). It is also important to point out that the control group described above does not include individuals laid off on an individual basis. The final control group used in the analysis is a 50% random sample of the initial control group. On the other hand, the treatment group is the sample of displaced workers formed by employees were involuntary separated during a mass-layoff in some year between 1999 and 2004. I estimate the impact of only the first observed job displacement for each individual during the relevant period. I do not separately include additional displacements for these workers because, as common in the literature, I consider future displacements as a cost of the initial displacement.

1.8.2 Definition of displacement

Different with most administrative datasets, the MCVL records whether a change of employer or a movement from employment to non-employment is the result of an employer-initiated separation (i.e. a displacement) or a voluntary movement by the employee (i.e. a quit). In order to define a displacement I use the cause of separation registered in the MCVL. The causes of separation included in the MCVL are: voluntary separations by the worker, involuntary separations (including unfair dismissal and termination of contracts), temporal incapacity, ERE (Record of employment regulation)[14], family or kids care leave, and plant closing. These separations are reported by the employer to the Social Security, and most of time even if the separation is due to an ERE or a plant closing, they declare an involuntary separation[15]. In the database, most of the cases are quits or involuntary separations.

We define displaced workers as those that have lost the job because of an ERE, or an involuntary termination of the spell, if they switch employer. That is, we only consider a separation if the employee change firms, in order to avoid recalls. This way we also avoid the use of repeated fixed term contracts within a firm, separated by some periods of inactivity. Firms, in order to reduce costs, renew fixed term contracts several times, in some cases in between some periods of inactivity.

In order to define a sample of exogenous displaced workers, we define a mass-layoff sample as those that have lost the job because of large employment adjustment, above 30% of the workforce in a given year[16]. Since we do not have information on the size

[14]The record of employment regulation, abbreviated with their initials, ERE, is a procedure under the Spanish law by which a company in crisis seeks for authorization to suspend or lay-off workers within a framework which guarantees certain rights of workers. This administrative procedure can be processed for the following reasons: collective dismissal based on economic, technical, organizational or productive reasons (the most usual reason); suspension or termination of the employment contract in case of superior force (like a natural disaster); termination of employment because of firm closure.

[15]This is the reason why besides considering EREs in the sample, we will include firms that suffer a reduction in the workforce defined as a mass-layoff

[16]We present here the results for the this definition of mass-layoff sample, but other cutoffs have been tried. The 40% and the 15% show very similar results. Also, using only plant-closing in the

of firms for all years in the sample, the employment adjustment needs to be defined in sample, defining the size of the firm with the number of employees in the sample by year. We disregard information on firms with less than 5 workers.

1.9 Appendix B: Robustness checks

1.9.1 Estimation with specific time trends

If firms tend to lay off workers partially on the basis of unobservable worker-specific time trends the baseline estimation in equation 1.21, will give consistent estimates in the presence of specific time trends, $\lambda_i t$.

$$y_{it} = \alpha_i + \mu_t + \lambda_i t + \sum_k \gamma_k D_{it}^k + \sum_k \delta_k D_{it}^k * PC^0 + \beta X_{it} + \varepsilon_{it} \qquad (1.21)$$

As seen in figure 1.8 PC workers suffer larger and more persistent wage losses than their FTC peers, including specific time trends. Results are robust and the wage loss gap is still statically significant, even if less persistent than the estimated with the fixed effect estimator. The wage loss gap amounts to 12 percent one quarter after displacement.

The estimate of wage reductions of the specific time trend estimators for PC workers, the first quarter after displacement is 15,2 percent with respect to the control group. In the fourth year after displacement, substantial recovery occurs and the estimated impacts averages 4,5 percent. The estimated wage losses for workers holding fixed term contracts at the time of displacement are much lower. The first quarter after displacement the wage loss is 3,7 percent, and after the four years substantial recovery occurs and the estimated impacts average 0,4 percent.

1.9.2 Wage losses by transitions

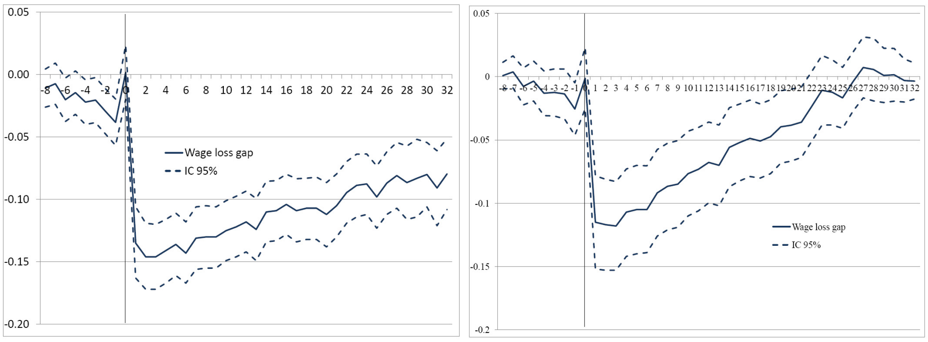
As shown in table 1.3 after displacement the majority of workers are re-hired as fixed term contracts [17], but two years later more than 60% of the workers displaced from PC managed to be again in PC, while still workers displaced from FTC are still in FTC. Hence, is fruitful to see if the results are robust to the different transitions or if wage losses are driven by some group of workers. We re-estimate equation 1.1, but now the set of dummies for displacement distinguish among transitions: workers displaced from PC and after two years with PC again (PC-PC), displaced from PC but after two years with FTC (PC-FTC), and finally for displaced from FTC we are only taking into account

sample show very similar results. Results available upon request.

[17] According to Güell and Petrongolo (2007) fixed term contracts account for most new hirings in all sectors and occupations

Figure 1.8: The wage loss gap δ^k with time specific trends

(a) Regression with fixed effects estimator. (b) Regression including specific time trends.



Source: Author's calculations with MCVL2008. Notes: Graphical representation of δ^k, wage loss gap between PC and FTC. Dependant variable: log real daily wages. Standard errors clustered at the individual level. Other Controls: dummy for Permanent contract, age, and its squared, sectoral, regional and qualification dummies, and time dummies. Displaced workers from 1999 to 2004.

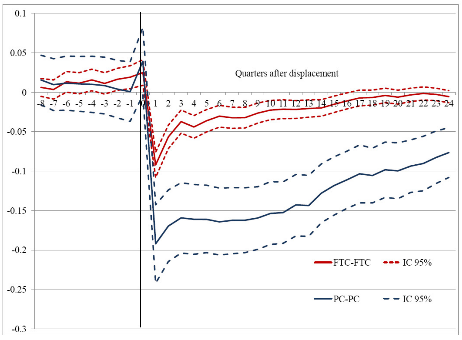
displaced from FTC and that were not hired afterwards with PC contracts (FTC-FTC).

Figure 1.9a shows the results comparing FTC-FTC, and PC-PC workers. This results should show the lower bound of the wage loss gap (figure 1.9b). Because of the possibility of premiums for the type of contract, even after controlling by fixed effects, and a dummy for type of contract, the latter transitions should show the lower bound for the wage losses after displacement between the two type of contracts. The wage loss gap is lower with respect to the baseline estimation in figure 1.2a. The estimated wage loss gap is 10% the first quarter, remaining more or less similar even 6 years after.

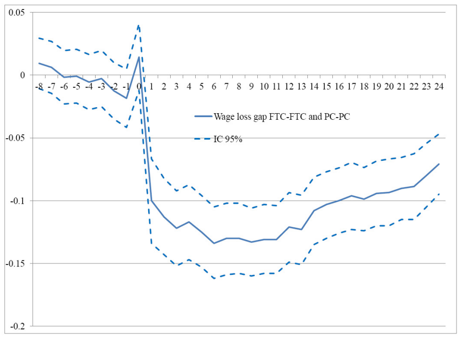
When we compare wage losses among permanent contracts with different transitions, we can see that PC-FTC suffer larger wage losses the first year after displacement, but these differences are not significant. A year later a recovery happens showing afterwards similar wage losses to the PC-PC workers (Figure 1.10).

Figure 1.9: Wage losses among different transitions

(a) Wage losses from separation depending on the transitions

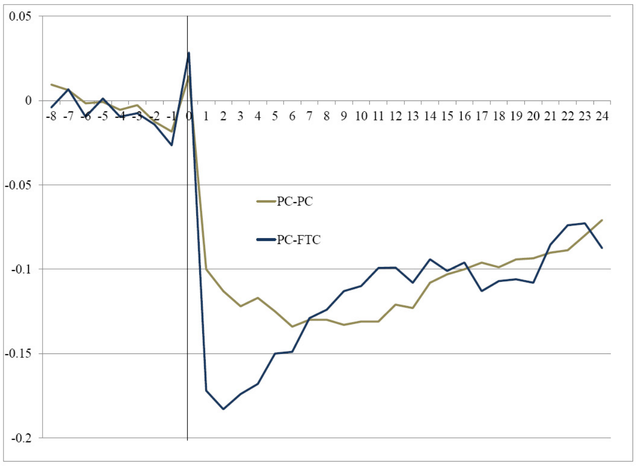


(b) Wage loss gap δ_k



Source: Author's calculations with MCVL2008. Notes: (a) Wage losses of workers PC-PC and FTC-FTC (b)Graphical representation of δ^k, wage loss gap between workers with transitions PC-PC and FTC-FTC. Dependant variable: log real daily wages. Standard errors clustered at the individual level. Other Controls: dummy for Permanent contract, age, and its squared, sectoral, regional and qualification dummies, and time dummies. Displaced workers from 1999 to 2004.

Figure 1.10: Wage losses from displacement: different transitions among permanent workers.



Source: Author's calculations with MCVL2008. Notes: Dependant variable: log real daily wages. Standard errors clustered at the individual level. Regression with individual fixed effects. Other Controls: dummy for Permanent contract, age, and its squared, sectoral, regional and qualification dummies, and time dummies. Distinction between PC workers re-gaining a PC (PC-PC) after two years of re-employment or still having a FTC (PC-FTC). Displaced workers from 1999 to 2004.

1.10 Appendix C: Surplus functions of the model

1.10.1 Fixed Term Contracts surplus

$$y_t = \begin{cases} \varepsilon + s & \text{if Investment} \\ \varepsilon & \text{if not investment} \end{cases}$$

$$S^T(y) = W^T(y) + J^T(y) - U$$

$$\begin{aligned} S_t^T(y) &= y_t + \beta(1-\delta)E_t[(1-\lambda)\int_0 max(S_{t+1}^T(z),0)\partial G(z) + \\ + \quad & \lambda \int_0 max(S_0^P{}_{t+1}(z),0)\partial G(z) + U_{t+1} + V_{t+1}] - (U_t + V_t) \end{aligned}$$

The surplus of employment in FTC is going to be equal to the income flow $y = \varepsilon + s$ of being employed in that contract, plus the discounted expected future income. The future income depends on the expiration λ. With prob $1 - \lambda$ keeps the FTC contract provided that the idiosyncratic productivity is higher than that threshold of firing temporary contracts, or with probability λ the contracts expires, and gets promoted if the idiosyncratic productivity is greater than the promotion threshold. Note that if PC workers invest, appears the payment of the cost of investment C. $i = I$

1.10.2 Permanent Contract Surplus

$$S_0^P(y) = W_0^P(y) + J_0^P(y) - U - V$$

$$\begin{aligned} S_{0t}^P(y) = \quad & y_t - F\beta(1-\delta) + \beta E_t[(1-\delta)\textstyle\int_0 max(S_{t+1}^P(z),0)\partial G(z) + \\ & +U_{t+1} + V_{t+1}] - (U_t + V_t) \end{aligned}$$

$$S^P(y) = W^P(y) + J^P(y) - U - V + F$$

$$\begin{aligned} S_t^P(y) = \quad & y_t + F(1 - \beta(1-\delta)) + \beta E_t[(1-\delta)\textstyle\int_0 max(S_{t+1}^P(z),0)\partial G(z) + \\ & +U_{t+1} + V_{t+1}] - (U_t + V_t) \end{aligned}$$

$$\Rightarrow S_0^P{}_t(y) = S_t^P(y) - F$$

The surplus from the match of a just promoted worker is S_0^P, total surplus of being employed following promotion from a temporary position to a permanent one. As is just promoted, firing costs are sunk, do not enter the wage bargaining, and hence are not in the surplus. While a continuing PC, already includes these costs. When a firm and a worker match, because there is no employment contract signed yet, in case of disagreement over the wage the firm does not have to pay firing costs. Note that in this case the firm is not entailed to F in the absence of agreement.
The surplus of employment in PC is going to be equal to the income flow of being employed in that contract, plus the discounted expected future income.

1.10.3 Steady state equilibrium conditions

$$\begin{aligned} 0 &= \varepsilon^P + s + F(1-\beta(1-\delta)) + \beta(1-\delta)\int_{\varepsilon^{PI}} S^{PI}\partial G(z) \\ &\quad -b - \beta p(\theta)\phi\int_{\varepsilon^{TNI}} S^{TNI}(z)\partial G(z) \end{aligned} \tag{1.22}$$

$$\varepsilon_0^{PI} = \varepsilon^{PI} + F \tag{1.23}$$

$$\begin{aligned} 0 &= \varepsilon^{TNI} + \beta(1-\delta)\Bigg((1-\lambda)\int_{\varepsilon^{TNI}} S^T(z)\partial G(z) + \\ &+ \lambda\int_{\varepsilon_0^{PI}} (S_0^{PI}(z) - C)\partial G(z) - b - \beta p(\theta)\phi\int_{\varepsilon^{TNI}} S^{TNI}(z)\partial G(z) \end{aligned} \tag{1.25}$$

$$\frac{a}{q(\theta)} = \beta(1-\phi)\int_{\varepsilon^{TNI}} S^{TNI}(z)\partial G(z) \tag{1.26}$$

1.10.4 Steady state employment

Separation rates are define as:

$$sep^P = \delta + (1-\delta)G(\varepsilon^P)$$

$$sep^T = \delta + (1-\delta)((1-\lambda)G(\varepsilon^T) + \lambda G(\varepsilon_0^P))$$

The conversion is defined by

$$conv = (1 - \delta)\lambda(1 - G(\varepsilon_0^P))$$

And the job finding rate

$$jfr = p(\theta)(1 - G(\varepsilon^T))$$

Thus, employment and unemployment in steady state are defined

$$u = 1 - n^T - n^P$$

$$sep^P * n^P = conv * n^T$$

$$sep^T * n^T = jfr * u - conv * n^T$$

Chapter 2

INFORMAL EMPLOYMENT OVER THE BUSINESS CYCLE

2.1 Introduction

The informal sector in Latin America employs a substantial fraction of the workforce. On average 50% of the urban work force is employed in the informal sector. According to the International Labor Organization (ILO) different groups have been termed "informal" because they share one common feature: they are not recognized or protected by the legal and regulatory framework. Perry et al. (2007) suggest that informality can be seen from two points of view: *Exclusion* and *Exit*. *Exclusion* refers to workers in the informal sector being excluded from more desirable formal jobs. *Exit* suggests that workers and firms are driven by voluntary motives, making optimal decisions when choosing whether or not to be part of the formal sector. These two different views have important implications in terms of the cyclical adjustment of the labor market. A countercyclical informal sector is consistent with the *Exclusion* view; the sector expands during downturns to absorb increased unemployment. While procyclicality would be consistent with the *Exit* view; the informal sector expands due voluntary entries in order to seize the increased opportunities.

Whether informal employment is countercyclical or procyclical is an understudied subject. While informal employment as a *share* of total employment has been found to be countercyclical in most countries (Loayza and Rigolini (2011), and Fiess et al. (2010)), informal employment *in absolute terms* (as percentage of working age population) has been found to be procyclical in some countries and countercyclical in others. In fact, empirical evidence presented in this chapter shows that while in Brazil informal employment *in absolute terms* is procyclical, it is countercyclical in Mexico. Both countries are characterized by a higher procyclical job finding rate from unemployment in the formal than in the informal sector. But this effect is much stronger in Mexico, which explains the countercyclical behavior of informality *in absolute terms*.

The goal of this chapter is to analyze in a simple search and matching model, extended to allow for an informal and a formal sector, the cyclical properties of labor market variables, and particularly explain the cyclical fluctuations of the informal sector. Within this framework the study answers if institutional differences between the formal and informal sector are important to explain the different cyclical fluctuations between Mexico and Brazil.

This research contributes to the literature in three different ways. First, it carefully documents cyclical properties over the business cycle of formal and informal sector in Brazil and Mexico. Second, it provides a simple search and matching model with formal and informal sector to study their cyclicality. Finally, the model gives a useful instrument to understand the factors that determine the cyclical behavior of informal employment over the business cycle. This has important implications in terms of priorities for policy development. Policies, such as social protection and pro-business stimulus policies depend essentially on how the informal sector behaves over the business cycle, specially during downturns.

The model extends Pissarides (2000) to allow for the presence of two sectors: formal and informal. The informal sector arises because the existence of fixed costs of operating formally. In the formal sector firms have to pay a fixed cost of production to the government every period they employ a worker, while the informal firms evade this cost. Yet, informal firms face the risk of being detected and jobs are destroyed instantaneously if the firm is monitored. Firms in the formal sector face more search frictions than in the informal sector, because finding a worker in that sector is more time consuming (more time for advertising, screening, and interviewing of applicants is needed)[1]. This translates into higher flow costs of posting vacancies, while enjoying higher labor productivity. On the supply side the model assumes that workers are homogeneous, and search is undirected.

First, in order to approximate the cyclical properties of the model, a comparative static analysis at different values of labor productivity is carried out. This exercise is done in order to understand how labor market variables move over the business cycle. Productivity shocks are known to be highly persistent, and the job finding rates high, leading to a fast adjustment of the unemployment rate. Hence, the elasticities derived from the steady state are basically the same as the dynamic response of the whole system. In a second step, to derive quantitative results, a calibration of the model to Brazil and Mexico data and simulations of the stochastic model are performed. Data quality and availability has restricted the choice to Brazil and Mexico in the analysis.

[1]Some papers, like Zenou (2008) see the formal sector as a sector with search frictions, while the informal sector as a competitive sector. This is an extreme view of the labor market. It implies that informal jobs can be found instantaneously, while formal jobs take time to be filled.

Results show that this very simple model can replicate the correlation of informal employment and unemployment with output that the data exhibit for Mexico and Brazil. For both countries, the calibration exercise predicts that the informal employment as a *share* is countercyclical as in the data, due to a stronger procyclical job finding rate in the formal than in the informal sector. While informal employment *in absolute terms* is countercyclical in Mexico, it is procyclical in Brazil.

The explanation of the different cyclical fluctuations of informal employment is a higher productivity gap and higher fixed cost of the formal sector relative to the informal one in Mexico with respect to Brazil. The mechanism depends on the relative reaction of the job finding rates in the two sectors to productivity shocks. If the job finding rates in both sectors are procyclical, then the countercyclicality of informal employment depends on how much stronger is the job finding rate in the formal sector, relative to the informal sector. The benchmark model predicts a countercyclical informal sector the higher the fixed cost in the formal sector and the higher the productivity gap between the two sectors by increasing the procyclicality of the formal job finding rate with respect to its informal counterpart. When this effect is sufficiently strong, the model can predict countercyclical informal employment *in absolute terms*. At the same time, lower flow costs of posting vacancies in the informal sector (i.e. less search frictions), hiring costs, and bigger bargaining power of the informal workers tend to increase the possibilities of having countercyclical informal employment.

Although this study explains part of the story, other rigidities in the formal sector can help explain the stronger job finding rate in the formal sector than in the informal sector. The inclusion of wage rigidities, productivity specific shocks, direct flows between the two sectors, and directed search are briefly discussed in this chapter.

The chapter is organized as follows. The next section gives an introduction to the definitions, concepts and measurement issues related to informal employment, and shows the cyclical fluctuations facts of two Latin American labor markets: Brazil and Mexico. Section 3 makes a brief review of the related literature and section 4 describes the model's setup. Section 5 analyzes how the equilibrium variables (tightness, and sector allocation) are affected by aggregate productivity shocks using steady state comparisons at different productivity levels. Section 6 calibrates and comments the simulation results. Section 7 is devoted to a brief discussion of the impact of other assumptions and other configuration of the model on the dynamic responses; such as specific productivity shocks, rigid wages in the formal sector, job-to-job transitions, and directed search. Finally, Section 8 concludes.

2.2 Informal employment: huge dimensions and cyclical fluctuations

2.2.1 Definition and measure of informal employment

In this chapter, informal employment refers to the employment condition in the informal sector. Informal workers are those working in firms that do legal activities but do not comply with government regulations, such as tax and/or labor laws. This definition is slightly different to the traditional definition of shadow economy, that includes all economic activities that contribute to the gross national product, but escape detection in the official GDP estimates.

There are two measures mostly used in the literature. The first is defined as the "productive" measure, where an individual is considered an informal worker if she belongs to any of the following categories: (i) unskilled self-employed, (ii) salaried worker in a small private firm, (iii) zero-income worker.[2] The second is the "legal" or "social protection" measure in which a salaried worker is informal if she does not have the right to a pension linked to employment when retired. That is, employed people can be labeled into two categories, formal or informal employed[3]. These two measures and the traditional shadow economy measure are all highly correlated.

Latin American labor markets are characterized by an informal sector of huge dimensions that on average accounts to 50% of total employment. Table 2.1 shows figures of average informality shares, i.e. as proportion of total employment, for the period 2000 to 2009. This figures are taken from Leonardo and Tornaroli (2009) [4] for Latin American countries and from OECD Employment Outlook 2008, for the other developing countries.

As we can see in the table 2.1 the size of the informal sector goes from 20, in Chile, to more than 70%, in Peru or Paraguay, as a *share* of total employment. This shows a substantial dispersion in informality rates across countries. This is not an exclusive phenomenon of Latin American countries. For example, other developing countries, such as Turkey have 20% of informal employment, while Korea 26%. No matter which measure we take into account the share of informal employment has taken huge dimensions in developing countries, which makes essential taking it into consideration when studying labor markets dynamics.

[2]ILO defines an informal workers as a self-employed or unpaid workers, and people working in firms with less than 5 workers

[3]Data on these definitions is available from labor surveys in most developing countries.

[4]The data is taken from household surveys for countries in which the existence or absence of social security contributions is registered for each employee in the sample

2.2.2 Informal employment and cyclical fluctuations

Two views of informality are on debate. The first dates back to Lewis (1952) and Harris-Todaro (1970) which equates the informal sector with the disadvantaged sector of a market segmented by rigidities in the formal sector. On the other hand, a second view, following De Soto (1989), sees the informal sector as an unregulated, largely voluntary sector. People opt to work or hire informally because, after weighing cost and benefits, they find that they are not better off working in the formal sector. These two views correspond to the *Exclusion* and *Exit* causes of informality defined in Perry et al. (2007), or the views of Loayza and Rigolini (2011) as safety-net or engine of growth. The engine of growth view sees the informal sector as a sector that allows new technologies and products to be introduced this sector, making it the mechanism trough which economic booms are propagated. Instead, the safety net view sees the informal sector, as an involuntary sector and alternative to unemployment.

These two ways of interpreting the informal sector have implications in terms of the cyclical movements of informal employment. The first sees informality as a countercyclical sector, being the buffer for the increased unemployment during recessions. While, the second sees informality as procyclical; workers opting to entry in order to seize increased opportunities in booms.

Although the literature on informality over the business cycle is relatively scarce, some studies focus the attention on business cycle fluctuations of informality, and more recently, worker flows.

Loayza and Rigolinni (2006) find that the informal employment share, measured as the proportion of self- employment over total employment, is countercyclical for the majority of countries, with the degree of counter-cyclicality being lower in countries with larger informal employment and better police and judicial services. Fiess et al. (2010) confirm episodes of expansion of informal employment consistent with the exclusion view. However, they also identify episodes consistent with the exit view. Leonardo and Tornaroli (2009) study the changes of the share of informality (over total employment) over the business cycle and find that some cases are consistent with the dualistic view of informality, while some others fit better into the voluntary view. Finally, Loayza and Rigolini (2011) using cross country panel analysis find that on average the informal sector, measured as the share self-employment on the labor force, reacts counter-cyclically, pointing strongly to the its role as a safety net of last resort.

Bosch and Maloney (2008) study the gross worker flows for Brazil and Mexico[5]. The authors show that gross worker flows behavior in the two countries challenge the conventional wisdom that has guided the modeling the sector that informal workers are primarily those rationed out of the formal labor market.

[5]These are the only two countries that have information on transitions between unemployment and employment in either formal or informal sectors, since they are the only two countries with panel data that allow the authors to estimate this transition rates.

This chapter will focus on the informal salaried workers, leaving aside self- employment[6]. Table 2.2 reports the level, relative volatilities, cross-correlations, and elasticities, all with respect to GDP. The data presented here has been quarterly averaged, logged and HP filtered, in order to get the cyclical component of every series. Both in Mexico and Brazil, employment rate is procyclical, while the unemployment rate is strongly countercyclical. At the same time the *share* of informal employment (over total employment) is also countercyclical in both countries. While, informal employment measured in *absolute terms* (as proportion to the working age population) is countercyclical in Mexico, is mildly procyclical in Brazil[7].

In the lower panel of table 2.2 we have information on the dynamics of the job finding rates from unemployment in the formal and informal sector. The formal sector shows highly procyclical job finding rate, while mildly procyclical o even acyclical in the informal sector. The relatively stronger procyclical behavior of the job finding rate in the formal sector explains the countercyclical behavior of the *share* of informal employment. That is, in relative terms the informal sector expands when the job finding rate in the formal sector responds more than its informal counterpart over the business cycle. When this effect is really strong, informal employment *in absolute terms* is countercyclical. For Mexico the job finding rate of the formal sector reacts 5 times more stronger than the informal one, while in Brazil is only two and a half times. The much stronger behavior of the job finding rate in the formal sector in Mexico, leaves the informal sector absorbing workers during downturns, that in other case would be unemployed.

The unemployment rate is highly volatile in these two developing countries. In Mexico it is more than seven times more volatile than output, while in Brazil is five times. Search and matching models suffer from the *volatility puzzle*. An extended literature, following Shimer (2005) shows that the standard matching model fails to reproduce the large volatility in unemployment and vacancies during the business cycle. In fact, these variables are much more volatile in the U.S. data than in the calibrated model subject to productivity shocks of a realistic magnitude. We will not use the model to account for the large volatility observed in developing countries. Finally, Bosch and Maloney (2008) show that the dynamics of the sectoral composition of employment are largely explained by the dynamics of the access to formal and informal jobs, more than to the shedding of these sectors[8]. Hence, in order to explain the cyclical behavior of informal employment we need only to focus on the explanation of the job finding rates in the two sectors.

[6]Dynamics on self employment requires models of occupational choice, while here we interested in the modeling of salaried workers.

[7]Note that the *share* of informal employment can be countercyclical, while at the same time *in absolute terms* procyclical. This can happen only when formal employment is even more strongly procyclical than informal employment.

[8]We do not present the data on separation rates for simplification purposes. Refer to Bosch and Maloney (2008)

2.3 Related literature

There has been a growing literature related to search and matching models with two sectors: formal and informal. This strand of literature can be seen in an intermediate position between the two views of informality (*"Exclusion"* and *"Exit"*). On the one hand, those models allow for a voluntary decision of entrepreneurs, the marginal worker will be indifferent between formal and informal sector. On the other hand, differential costs to both sectors, differential productivity in sectors, labor market taxes and other labor market regulations may reduce labor demand without introducing segmentation per se.

Previous papers have modeled the informal sector embedded in a search and matching framework. The goal of these studies was to understand the impact of government policies, such as taxation and the capability of enforcing compliance, on the size of the informal sector. Papers have modeled the way in which informal jobs are created in two different ways. First, a series of models focus on the worker's decision to participate in the informal labor market. In these papers it is usually assumed the exogenous existence of both formal and informal firms posting vacancies. Then, heterogeneous workers direct their search towards one of the two sectors according to the worker's education (Kolm and Larsen (2004)), their moral costs of operating in the informal sector (Fugazza and Jacques (2004)), or productivity differences (Boeri and Garibaldi (2006)). Albrecht et al. (2009) argue that worker's productivity is the major determinant of participation in the informal sector. In a model with heterogeneous workers, they show that the appearance of informal jobs is rooted in the decision of low productivity workers to become informal self-employed. The authors treat the informal sector as exogenous, where opportunities to work in that sector arise exogenously. Zenou (2008) considers a model where the formal sector is subject to search frictions, whereas the informal market is competitive. The paper shows that informality is the result of matching frictions in the formal sector. As in Albrecht et al. (2009) the author distinguishes three labor markets: formal sector, informal sector and formal "unemployment".

Other type of models endogenize the firms choice. Bosch (2007) set up an occupational choice model where agents are allowed to decide between becoming a formal entrepreneur, an informal entrepreneur or workers in search of a job. Agents differ in their managerial ability and informality arises because of regulations and constraints affect heterogeneous agents in different ways. Three thresholds in the managerial ability distribution are relevant in order to define what type of agent will be. Formal entrepreneurs search for workers that are ex-ante equal, but when they are brought together some match pairs result to be more productive than others.

To the best of my knowledge, the only previous paper analyzing the cyclical fluctuations of developing countries labor markets with a search and matching model is Bosch and Esteban-Pretel (2012). The authors develop a stochastic job matching model with endogenous separation rates, where firms have the choice of making formal or informal contracts to a newly arrived worker. The authors also use heterogeneity of workers to generate the informal sector. Firms post undefined vacancies, and in the moment of the match according to the specific productivity decide if write a formal or informal contract. Hence, firms have a threshold level of formal productivity. The authors use the model to replicate the cyclical properties of the separation and finding rates in the formal and informal sector of Brazil, and study the effects of different policy regulations on the share of formal employment and unemployment.

I follow this literature but developing the most simple search and matching model with two sectors to analyze in which cases a countercyclical informal sector arises. To the best of my knowledge, the model in this chapter is the first one that combines homogeneous workers and undirected search[9], with two separate sectors, in which firms decide where to post vacancies. The model endogenizes the decision of firms, and workers are thought to be homogeneous.

2.4 A two sector model

2.4.1 The main idea

The model is a simple continuous time search and matching model à la Pissarides (2000) with two sectors: formal and informal. Basically, this model extends the standard search and matching model with one sector to a two sector model. In this chapter informal employment is seen as resulting from efforts of entrepreneurs to trade off costs and benefits of functioning in compliance with formal regulations. Perry et al. (2007) argue that is reasonable to assume that private firms voluntarily chose to operate in the formal or the informal sector based on rational profit maximizing calculations. In particular, the extent to which firms comply with government regulations is likely to depend on their weighing of the various costs and benefits associated with operating formally or informally. The authors show that the main factors that firms are likely to take into account are the nature of the regulatory framework, the extent to which regulations are enforced, and the various opportunity costs associated with operating informally.

In the model, firms have to decide where to post a vacancy at the flow cost of maintaining an open vacancy. This cost can be different in both sectors. In fact, if different, the assumption is that costs in the formal sector are bigger than its informal counterpart. These flow costs represent the matching frictions in both sectors. The assumption of

[9]Directed search is a very strong assumption, forcing workers to look only for jobs in one of the two sectors. Could be that highly educated workers do so for formal jobs, but is less arguable for low educated workers.

higher costs of posting vacancies in the formal sector, reflect that entering the formal sector is more time consuming, because of more advertising, screening and interviewing of applicants. While the lower cost in the informal sector represents the existence of more informal mechanisms of hiring workers.

The second type of costs formality is subject to is a fixed cost of production, such as taxes or contribution to social security. I model this as a lump sum tax that an entrepreneur has to pay to the government every period she employs a worker if decide to operate formally[10]. Functioning informally does not involve those cost, but there is a positive probability of being caught every period. If the latter happens it is assumed the match is destroyed. This implies that the duration of jobs in the informal sector is shorter. Finally, operating formally has the benefit of enjoying higher labor productivity. The positive gap in labor productivity of formal firms is the result of more extensive infrastructure and greater accessibility to the production factors, and thus a better technology. At the same time, complying with government regulations allows formal firms to benefit from service and public goods, enforcement of property rights and thus better access to the credit markets.

This trade-off, given by the different costs, allows both sectors to coexist in equilibrium. The equilibrium allocation is going to be determined by the free entry condition in both sectors and the resultant zero profit conditions.

Workers are homogeneous, and can be employed formally, informally or be unemployed. The match is assumed to be undirected, hence, workers end up being in one or the sector randomly. This implies that workers in equilibrium are going to be indifferent between working in any of the two sectors.

Separation rates are assumed to be constant and exogenous. The model abstracts from separations dynamics. On the one hand, Bosch and Maloney (2008) show that the job finding rate in both sectors explains most of the dynamics of the relative size of the sectors over the business cycle. On the other hand, one way of introducing endogenous separation rates is by modeling it à la Mortensen and Pissarides (1994), but this implies knowing about the distribution of the idiosyncratic productivity levels in both sectors something we know really little about. Results depend on the distribution of the these two idiosyncratic distributions.In fact, one can always choose these distributions in order to match labor market volatilities. In this study the focus is in the job finding rates dynamics in the two sectors, in search of transparency of the mechanisms, analyzing the pro or countercyclicality of both sectors.

[10]The interpretations of this fixed cost can be either a tax or the social contribution the employer needs to make for the worker. This fixed cost is going to have the same effect, in terms of dynamics, as a hiring or training costs. Section 2.5.3 analyzes the effects of hiring costs.

2.4.2 Setup of the model

The matching technology

The trade in the labor market is uncoordinated and time consuming. Meeting of vacant jobs and unemployed workers is assumed to be regulated by a matching function in each sector with constant returns to scale. In fact, a Cobb Douglas function is assumed.

$$m^j(u, v^j) = Au^\eta (v^j)^{1-\eta}$$

where $j = F, I$

$m(u, v^j)$ is the number of matching in both sectors, formal (F) and informal (I), and u and v^j are the total unemployed workers and vacancies in each sector. η is the elasticity of the matching function with respect to unemployment, and A is a scaling parameter, that can be interpreted as an efficiency parameter. Each matching function is increasing in both arguments (first derivative is positive), but the marginal contribution of u and v^j to the aggregate number of matching is decreasing (the second derivative is negative). As in Pissarides (2000) we can define the so called market tightness in each sector $\theta^j = v^j/u$, determined by ratio of vacancies posted in sector j and the aggregate unemployment. Since search is random, what matters is the total number of unemployed. Displaced workers are a pool of undifferentiated unemployed that search for jobs in both sectors with the same intensity, hence, the total pool of searches is the same in both sectors, equal to the pool of unemployed workers. Since the pool of searches is the same for both sectors, the structure of the model creates a straight link between the formal and informal sector. Vacancy posting decisions in one sector directly affect agent's decisions in the other sector trough the denominator of the market tightness.

It can be defined the vacancy filling rate of firms as $q(\theta^j) = \frac{m(u,v^j)}{v^j}$, for $j = F, I$ and the job finding rate for workers as $p(\theta^j)$ for $j = F, I$. As usual in this literature, $p(\theta^j) = \theta^j q(\theta^j)$ with $q'(\theta) > 0$ and $p'(\theta) < 0$.

Firms

There is a continuum of risk neutral entrepreneurs. Firms in each sector produce goods with only one input: labor. Firms in the formal sector pay a fixed cost of production: τ, while firms operating informally enjoy evasion. Jobs in the two markets are destroyed at an exogenous and instantaneous rate s. In the informal sector, entrepreneurs face the risk of being caught, having an instantaneous monitoring rate equal to ρ. Conditional on being monitored in the informal sector, the job is destroyed. Productivity in both sectors differs, represented by the parameter δ, making the productivity in the formal sector higher. Both sectors have a constant returns technology in labor. In each sector one worker produces output, as a combination of a general productivity: y, and if formal, specific productivity, δ. rJ, the flow capital cost of a job in each sector, satisfies:

$$rJ^F = (1+\delta)y - w^F - \tau + s(V^F - J^F) \tag{2.1}$$

$$rJ^I = y - w^I + (s+\rho)(V^I - J^I) \tag{2.2}$$

where, J^j $(j = F, I)$ is the present-discounted value of the expected profit of an occupied formal or informal job, r is the flow rate of return on having the job filled (the interest or discount rate), and w^j $(j = F, I)$ is the wage payed in the formal and informal sector, respectively. That is, the return to the firm on a filled job is equal to the difference between worker's productivity and costs, plus a potential change in the value in case of the match break-up (for informal firms this includes the probability of being caught). The assumption is that the productivity of a match, is high enough to pay wages, and other possible costs.

$$rV^F = -c^F + q(\theta^F)(J^F - V^F) \tag{2.3}$$

$$rV^i = -c^I + q(\theta^I)(J^I - V^I) \tag{2.4}$$

Having a vacant job is like having an asset, where V^j $(j = F, I)$ is the present-discounted value of an expected profit of this asset. rV is the return on this asset, equal to the flow cost per unit of time c^j $(j = F, I)$, plus the possible changes in value due to the change in state with probability $q(\theta^j)$. The change in state yields $J^j - V^j$. As we explain in section 2.4.1 the flow cost of posting vacancies is assumed to be higher in the formal sector, i.e. $c^F \geq c^I$.

We abstract from the capital gain or losses from expected changes in the valuation of the assets, since first we are going to analyze steady states responses.

Workers

There is a fix, normalized to one mass of risk neutral workers, with discount rate r, equal to the firm's discount rate. Workers cannot simultaneously work and search in both sectors and the transitions between sectors is assumed to happen going first through unemployment spell. Unemployment is a full time activity, and workers can not work in the formal or informal sector during an unemployment spell. When working they earn a wage w^j $(j = F, I)$, and search for a job if unemployed. During search the workers enjoy a return, b, the value of unemployment[11]. b can be thought of as the unemployed income, i.e. unemployment benefits, home productivity or the value of leisure. The discounted value of the expected income stream when employed is denoted by E^j

[11]More realistic would be to assume a lower income from unemployment for informal workers since they do not enjoy social security benefits. But since we have purely random search, we cannot set different values. In equilibria unemployed workers are all the same.

$(j = F, I)$, whereas the expected discounted value of being unemployed by U.

$$rE^F = w^F + s(U - E^F) \tag{2.5}$$

$$rE^i = w^I + (s + \rho)(U - E^I) \tag{2.6}$$

The asset value of being employed is equal to the wage earned plus the probable gain/loss of changing state. Workers in the formal sector become unemployed at the rate s, while in the informal sector jobs last for a shorter time, because of the positive probability of being caught, ρ.

$$rU = b + p(\theta^F)(E^F - U) + p(\theta^I)(E^I - U) \tag{2.7}$$

This equation has the same interpretation as an asset equation. rU is the value of an unemployed worker, which can be thought as the average expected return on worker's human capital or the minimum compensation that an unemployed worker requires to accept an offer. This is made up by the yield b and the expected gain from changing state (to employment). Since the search is random, workers can be employed in the formal sector with probability $p(\theta^F)$ or in the informal sector with probability $p(\theta^I)$. Hence, formal job offers arrive at a rate $p(\theta^F)$, while informal at the rate $p(\theta^I)$.

As before, only a steady state comparison is going to be made, hence there are no gain or losses from expected changes in the valuation of employment and unemployment, being E and U constant.

Wage Bargaining

Each match enjoys of pure economic rents to be split between workers and entrepreneurs. Wages are the result of a Nash Bargaining process, with workers bargaining power equal to β. The problem solved chooses the wage to $max(E^j - U^j)^{\beta}(J^j)^{(1-\beta)}$. This implies that the surplus of each match is split by the following rule:

$$\beta(J^I - V^I) = (1 - \beta)(E^I - U^I) \tag{2.8}$$

$$\beta(J^F - V^F) = (1 - \beta)(E^F - U^F) \tag{2.9}$$

2.4.3 Equilibrium

The creation of vacancies is driven by the free entry of firms in the labor market. This implies that in equilibrium, firms post vacancies to the point at which posting an extra vacancy has a present discounted value of zero. Using the free entry condition in both sectors, $V^F = 0$ and $V^I = 0$ and equations 2.3 and 2.4 we get:

$$J^F = \frac{c^F}{q(\theta^F)}$$

$$J^I = \frac{c^I}{q(\theta^I)}$$

This means that in each sector the marginal expected discounted cost of opening a vacancy or hiring must be equal to the marginal value of creating a job. Hence, in both sectors firms are making zero profits, being the expected cost of posting a vacancy equal to the return.

The free entry condition, together with equations 2.1 and 2.2 give the job creation conditions in the two sectors:

$$(r+s)\frac{c^F}{q(\theta^F)} = (1+\delta)y - w^F - \tau \tag{2.10}$$

$$(r+s+\rho)\frac{c^I}{q(\theta^I)} = y - w^I \tag{2.11}$$

Wages can be obtained with the sharing rules equations (2.8 and 2.9) together with the equations for rJ^j, rE^j and rU, and the fact that in equilibrium there is free entry in both sectors.

$$w^F = \beta((1+\delta)y - \tau) + (1-\beta)rU \tag{2.12}$$

$$w^I = \beta y + (1-\beta)rU \tag{2.13}$$

An equilibrium in this economy is characterized by the labor market tightness θ^F and θ^I, such that equations 2.1 to 2.13 are satisfied. We need to note, that since we are assuming random search, workers accept both types of jobs if they are offered a wage at least equal to their outside option.

Substituting equations and 2.12 and 2.13 into 2.10 and 2.11, we obtain the zero profit conditions (ZPC) in each sector: two equations with two unknowns; θ^F and θ^I.

$$(1-\beta)\left[(r+s)\frac{c^F}{(1-\beta)q(\theta^F)} - ((1+\delta)y - \tau - rU)\right] = 0 \tag{2.14}$$

$$(1-\beta)\left[(r+s+\rho)\frac{c^I}{(1-\beta)q(\theta^I)} - (y - rU)\right] = 0 \tag{2.15}$$

These two equations define two loci for formal and informal jobs in the plane θ^F,θ^I. Equation 2.14 can be read as, after the consummation of the match, the match give rents, that are going to be slit between entrepreneurs and workers. The match in the formal sector produces $(1+\delta)y$, which must be enough to cover taxes τ, the opportunity cost of having post a vacancy in the formal sector $(r+s)\frac{c}{q(\theta^F)}$, and compensate the worker for the outside option rU. From the negotiation process the firm gets $(1-\beta)$ and the worker β. Symmetrical intuition applies for equation 2.15 in the informal sector.

These two loci depend on two endogenous variables, θ^F and θ^I, and the parameters values of r, s, ρ, δ, b, c^F, c^I, τ, β. To find the equilibrium and look for a unique and stable equilibrium we can analyze the properties of equations 2.14 and 2.15. An equilibrium with the coexistence of both sectors is found where both locus intersect. Intersection and slopes of the two loci depend on the parameters values of the model.

The slopes of the two loci are given by:

$$\frac{\theta^F}{\theta^I}\Bigg|_{ZPC^F} = -\left[\frac{\frac{rU}{\theta^I}}{\frac{-(r+s)c^F q'(\theta^F)}{(1-\beta)q^2(\theta^F)} + \frac{rU}{\theta^F}}\right]$$

$$\frac{\theta^F}{\theta^I}\Bigg|_{ZPC^I} = -\left[\frac{\frac{-(r+s+\rho)c^I q'(\theta^I)}{(1-\beta)q^2(\theta^I)} + \frac{rU}{\theta^I}}{\frac{rU}{\theta^F}}\right]$$

We can easily check that rU is increasing in both θ^F and θ^I. Hence, both loci have negative slope. Remember $q'(\theta^j) < 0$. The magnitude of the slopes again depends on parameters values. It can be easily checked that the informal locus is steeper than the formal one. Also, if the parameters values that represent the trade-offs of being in one or the other sector are not extreme, the intersection of the two curves exists and is always a stable equilibrium. Hence, always that the fixed costs is not very high, the productivity differential is not extreme, and the monitoring rate is not high a mixed equilibrium is found. We will restrict to this cases.

2.4.4 Determinants of the size of the informal and formal sector and unemployment

The only thing left is the flows out and in to both sectors, and the fact that $1 = u + n^F + n^I$ for every moment of time.

The steady states flows are characterized by zero growth in employment and unemployment rate, that is inflows to unemployment in both sectors must be equal to the outflows of unemployment:

$$\dot{n^F} = p(\theta^F)u - sn^F = 0$$

$$\dot{n^I} = p(\theta^I)u - (\rho + s)n^I = 0$$

We can re-express these equations as:

$$u = \frac{1}{1 + \frac{p(\theta^F)}{s} + \frac{p(\theta^I)}{s+\rho}} \tag{2.16}$$

$$n^F = \frac{\frac{p(\theta^F))}{s}}{1 + \frac{p(\theta^F)}{s} + \frac{p(\theta^I)}{s+\rho}} \tag{2.17}$$

$$n^I = \frac{\frac{p(\theta^I)}{s+\rho}}{1 + \frac{p(\theta^F)}{s} + \frac{p(\theta^I)}{s+\rho}} \tag{2.18}$$

The size of each sector is an increasing function of the respective market tightness, and decreasing on the other. Hence, every time the informal sector expands, the formal sector contracts[12]. What happens to the unemployment rate depends on the magnitude of the different responses. It can be shown that increases in the fixed cost increase also the unemployment rate in the model.

Proposition 1: *The size of the informal sector is increasing in the fixed cost τ, and decreasing in the auditing rate, ρ, the productivity gap, δ, and the flow cost of posting a vacancy c^I.*

2.5 Analyzing the properties over the business cycle: Steady state elasticities

This section is devoted to an analysis of the steady state elasticities of labor market variables with respect to labor productivity. As has been largely argued in the literature (Pissarides (2009), Mortensen and Nagypal (2007)) we can approximate the cyclical properties of a model by comparative static results with a continuous time model that compares steady states at different values of labor productivity. The argument is that the high persistence of productivity and high job finding rates determine a high speed

[12] Derivation of θ^F and θ^I in equations 2.14 and 2.15 with respect to the different parameters in the model leads to:

$\frac{\theta^F}{\tau} < 0$ and $\frac{\theta^I}{\tau} > 0$ $\frac{n^F}{\tau} < 0$ and $\frac{n^I}{\tau} > 0$
$\frac{\theta^F}{\rho} > 0$ and $\frac{\theta^I}{\rho} < 0$ $\frac{n^F}{\rho} > 0$ and $\frac{n^I}{\rho} < 0$
$\frac{\theta^F}{\delta} > 0$ and $\frac{\theta^I}{\delta} < 0$ $\frac{n^F}{\delta} > 0$ and $\frac{n^I}{\delta} < 0$
$\frac{\theta^F}{c^I} > 0$ and $\frac{\theta^I}{c^I} < 0$ $\frac{n^F}{c^I} > 0$ and $\frac{n^I}{c^I} < 0$

of adjustment of the unemployment rate. A standard model with exogenous separation rates, make the comparative static results essentially the same as the response of the full dynamic system. I use the elasticities in order to understand the responses of labor market variables to productivity shocks. In the next section a calibration and simulation of the dynamic stochastic model is performed to get quantitative results and compare to data.

2.5.1 A zero productivity gap

First, the most simple case is analyzed, setting most of the differences between the two sectors to zero. That is, the assumption is that $\delta = 0$, and the flow cost of vacancies is the same in both sectors, $c^F = c^I$. Hence, in this case the cost of being formal is the fixed cost τ, while informal firms enjoy evasion, but are audited with probability a positive probability ρ. Conditional on ρ, the match is destroyed. The idea is to clarify the mechanisms that give the sign and magnitude of the labor market variables responses to labor productivity. In the next subsections we are going to evaluate the impact on the labor market dynamics of the different assumptions.

Market tightness responses

From this simple model with two sectors, we can analytically derive the elasticities of θ^F and θ^I with respect to the aggregate productivity:

$$\xi_{\theta^F,y} = \frac{ln\theta^F}{lny} = \frac{(r+s)+\beta p(\theta^F)}{(r+s)\eta+\beta p(\theta^F)}\left[\frac{y-\frac{\beta}{(1-\beta)}c\theta^I\xi_{\theta^I}}{y-\tau-b-\frac{\beta}{(1-\beta)}c\theta^I}\right] \tag{2.19}$$

$$\xi_{\theta^I,y} = \frac{ln\theta^I}{lny} = \frac{(r+s+\rho)+\beta p(\theta^I)}{(r+s+\rho)\eta+\beta p(\theta^I)}\left[\frac{y-\frac{\beta}{(1-\beta)}c\theta^F\xi_{\theta^F}}{y-b-\frac{\beta}{(1-\beta)}c\theta^F}\right] \tag{2.20}$$

These two elasticities are exactly the same as the one derived from the standard one sector model if we set all the institutional parameters to zero, and shut down the dependence on the other's sector market tightness.

The sign and magnitude of the two elasticities, and hence, the property cycles of unemployment, informal and formal employment depend on the parameter values of the model. We assume a unique and stable equilibrium exists. Simple algebra leads to the second proposition of this chapter.

Proposition 2a: $\xi_{\theta^f} > 0$ and $\xi_{\theta^I} > 0$

When there is no productivity gap between the two sectors, both market tightness of the formal and informal sector are always going to be procyclical with respect to labor productivity[13].

Steady State Employment responses to labor productivity

From the steady state flows described in the previous section I can derive the elasticity of employment statuses and unemployment with respect to productivity.

$$\xi_{u,y} = -(1-\eta)[n^F \xi_{\theta^F} + n^I \xi_{\theta^I}]$$
$$\xi_{n^F,y} = (1-\eta)\xi_{\theta^F} + \xi_u$$
$$\xi_{n^I,y} = (1-\eta)\xi_{\theta^I} + \xi_u$$
$$Share_I = \frac{n_I}{n_I + n_F} \Rightarrow \xi_{share} = \frac{n_f}{n_I + n_F}(1-\eta)(\xi_{\theta^I} - \xi_{\theta^F})$$

These elasticities can all be written as function of the elasticities of the two market tightness. From here we can see the differences with a one sector model. While in a one sector model employment responses to productivity are an increasing function of the market tightness elasticity[14]; in the two sector model the sign of the responses of employment in the two sectors depend on the relative size of the market tightness elasticities in both sectors. Hence, all the determinants from the elasticities of the market tightness of both sectors are going to determine the cyclicality of employment and unemployment in this model. We are going to focus only in the cyclicality of informal employment.

Proposition 3: *Cyclicality of the informal sector*

- $\xi_{\theta^I} < 0 \Rightarrow \xi_{n^I} < 0$
- $\xi_{\theta^I} > 0 \Rightarrow \xi_{n^I} < 0$ iff $\frac{\xi_{\theta^F}}{\xi_{\theta^I}} > 1 + \frac{u}{n^F}$

According to this proposition, if the informal market tightness is countercyclical, then the size of the informal sector is always countercyclical.

But, when there is no productivity gap between both sectors, both the job finding rate in the formal and informal sector are always procyclical. Informal employment is going to respond negatively to productivity shocks depending on how strong the vacancies in each sector react to productivity changes. In fact, the ratio of elasticities (formal over

[13] When $\delta = 0$, $\xi_{\theta^F} = \frac{\frac{yc(r+s+\rho)\eta}{(1-\beta)q(\theta^I)}}{B^f B^i - \theta^F \theta^I \beta/(1-\beta)c^2} > 0$ and $\xi_{\theta^I} = \frac{\frac{yc(r+s)\eta}{(1-\beta)q(\theta^F)}}{B^f B^i - \theta^F \theta^I \beta/(1-\beta)c^2} > 0$, where $B^f = \frac{c\eta(r+s)}{(1-\beta)q(\theta^F)} + \frac{\beta c \theta^F}{1-\beta}$ and $B^i = \frac{c\eta(r+s+\rho)}{(1-\beta)q(\theta^I)} + \frac{\beta c \theta^I}{1-\beta}$

[14] In a one sector model the elasticity of employment with respect to labor productivity is $\xi_n = (1-\eta)\xi_\theta(1+n)$

informal market tightness) should be bigger than $1 + \frac{u}{n^F}$. Meanwhile, the *share* of informal employment (over total employment) will be countercyclical always that formal vacancies have a stronger response than informal vacancies. That is, informal employment *share* can be countercyclical, while not so informal employment in *absolute terms*. In other words, always that the job finding rate in the formal sector is more procyclical than the informal one, the *share* of informal employment is countercyclical, and when is much stronger, even the informal employment in *absolute terms* can be countercyclical.

To sum up, when both job finding rates are procyclical, the countercyclicality of informal employment depends on the ratio $\frac{\xi_{\theta^F}}{\xi_{\theta^I}}$. This ratio is increasing in the fixed cost the formal sector has to pay[15]. That is, informal employment is going to be countercyclical the higher the taxes the formal firms have to pay. Next subsection analyzes the intuition of this result.

What is behind the countercyclicality of informal employment?

Every match generates rents. The surplus of every match can be written as $S^j = E^j - U^j + J^j$. Using equations from 2.1 to 2.13, we can re-write the surplus in both sectors as:

$$(r + s)S^F = y - \tau - rU \tag{2.21}$$

$$(r + s + \rho)S^I = y - rU \tag{2.22}$$

Notice that the formal surplus is lower for every productivity value when we account for the fixed cost of production, τ. Since there is Nash Bargaining, the surplus is proportional to value of a job, and hence directly related to the movements in θ^F. In presence of the fixed cost, the surplus variation is greater in case of a productivity shock. This makes vacancies of the formal sector respond stronger to a productivity shock. The fixed cost, τ, leads to a "small surplus" in the formal sector, making the market tightness responses in that sector larger[16]. Since there is no fixed cost present in the informal sector, the job finding rate in the formal sector is going to be more procyclical than its informal counterpart. If the job finding rate in the formal sector is sufficiently more procyclical

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[15]Doing some algebra we can get: $\frac{log \frac{\xi_\theta^f}{\xi_\theta^i}}{log\tau} = \eta \left[\frac{log\theta^i}{log\tau} - \frac{log\theta^f}{log\tau} \right]$. This has positive sign since $\frac{\theta^f}{\tau} < 0$ and $\frac{\theta^f}{\tau} > 0$.

[16]The same effect has a bigger b, the income received when unemployed. For a detailed analysis on the role of b see Hagedorn and Manovskii (2008). This "small surplus" assumption helps to solve the unemployment volatility puzzle (Mortensen and Nagypal (2007), Hagedorn and Manovskii (2008) and Silva and Toledo (2009)). The mechanism of the "small surplus" assumption in these papers works trough increasing the volatility of the job finding rate, and, hence, the unemployment volatility.

than its informal counterpart, informal employment is countercyclical.

2.5.2 A positive productivity gap

Assume formal firms have a positive productivity gap, that is $\delta > 0$. While the elasticity of the informal market tightness is exactly the same as before, the elasticity of the formal market tightness is:

$$\xi_{\theta^F,y} = \frac{(r+s)+\beta p(\theta^F)}{(r+s)\eta+\beta p(\theta^F)}\left[\frac{(1+\delta)y-\frac{\beta}{(1-\beta)}c\theta^I\xi_{\theta^I}}{(1+\delta)y-\tau-b-\frac{\beta}{(1-\beta)}c\theta^I}\right]$$

Proposition 2b: $\xi_{\theta^F} > 0$, $\xi_{\theta^I} \leq 0$ *iff* $(r+s)\eta \leq \beta\delta p(\theta^F)$

Market tightness of the formal sector is going to be always procyclical with respect to labor productivity, while the sign of the elasticity of the informal depends on the parameters' values[17]. In fact, we can find a cut-off of the productivity gap δ, above which the dynamic response of the informal market tightness is negative in case of a productivity shock. The cut off for the productivity gap, for which the ξ_{θ^I} is equal to zero is:

$$\delta^* = \frac{\eta(r+s)}{\beta p(\theta^F)}$$

The cut-off is going to be increasing in the elasticity of the matching function, the separation rate s, and the discount rate r, and decreasing on the bargaining power of the workers, and the job finding rate $p(\theta^F)$. Trough the latter depends also on the determinants of θ^F. That is, indirectly is a function of ρ and τ, as shown in the previous section.

Hence, when the productivity gap is sufficiently high, higher than the cut-off, the job finding rate in the informal sector is countercyclical. This makes the informal employment in *absolute terms*, and hence also the *share* of informal employment, countercyclical. The intuition behind this is that the informal sector contracts during booms, because the formal sector can seize much better the increased productivity than in the informal sector due a much higher labor productivity. This happens because wages in the informal sector react much stronger to a productivity shock than formal wages, increasing the incentives to post vacancies in the formal sector, while decreasing the incentives to post in the informal sector.

[17] After some algebra we can re-write the elasticities as: $\xi_{\theta^F} = \frac{(1+\delta)y\frac{(r+s+\rho)\eta c}{q(\theta^I)}+\delta y\beta c\theta^I}{(1-\beta)\left[B_F B_I-(\frac{\beta c}{1-\beta})^2\theta^I\theta^F\right]} > 0$ and $\xi_{\theta^I} = \frac{y\frac{(r+s)\eta c}{q(\theta^F)}-\delta y\beta c\theta^F}{(1-\beta)\left[B_F B_I-(\frac{\beta c}{1-\beta})^2\theta^I\theta^F\right]}$ where $B^F = \frac{c\eta(r+s)}{(1-\beta)q(\theta^F)}+\frac{\beta c\theta^F}{1-\beta}$ and $B^I = \frac{c\eta(r+s+\rho)}{(1-\beta)q(\theta^I)}+\frac{\beta c\theta^I}{1-\beta}$

We can re-write the elasticities of the market tightness as:

$$\xi_{\theta^F} = \frac{1}{\eta}\frac{(1+\delta)y - w^F\xi_{w^F}}{(1+\delta)y - \tau - w^F}$$

$$\xi_{\theta^I} = \frac{1}{\eta}\frac{y - w^I\xi_{w^I}}{y - w^I}$$

Assuming both ξ_{w^F} and ξ_{w^I} are equal to one, then the elasticity of the formal market tightness is always bigger than $\frac{1}{\eta}$, and bigger the higher the fixed cost, τ. Meanwhile, ξ_{θ^I} is always positive and equal to $\frac{1}{\eta}$. Hence, ξ_{θ^I} can be negative only when the elasticity of informal wages with respect to labor productivity is bigger than one.

2.5.3 Other parameters

Hiring costs in the formal sector

In order to discuss the effects of introducing hiring costs in the formal sector, we set again the productivity gap between the two sectors to zero, although the analysis would remain practically unchanged. Now, the formal sector is subject to hiring costs, that can be interpreted as turnover costs. Hiring costs can be thought of as recruiting, and screening costs, and the time required for interviewing applicants and training the new worker.

All the equations for the informal sector remain unchanged.

For the formal sector the return to posting a vacancy in the formal sector is changed. Equation 2.3 is modified to include the hiring costs:

$$rV^F = -c + q(\theta^F)(J^F - V^F - H)$$

The employer's surplus is $J^F - H$. Re-writing the zero profit condition in the formal sector leads to:

$$(r+s)\frac{c}{q(\theta^F)} + \beta c(\theta^F) = (1-\beta)(y - \tau - (r+s)H - b) - \beta c(\theta^I)$$

From the above equation we can check that the responses of the formal market tightness are going to be stronger, because of the presence of the hiring costs, H. In fact, H has exactly the same effect as the fixed cost τ, and b. As has been pointed out by several authors (see Mortensen and Nagypal (2007); Silva and Toledo (2009); and Yashiv (2005)), the presence of fixed turnover costs makes a firm's net payoff (after paying the hiring cost) more responsive to productivity variation. Hence, the presence of hiring costs does not change the results obtained until here. If the job finding rates in both sectors are procyclical, then the countercyclicality of informal employment depends on how much stronger is the job finding rate in the formal sector, relative to the informal sector. In the case of having hiring costs, the job finding rate in the formal sector would even be stronger than in the informal sector.

Lower flow vacancy cost in the informal sector

We go now back to the assumption of different flow vacancy costs in the two sectors. In fact, the assumption is that $c^F > c^I$. This can be interpreted as the formal sector having more search frictions than the informal sector. The extreme case would be the informal sector being completely competitive, but this case is highly unrealistic. Searching workers in the informal sector is also costly and time consuming, although maybe less than in the formal sector, because the mechanism are intrinsically more informal.

Results are also strengthen in this case. Maintaining the assumption of $\delta = 0$, and deriving the ratio of elasticities for this case, let us with the following equation:

$$\frac{\xi_\theta^F}{\xi_\theta^I} = \frac{r+s+\rho}{r+s} \frac{c^I}{c^F} \frac{q(\theta^F)}{q(\theta^I)}$$

If we do not take into account the effect of lowering c^I on the market tightness of the two sectors, this ratio is lower when $c^I < c^F$. But considering all the effects, for lower values of c^I, there are more incentives to post vacancies in the informal sector and less in the formal sector. Hence, the market tightness in the informal sector increase, while the formal one decreases. This has the reverse effect on the vacancy filling rate for the two sectors, increasing the ratio $\frac{q(\theta^F)}{q(\theta^I)}$. In a quantitative exercise it can be checked this effect dominates, and hence the ratio of elasticities of the market tightness is increased for lower values of c^I[18]. Hence, the assumption of lower flow vacancy cost in the informal sector does not change the results obtained until here.

Lower bargaining power of workers in the informal sector

Another exercise in order to try to test the robustness of the results here is set different bargaining power of workers. In fact, due to the existence of unions in the formal sector, we can think workers in this sector have more bargaining power. Hence, the assumption

[18]It can be checked that $\frac{\theta^F}{c^I} > 0$ and $\frac{\theta^I}{c^I} < 0$. At the same time $\frac{log\frac{\xi_{\theta^F}}{\xi_{\theta^I}}}{logc^I} = 1 + \eta\left[\frac{log\theta^I}{logc^I} - \frac{\theta^F}{logc^I}\right] < 0$ for a the big range of possible values of parameters of the calibration of this model.

to be discussed here is $\beta^F > \beta^I$[19].

As Hagedorn and Manovskii (2008) showed the bargaining power has important implications on the responses of market tightness to productivity shocks. In fact, lower bargaining power makes the wage less procyclical, and increasing the response of the job finding rate.

The role of the different bargaining power in this two sector model is exactly the same as in the one sector model. In order to analyze the cyclicality of the informal wages, from equation 2.2 and the free entry condition, $V^I = 0$, we can write informal wages as:

$$w^I = y - \frac{(r+s+\rho)(1-\beta^I)}{r+s+p(\theta^I)}(y - b - p(\theta^f)\beta^F S^F)$$

Considering the derivative of informal wages with respect to labor productivity, y:

$$\begin{aligned}\frac{w^I}{y} \quad &= \quad 1 - \frac{(r+s+\rho)(1-\beta^I)}{r+s+\rho+p(\theta^I)} + \frac{(r+s+\rho)(1-\beta^I)}{(r+s+\rho+p(\theta^I))^2}\left[y - b - p(\theta^F)\beta^F S^F\right]\frac{p(\theta^I)}{y} + \\ &+ \frac{(r+s+\rho)(1-\beta^I)}{r+s+\rho+p(\theta^I)}\left[\beta^F S^F \frac{p(\theta^F)}{y} + p(\theta^F)\beta^F \frac{S^F}{y}\right]\end{aligned}$$

From the latter equation we can see that $\frac{w^I}{y}$ will be lower the lower the bargaining power in the informal sector. This makes the responses of the informal market tightness larger, hence decreasing the ratio $\frac{\xi_\theta^F}{\xi_\theta^I}$. Depending on parameters, if β^I is much smaller than its formal counterpart we can have a ratio of elasticities smaller than one, and hence informal employment procyclical. A simple quantitative exercise shows that, in fact, if the bargaining power of the two sectors are very different then informal employment is always procyclical, and could be the case that formal employment turns out to be countercyclical. Since the unions are not too strong in Latin America we can think that bargaining power in the two sectors are not very different, even when $\beta^I < \beta^F$. At the same time, it can be argued that informal workers have bargaining power since they are working out of the law and can always threaten the entrepreneurs with a public denounce.

[19]During the nineties the union power has decreased a lot in Latin American countries, partly due to changes in labor legislation, decentralization of the collective bargaining process, and because the increase in the use of temporary contracts.

2.6 Calibration and simulation results

2.6.1 Parametrization of the baseline model

Once we have understand how labor market variables move in response to productivity shocks with the analysis of steady state elasticities, we can move to simulations to get quantitative results. A subset of the parameters are fixed according to what has become standard in the literature, other are calibrated with data of two Latin American countries: Brazil and Mexico. Some other parameters are not really known. For the latter we are going to let them free and see how the results change in response to a change in these parameters.

The time period of the simulations is one quarter. We set the quarterly interest rate to $r = 0.018$, that implies a discount factor of 0.982. The matching functions in both sectors are assumed to be Cobb-Douglas, with unemployment elasticity $\eta = 0.5$, as standard in the literature. The scaling parameter, A, is calibrated jointly with other model parameters, as will be discussed later. Following the standard literature, we assume that the bargaining power of workers internalizes the search externalities in a standard one sector model, that is, $\beta = \eta = 0.5$[20].

s, the separation rate is set to 0.04, as the average in the data for Brazil and Mexico[21]. Calibration of the flow value of unemployment, b, has attracted significant attention in the recent U.S. literature. This parameter captures elements such as the value of leisure, unemployment benefits, home production, and the dis-utility of work. Shimer (2005) sets it to 0.4, whereas Hagedorn and Manovskii (2008) use a value of 0.955. We choose b to be 0.4, since we are considering developing countries where unemployment benefits are lower than in developed countries. As expected, the volatility of the model changes with the value of this parameter, but we set it fix in order to analyze how results change depending on the other parameters.

We target a unique process for the labor productivity, because both process have very similar statistics, and in order to strictly compare between different calibrations. We calibrate the remaining parameters of this process to match the cyclical behavior of labor productivity, measured as GDP per worker for Brazilian quarterly data. The first order autocorrelation and standard deviation of labor productivity in the data are $\rho_z = 0.8$ and $\sigma_z = 0.022$.

The estimated parameters are chosen to match the mean size of informal employment as a percentage of the labor force in Latin America and the average job finding rate in the formal sector. θ^F is normalized to one, to get A, the scaling parameter in

[20] Should be checked if the same condition internalizes the externalities in this two sector model. Charlot et al. (2013) show i dual labor market with a frictional formal sector and a competitive informal sector the size of the informal sector is generally too large compared to the optimal allocation of the workers

[21] Data on separations rates and job finding rates has been taken from Bosch and Maloney (2008)

the matching function. The flow cost of posting a vacancy, c is calibrated to match the job finding rate in the formal sector, while the fixed cost of the formal sector, τ, is set in order to match the informal employment sector size. For simplification the flow cost of posting vacancies are set equal, $c^F = c^I$. This is a conservative assumption, since assuming $c^F > c^I$ exacerbates the results, as discussed in section 2.5.3. And, second, there is no available reliable data on these costs.

The productivity wedge between formal and informal jobs δ, and the monitoring rate, ρ, summarize the costs of employing informal or formal labor. Some authors have estimated these two parameters, so we can have an approximation for the values of these parameters. Just for illustration, Perry et al. (2007) estimate the effects on labor productivity of informality using World Bank's Enterprise Survey Database. This represents the coefficient of an informality dummy on the log of output per worker (labor productivity) controlling for firm size, time in business, sector and region and other firm characteristics. The estimates show that for an average Latin American country the productivity gap is around 30%, going from 20% in Argentina to 50% in Peru. For Mexico the estimated gap is 30%, but unfortunatly for Brazil we do not have this information. Other studies[22] have estimated the productivity gap for Brazil using wages. The estimate is around 20% in these cases.

For the monitoring rate, Almeida (2009), using the Investment Climate survey (2003) of the World Bank for Brazil, calculate the number of firms inspected by labor authorities over the total number firms in the survey. The mean of this variable is 8%. This can be taken as an approximation of the enforcing rate. Is a rough measure, since the survey is biased to formal and large firms. Hence, we are going to use 10% as baseline measure, but changing it to see how the results change.
Table 2.3 summarizes the parametrization of the calibration excersice.

2.6.2 Simulation results

We simulate 500 periods, and drop 420, in order to get 80 quarters (20 years) of simulations, similar to what we have for Brazil and Mexico. We repeat this 100 times and present the results for the averages series and average statistics.

The case of no productivity gap

Table 2.4 shows the results of the simulations, as well as the data for Brazil and Mexico when there is no productivity gap. That is $\delta = 0$. I set the monitoring rate to be equal to $\rho = 0.1$, while the estimated fixed cost is .08 and 0.1, for Mexico and Brazil, respectively. The table reports the cross-correlations, volatilities, and elasticities, all with

[22] Carneiro and Henley (2001) and Bargain and Kwenda (2009)

respect to labor productivity, for the simulated series and data. We obtain, in the two countries, a strong procyclical job finding rate in the formal sector, stronger than its informal counterpart, but both are underestimated. At the same time, the job finding rate in the formal sector is not strong enough, in the case of Mexico, to get countercyclical informal employment as in the data. In fact, in neither of both cases we get a countercyclical informal sector. This is due to the calibration, and the need of the coexistence of both sectors in equilibrium. When we set δ to zero, the calibrated fixed cost, τ, is not big enough to generate a countercyclical informal sector. It would be needed a higher monitoring rate, in order to have larger fixed cost. This will not be the case when we add a productivity gap. In the case of Brazil, we manage to get the correct elasticities; strong countercyclical unemployment and procyclical informal employment.

A positive productivity gap between the two sectors

For this exercise ρ is set to 0.10, and δ is 0.3 for Mexico, while to 0.2 in the case of Brazil. As in the previous exercise, table 2.5 reports the cross-correlations, volatilities, and elasticities, all with respect to output per worker, for the simulated series and data. The main message of this table is that the model does a good job at replicating the directions of the correlations of most of the variables, but clearly underestimates the volatility of most of them. Looking at the simulation results in detail, we can see in the table that the model is capable of capturing the countercyclicality of unemployment and the countercyclicality of the informal employment in the case of Mexico, and procyclicality in Brazil. The job finding rate from unemployment is strongly procyclical in both cases, but its elasticity is over estimated for Mexico and underestimated for Brazil. Similarly, the job finding rate for informal jobs is much less volatile than its formal counterpart in the Brazilian case, and does not have a strong cyclical pattern. In the case of Mexico, the sign of this correlation is incorrectly predicted. The model predicts a countercyclical job finding rate, while in the data is acyclical.

Finally, although is not the objective of the study to target the relative volatilities of the variables, we have to notice that the volatility of all variables, specially unemployment, is underestimated. In Mexican data, unemployment is 7 times more volatile than GDP, while the job finding rate in the formal sector (JFR^F) 6 times, and the JFR^I almost 3 times. Here, we fall really short in the volatility of unemployment, while closer to JFR^F (5), and far from the JFR^I (0.5). For Brazil the model also underestimates most of the volatilities. Unemployment is 5 times more volatile than GDP per worker, while JFR^F 6 times, and the JFR^I little more than two times. The model under-predicts the volatility of the three variables. This problem is commonly known in the literature as the "Shimer-puzzle". Possible solutions are includying to the model endogenous separations, or changing the calibration to allow for a stronger "small surplus" assumption with higher unemployment benefits, b. This is out of the scope of the study.

In the next exercise a calibration with $\delta = 0.15$ in both countries is performed. The estimated τ is 0.23 and 0.16 for Mexico and Brazil, respectively. Table 2.6 shows the results. In the case of Brazil the model falls even shorter estimating the volatilities of unemployment and the informal employment. For Mexico, the exercise delivers the right sign of the correlation of the job finding rate in the informal sector with labor productivity. Although the relative volatility is underestimated, the elasticity now is pretty close to the one in the data. But at the same time, the model is not capable of replicating the elasticity of the informal employment.

In the second exercise, I set δ as in the first exercise while, lowering ρ to 0.05. Elasticities are really underestimated, and for Mexico still predicting the incorrect correlation of the job finding probability in the informal sector. Basically, this shows less countercyclical informal sector, due to less ρ.

To sum up, this very simple model can replicate the correlation of informal employment and unemployment with output in the data, in the case of Mexico and Brazil. For both countries the calibration exercise predicts that informal employment *share* is countercyclical as in the data, due to a stronger procyclical job finding rate in the formal than in the informal sector. But for the case of Mexico, in the baseline calibration, the correlation of the job finding rate in the informal sector is predicted to be countercyclical, while in the data is procyclical. We can predict this correlation in the right direction setting a lower productivity gap, but in this case the relative volatility of informal employment and the job finding rates with respect to labor productivity is even more underestimated. Even if the objective of the chapter is not to target the relative volatilities, a lower δ leads to a mildly countercyclical informal sector. Even if these institutional differences are part of the story, there are probably other rigidities in the formal sector that are also explaining the stronger job finding rate in the formal sector, while not so in the informal sector. The next section discusses briefly some of these rigities.

2.7 Robustness checks

2.7.1 Sector specific productivity shocks

The formal sector can be thought as a sector with specific labor productivity, in this model represented by δ. Shocks to δ can be interpreted as demand shocks in the formal sector, or shocks to the access to credit markets for formal firms, or even, specific shocks to the production function in the formal sector, which can be assumed to be inherently different from the informal one, since formal firms are probably using more capital than informal firms.

When a positive productivity shock, that is specific the formal sector, occurs the surplus match in the formal sector increases. At the same time, the outside option for workers increases due to the increase in the productivity in the formal sector, that given

θ^I reduces the surplus in the informal sector (see equation 2.22). This makes the share of informal employment countercyclical, even in absolute terms.

Table 2.7 shows the results of the simulation when there is only one shock: δ. Results are only shown for Brazil, since in the previous exercise we had informal employment and job finding rates in the informal sector, procyclical. I calibrate this process exactly the same as the aggregate productivity, since there is no available data to carry on an exercise like this. As expected, results indicate that informal employment is countercyclical, even if the rest of the parameters of the model are constant. At the same time, the model predicts a job finding rate in the informal sector countercyclical, while in the data is procyclical.

2.7.2 Wage rigidities in the formal sector

Wage rigidity in the formal sector could help explain the more volatility in job finding rate in the formal sector. If there is a negative productivity shock, intuitively, since the expected surplus of a formal match is affected downwards there are less incentives to post vacancies in that sector. The assumption is a downward wage rigidity (for example, can be thought as a minimum wage set by law: $\underline{w} > w^F$). Since wages in the formal sector do not adjust to adverse aggregate productivity shocks, the expected formal surplus of the match falls even more than it would do in the absence of rigidities[23]. Although the expected surplus of the match in the informal sector lowers due to the negative productivity shock, it does less than in the formal sector, since informal wages can freely adjust downwards. As a result the job finding rate of the formal sector is even stronger procyclical than the informal with respect to the baseline model discussed here.

2.7.3 Job-to-job transitions between sectors

Hence, a possible extension is on the job search while informally employed. In fact, results show that flows from informal to formal employment are procyclical. Informal workers are searching for jobs in the formal sector while employed in that sector. The pool of searchers in the formal sector is no longer just the pool of unemployed, but includes the employed in the informal sector. The market tightness are defined as: $\theta^F = \frac{v^F}{u+n^I}$ and $\theta^I = \frac{v^I}{u}$.

This change of the model, although complicates the algebra, leads to similar analysis in terms of the cyclicality of the job finding rate of the formal and informal sector. In fact, the elasticity of the market tightness in the formal sector with respect to labor productivity is exactly the same as before. Meanwhile, the elasticity of the informal market

[23] Works as the small surplus assumption discussed in section 5.3.

tightness is much more complicated. In this framework, we can re-write the zero profit condition for the informal sector as:

$$\frac{c^I(r+s+\rho+p(\theta^f))}{q(\theta^i)}+c^I\theta^I\beta=(1-\beta)(y-b)$$

The above equation shows that the responses of the informal market tightness is possibly lower than in the benchmark model, since informal entrepreneurs have less incentives to post vacancies because workers search on the job. This could help explain the less cyclical fluctuations of the job finding rate in the informal sector.

2.7.4 Directed search

A model with directed search search would need to include some kind of heterogeneity of workers. In this two sector framework, a directed search model without any heterogeneity has no solution, since would require that the value of a job is exactly the same in both sectors. A possible assumption is heterogeneous workers in the home productivity, b. The analysis of such a model would need of a separate study, but the intuition of the model can be analyzed.

There would be a threshold value for the home productivity, for which the worker is indifferent between working in one or the other sector. Under reasonable parameters assumptions, workers with home productivity above this threshold will search only in the formal sector, while the workers with less home productivity in the informal sector. Hence, workers with high home productivity will only search for formal jobs, while workers with low home productivity only for informal jobs. Workers in the middle could change sectors depending on labor market conditions. This threshold depends on labor market conditions (both job finding rates), while the elasticities of each market would be independent of the other sector market tightness, but will depend indirectly through the threshold of home productivity.

It can be shown that this threshold will be an inverse function of the aggregate productivity, and hence when labor productivity increases, the threshold decreases, being more searchers in the formal sector while less in the informal one. In this case, the expansion of one sector will be done at the expense of the other. Maintaining the assumption of the fixed cost $\tau > 0$ and productivity gap $\delta > 0$, the formal employment will be procyclical while informal employment countercyclical. Within this framework Mexican data could be easy to match, but no so Brazilian data.

2.8 Concluding remarks

Informal labor markets in Latin America capture a large fraction of employment. In those countries on average 50% of workers are employed in the underground or shadow economy, where lack of protection and regulations is a fact. In the recent literature, there are two views of informality, which according to the empirical evidence a mixture of the two is present in reality. The first refers to the traditional view of informality, which sees the informal sector as disguised unemployment, while the other view refers to it as offering better opportunities to entrepreneurs and workers opting to become informal.

These views have implications in terms of the cyclical fluctuation of the labor market. The first predicts the informal sector to be countercyclical: the sector expands during downturns to absorb increased unemployment; while for the second the inverse is true, the sector expands due to voluntary entries in order to seize of the increased opportunities. Empirical evidence indicates that the informal employment *share* of total employment is countercyclical in Mexico and Brazil. Instead, informal employment in *absolute terms* (as percentage of the working age population) is countercyclical in Mexico, while procyclical in Brazil. This is due to a much higher procyclical job finding rate in the formal sector than in the informal in Mexico, relative to Brazil.

The main goal of this chapter was to analyze and understand the cyclical fluctuation of informal employment in a two sector search and matching model. Within this framework I explain how institutional differences between the informal and formal sectors explain the different cyclical fluctuations between Mexico and Brazil.

First, I derived the steady state elasticities and do comparative statics that describe how the endogenous variables implied by the model change with aggregate productivity across steady states. The benchmark model predicts a countercyclical informal sector the higher the fixed cost in the formal sector, and the higher the productivity gap between the two sectors. At the same time, lower flow costs of posting vacancies in the informal sector (i.e. less search frictions), hiring costs, and bigger bargaining power of the informal workers tends to increase the possibilities of having countercyclical informal employment by increasing the procyclicality of the formal job finding rate with respect to its informal counterpart. When this effect is sufficiently strong, the model can predict countercyclical informal employment in *absolute terms*.

The calibration and simulation of the model show that this simple model can replicate the correlation of informal employment with labor productivity in the data for the case of Mexico and Brazil. In fact, the exercise predicts that informal employment *share* is countercyclical due to a stronger procyclical formal job finding rate with respect to its informal counterpart. On the other side, informal employment in *absolute terms* is countercyclical in Mexico, while it is procyclical in Brazil.

The mechanism depends of the relative reaction of the job finding rates in the two sectors to productivity shocks. If the job finding rates in both sectors are procyclical, then the countercyclicality of informal sector depends on how much stronger is the job finding rate in the formal sector, relative to the informal sector. The observed different cyclical fluctuations of informal employment in Mexico and Brazil, can be explained by a higher productivity gap and higher fixed cost of the formal firms compared to the informal ones in Mexico with respect to Brazil. At the same time, lower flow costs of posting vacancies in the informal sector (i.e. less search frictions), hiring costs, and bigger bargaining power of the informal workers tends to increase the possibilities of having countercyclical informal employment.

Tables

Table 2.1: Share of informal employment

	Productive definition	Legal definition
Argentina	42.3	43.9
Bolivia	73.5	69.4
Brazil	53.4	33.8
Chile	36.3	22.1
Costa Rica	41.0	30.8
Ecuador	61.7	66.7
El Salvador	56.5	47.9
Mexico	50.7	59.1
Nicaragua	64.2	67.3
Paraguay	71.0	73.2
Peru	66.4	66.5
Uruguay	41.8	24.0
Venezuela	50.3	38.0
Average LA	54.5	49.4
Turkey	–	21.7
Korea	–	25.8
South Africa		24.0
Hungary	–	19.4

Source: Prepared by the author based on data from SEDLAC (CEDLAS and The World Bank) and OECD Employment Outlook 2008. Productive definition: Informal=salaried workers in small firms, non-professional self-employed and zero-income workers. Legal definition: Informal salaried workers if (s)he does not have the right to a pension when retired.

Table 2.2: Cyclical fluctuations in Mexico and Brazil

	Mexico			Brazil		
x	$\frac{\sigma(x)}{\sigma(y)}$	*Corr(x,y)*	$\xi_{x,y}$	$\frac{\sigma(x)}{\sigma(y)}$	*Corr(x,y)*	$\xi_{x,y}$
Employment rate	0.52	0.61	0.32	0.53	0.60	0.31
Unemployment rate	7.41	-0.68	-5.08	5.27	-0.84	-4.49
Informality (%working age pop)	1.44	-0.57	-0.82	0.87	0.23	0.28
Informal share (% employment)	1.92	-0.81	-1.22	1.15	-0.35	-0.4
JFR^i	2.83	0.37	0.75	2.58	0.62	1.63
JFR^f	6.18	0.80	3.55	6.35	0.65	4.29

Sources: Author calculations using data from National Statistics Institutes (IBGE and INEGI) and Bosch and Maloney (2008). Period: 1983.Q1-2001.Q2 for Brazil and 1988.Q1-2004.Q4 for Mexico. Notes: Relative standard deviation, correlation and elasticity with respect to output per worker of the logged and HP filter de-trended of different employment statuses for Mexico and Brazil. The series have been smoothed using a 4 quarter moving average to remove high frequency fluctuations. JFR^j is the job finding rate from unemployment from formal $j = f$ and informal $j = i$.

Table 2.3: Parameter configuration

Parameter	Description	Value	Target
β	worker's bargaining power	0.5	Standard literature
η	matching function elasticity	0.5	Standard literature
b	leisure and UI	0.4	Shimer (2005)
s	separation rate	0.04	Data
r	discount rate	0.018	Annual interest rate of 7,5% for LA
n^i	informal sector size	0.3	Mexico. Inf salaried/LF
		0.2	Brazil. Inf salaried/LF
$p(\theta^f)$	formal job finding rate	0.65	Data for Mexico
		0.4	Data for Brazil
ρ_z	Autocorrelation	0.8	Data
σ_z	Standard deviation	0.022	Data
τ	Lump sum taxes	–	Size of the informal sector
c	Flow vacancy cost	–	JFR^f
ρ	auditing rate	0.10	Free parameter
δ	Gap in labor productivity	0.3 Mexico	Free parameter
		0.2 Brazil	

Table 2.4: The case of no productivity gap

	Mexico			Brazil		
Simulation	$\frac{\sigma(x)}{\sigma(y)}$	*Corr(x,y)*	$\xi_{x,y}$	$\frac{\sigma(x)}{\sigma(y)}$	*Corr(x,y)*	$\xi_{x,y}$
$p(\theta^i)$	0.60	1.00	0.60	0.69	1.00	0.69
$p(\theta^f)$	1.70	1.00	1.69	1.20	1.00	1.20
n^i	0.21	0.10	0.02	0.15	0.68	0.10
u	1.25	-0.64	-0.81	0.81	-0.67	-0.54
δ	0			0		
ρ	0.10			0.10		
τ	0.08			0.10		
Data	$\frac{\sigma(x)}{\sigma(y)}$	*Corr(x,y)*	$\xi_{x,y}$	$\frac{\sigma(x)}{\sigma(y)}$	*Corr(x,y)*	$\xi_{x,y}$
$p(\theta^i)$	2.83	0.37	0.75	2.58	0.62	1.63
$p(\theta^i)$	6.18	0.80	3.55	6.35	0.65	4.29
n^i	1.44	-0.57	-0.82	0.87	0.23	0.28
u	7.41	-0.69	-5.08	5.27	-0.84	-4.44

Sources: Author's calculations using National Statistics Institutes and Bosch and Maloney (2008). Notes: Relative standard deviation, correlation and elasticity with respect to output per worker of the logged and HP filter de-trended of different employment statuses for Mexico and Brazil calibration and data. $p(\theta^j)$ is the job finding rate from unemployment from formal $j = f$ and informal $j = i$. n^i is informal employment in absolute terms, u is unemployment rate.

Table 2.5: Simulation results for Mexico and Brazil

	Mexico			**Brazil**		
Simulation	$\frac{\sigma(x)}{\sigma(y)}$	*Corr(x,y)*	$\xi_{x,y}$	$\frac{\sigma(x)}{\sigma(y)}$	*Corr(x,y)*	$\xi_{x,y}$
$p(\theta^i)$	0.47	-0.91	-0.43	0.23	0.99	0.23
$p(\theta^f)$	4.59	0.97	4.46	1.83	1.00	1.83
n^i	0.85	-0.24	-0.20	0.33	0.05	0.02
u	1.94	-0.61	-1.19	0.94	-0.64	-0.60
Informal share	0.84	-0.32	-0.27	0.34	-0.16	-0.06
δ		0.30			0.20	
ρ		0.10			0.10	
τ		0.38			0.20	
Data	$\frac{\sigma(x)}{\sigma(y)}$	*Corr(x,y)*	$\xi_{x,y}$	$\frac{\sigma(x)}{\sigma(y)}$	*Corr(x,y)*	$\xi_{x,y}$
$p(\theta^i)$	2.83	0.37	0.75	2.58	0.62	1.63
$p(\theta^f)$	6.18	0.80	3.55	6.35	0.65	4.29
Informality	1.44	-0.57	-0.82	0.87	0.27	0.28
u	7.41	-0.69	-5.08	5.27	-0.84	-4.44
Informal share	1.92	-0.81	-1.22	1.15	-0.35	-0.40

Sources: Author's calculations, National Statistics Institutes and Bosch and Maloney (2008). Notes: Relative standard deviation, correlation and elasticity with respect to output per worker of the logged and HP filter detrended of different employment statuses for Mexico and Brazil calibration and data. $p(\theta^j)$ is the job finding rate from unemployment from formal $j = f$ and informal $j = i$. n^i is informal employment in absolute terms, and informal share is the ratio $\frac{n^i}{n^i+n^f}$, u is unemployment rate.

Table 2.6: Alternative calibration for Mexico and Brazil

Simulation	Mexico			Brazil		
	$\frac{\sigma(x)}{\sigma(y)}$	*Corr(x,y)*	$\xi_{x,y}$	$\frac{\sigma(x)}{\sigma(y)}$	*Corr(x,y)*	$\xi_{x,y}$
$p(\theta^i)$	0.12	0.82	0.10	0.35	1.00	0.35
$p(\theta^f)$	3.10	0.99	3.07	1.67	1.00	1.67
n^i	0.522	-0.17	-0.09	0.28	0.14	0.04
u	1.608	-0.63	-1.01	0.91	-0.65	-0.60
Informal share	0.51	-0.28	-0.15	0.28	-0.11	-0.03
δ		0.15			0.15	
ρ		0.10			0.10	
τ		0.23			0.16	
Simulation	Mexico			Brazil		
	$\frac{\sigma(x)}{\sigma(y)}$	*Corr(x,y)*	$\xi_{x,y}$	$\frac{\sigma(x)}{\sigma(y)}$	*Corr(x,y)*	$\xi_{x,y}$
$p(\theta^i)$	0.49	-0.97	-0.47	0.32	1.00	0.32
$p(\theta^f)$	2.46	0.99	2.45	1.19	1.00	1.20
n^i	0.417	-0.19	-0.08	0.14	0.30	0.04
u	1.085	-0.68	-0.74	0.71	-0.64	-0.46
Informal share	0.84	-0.32	-0.27	0.34	-0.16	-0.06
δ		0.30			0.20	
ρ		0.05			0.05	
τ		0.30			0.14	

Sources: Author's calculations. Notes: Relative standard deviation, correlation and elasticity with respect to output per worker of the logged and HP filter de-trended of different employment statuses for Mexico and Brazil calibration and data. $p(\theta^j)$ is the job finding rate for formal $j = f$ and informal sector $j = i$. n^i is informal employment in absolute terms, and informal share is the ratio $\frac{n^i}{n^i+n^f}$, u is unemployment rate.

Table 2.7: Simulation for Brazil: specific productivity shock

	$\frac{\sigma(x)}{\sigma(y)}$	*Corr(x,y)*
$p(\theta^i)$	2.16	-1.0
$p(\theta^f)$	0.94	1.0
n^i	0.84	-0.46
u	0.20	-0.24
Informal share	0.84	-0.46
ρ	0.10	
τ	0.3	

Sources: Author's calculations. Notes: Relative standard deviation and correlation with respect to output per worker of the logged and HP filter detrended of different employment statuses. $p(\theta^j)$ is the job finding rate for formal $j = f$ and informal sector $j = i$. n^i is informal employment in absolute terms, and informal share is the ratio $\frac{n^i}{n^i+n^f}$, u is unemployment rate.

Chapter 3

THE INS AND OUTS OF FORECASTING UNEMPLOYMENT ACROSS COUNTRIES

written jointly with Regis Barnichon

3.1 Introduction

Forecasting the unemployment rate is an important and difficult task for policymakers. Despite decades of research on the topic, policy makers often rely on Okun's law–the empirical relationship between output growth and unemployment changes–or simple time series models to forecast unemployment.

Incorporating information from labor force flows has been recently shown to improve near-term (one-quarter ahead) forecasts of the U.S. unemployment rate (Barnichon and Nekarda (2012)). In this paper, we provide the theoretical and empirical foundations to this new approach to unemployment forecasting. We theoretically study the properties of this class of forecasting model, and we empirically evaluate the performance of the model across a range of OECD countries, finding dramatic improvements in forecast accuracy as far as one- to two-year ahead.

A simple analogy helps explain the main idea behind the use of labor force flows to forecast unemployment. The unemployment rate can be thought of as the amount of water in a bathtub, a stock. Given an initial water level, the level of the water in next period is determined by the rate at which water flows into the tub from the faucet and the rate at which water flows out of the tub through the drain. When the inflow rate equals the outflow rate, the amount of water in the tub remains constant. But if the inflow rate increases, we know that the water level will be higher in the future. In other words, the inflow rate and the outflow rate provide information about the future level of water– in this case, unemployment. This insight forms the cornerstone of our forecasting model.

More specifically, our unemployment forecasting model is based on two elements: (1) a non-linear law of motion describing how the unemployment rate converges to its steady-state, the rate implied by the flows into and out of unemployment, and (2) a forecast of the labor force flows that feeds into that law of motion.

Theoretically, we show that our model performs better than standard time-series models for two reasons. First, the dynamics of unemployment can be approximately characterized by an AR(1), thereby explaining why simple time series models do so well at forecasting unemployment. However, the AR representation is only an approximation –the AR coefficient is in fact time-varying and depends on the level of flows–, so that linear time series models are mis-specified. By incorporating information from labor force flows and using the correct (non-linear) law of motion for unemployment, our model can better capture the dynamics of unemployment. Second, we show that any innovation to unemployment can be written as a function of the labor force flows. Because our model acknowledges this property and forecast the labor force flows, it can better forecast the innovations affecting unemployment and produce better forecasts.

We then show that the model's performance relative to standard time-series models depends on four factors: (1) the magnitude of the flows, with smaller flows implying improvements over standard models at longer horizons and larger flows implying improvements at short horizons, (2) the volatility of the flows, with more volatile flows implying larger improvements,[1] (3) the persistence (or "forecastability") of the flows, with more persistent flows implying larger improvements, and (4) the heterogeneity of the time-series properties of the flows, with higher heterogeneity in the persistence of the flows implying larger improvements.

While we leave a detailed explanation of factors (2)-(4) for the main text, we briefly discuss the intuition behind (1). The magnitude of the flows governs the speed of convergence to steady state, or using the bathtub analogy, the time needed for the level of water to stabilize at a level consistent with the flows. Figure 3.1 reveals substantial cross country variation in the level of flows. In fact, one can discern a natural partition of developed economies between Anglo-Saxon, Nordic and Continental European economies. In one extreme the US, with very high level of flows, and in the other continental Europe, with very low level of flows. With large (labor market) flows, as in the US, convergence occurs relatively rapidly (in the order of magnitude of a quarter), and the flows provide information about movements in unemployment in the short run. In other words, the model can generate good forecasts in the near term. With small flows, as in Europe, convergence occurs much more slowly (in the order of magnitude of a year),

[1] An implication of (2), which is later verified empirically, is that the model performs especially well, relative to others, during times of high volatility in the labor force flows, i.e., during turbulent times, when forecasting the jobless rate is most valuable.

and the flows provide information about movements in unemployment in the longer run. In other words, the model can generate good forecasts in the longer run.

On the empirical side, we then evaluate the performance of our model over a range of OECD countries and find that the model yields dramatic improvements in forecast accuracy, with large reductions in the mean-squared errors of the best alternative models for forecasts as far as one- to two-year ahead. For instance, it reduces the one year-ahead root-mean-squared-forecast error of professional forecasts by more than 30% in Japan, 30% in Germany, 50% in France and 60% in the UK. Moreover, we find that, consistent with (2), our model has the highest predictive ability during turbulent times, precisely when forecasts are especially valuable.

This paper builds on the influential work of Montgomery et al. (1998), and extends a growing literature aimed at improving unemployment forecasts[2]. In particular, extends the recent work by Barnichon and Nekarda (2012) in two dimensions: first, by providing an explicit study of the conditions under which our model outperforms standard time series models, and second by showing that this model performs dramatically better than conventional forecasting methods at horizons as far as two-year ahead in several OECD countries. This paper is also related to a strand literature regarding labor force flows that tries to understand labor market fluctuations, which has been ignored by the forecasting literature[3].

The paper is organized as follows. Next section presents the model for forecasting unemployment using labor flows. In section 3.3 we analyze why and when our model's forecasting performance should be better than standard time series models. In section 3.4 we present the data used in the paper, and section 3.5 evaluates empirically the forecasting performance of our model. Finally, we conclude.

3.2 Using labor force flows to forecast unemployment

This section presents the unemployment forecasting model based on labor market flows. Our model is built on two elements: (1) A law of motion describing how the unemployment rate converges to its steady-state value, from now on the *conditional steady state unemployment rate*-SSUR, and (2) a forecast of the labor force flows determining the conditional steady-state unemployment rate and the speed at which actual unemployment converges to the steady-state. We now present these two elements.

[2]See, for example, Rothman (1998), Golan and Perloff (2004), Brown and Moshiri (2004), and Milas and Rothman (2008).

[3]Some related papers are Shimer (2012), Petrongolo and Pissarides (2008), Solon et al. (2009), Elsby et al. (2013), Barnichon (2012), Nekarda (2009) and Fujita and Ramey (2012)

3.2.1 The law of motion for unemployment

Individuals can be in one of two labor force states: employed or unemployed, and we assume that movements into and out of the labor force are negligible.[4] This approach is consistent with recent literature (Elsby et al. (2013)) showing that a two-state model does a good job of capturing unemployment fluctuations across OECD countries. In addition to providing a simple framework for understanding the basic flow-based accounting of the conditional steady-state unemployment rate, the data requirements are relatively benign, so that the approach can be applied to a broad set of countries.

Denote $u_{t+\tau}$ the unemployment rate at instant $t+\tau$ with t indexing quarters and $\tau \in [0,1]$ a continuous measure of time within a quarter. Assume that between quarter t and quarter $t+1$ all unemployed persons find a job according to a Poisson process with constant arrival rate f_{t+1}, and all employed workers lose their job according to a Poisson process with constant arrival rate s_{t+1}.[5] The unemployment rate then evolves according to

$$\frac{du_{t+\tau}}{d\tau} = s_{t+1}\left(1-u_{t+\tau}\right) - f_{t+1}u_{t+\tau}, \tag{3.1}$$

as changes in unemployment are given by the difference between the inflows and the outflows. Solving equation 3.1 yields

$$u_{t+\tau} = \beta_{t+1}(\tau)u^*_{t+1} + \left[1-\beta_{t+1}(\tau)\right]u_t, \tag{3.2}$$

where

$$u^*_{t+1} \equiv \frac{s_{t+1}}{s_{t+1}+f_{t+1}} \tag{3.3}$$

denotes the *conditional steady-state unemployment rate*, and $\beta_{t+1}(\tau) \equiv 1-e^{-\tau(s_{t+1}+f_{t+1})}$ is the rate of convergence to that steady state.

Equation 3.2 relates variation in the unemployment stock $u_{t+\tau}$ over the course of a quarter to variation in the underlying flow hazards, f_{t+1} and s_{t+1}. A one-quarter-ahead forecast for the unemployment rate, $\hat{u}_{t+1|t}$, can thus be obtained from

$$\hat{u}_{t+1|t} = \hat{\beta}_{t+1}u^*_{t+1} + \left(1-\hat{\beta}_{t+1}\right)u_t, \tag{3.4}$$

[4] Although a three state model with unemployment, employment and inactivity (which allows for movements in-and-out of the labor force) is theoretically possible, the data requirements are strong (relying on household survey micro data), so that such a model is very difficult to implement for most countries. Moreover, micro data are typically available with a significant delay, making them generally ill-suited for use in forecasting models. In contrast, a two-state model is easy to implement for many countries.

[5] We adopt this timing convention to reflect data availability, as the hazard rate is only observed in quarter $t+1$. Indeed, in real time a forecaster does not observe s_{t+1} and f_{t+1}, but only s_t and f_t. This is because at date t one can only observe labor force flows from $t-1$ to t.

where $\hat{\beta}_{t+1}$ is the quarter t forecast of β_{t+1}, the convergence speed between t and $t+1$.

Figure 3.2 shows the tight, leading relationship between the conditional steady-state unemployment rate, u^*, and the actual unemployment rate, u for a range of OECD countries. This leading relationship differs across countries. While, for the US, the series are almost indistinguishable, for Germany, steady-state unemployment rate leads unemployment by more than one year. Indeed, Germany has a much lower convergence rate than the US. As can be seen in figure 3.1, the sum of monthly unemployment inflow and outflow rates averaged 0.61 in US, while in Germany is 0.065. As a result, unemployment gets 90 percent of the way to its conditional steady-state value in about four months on average in US, while in Germany takes almost three years. Figure 3.3 shows the time in quarters needed to close 90 percent of the gap with the steady state unemployment across countries, that ranges from one quarter in US to more than four years in Italy.

3.2.2 Forecasting labor force flows

Because equation 3.4 only forecasts the unemployment rate one period ahead given current values of the hazard rates, forecasting the unemployment rate at longer horizons requires making forecasts of the hazard rates.

A simple approach is to assume that the hazard rates remain constant at their last observed value over the forecast horizon. In that case, the j-period-ahead forecast of the unemployment rate can be formed from the time t values of s and f by

$$\hat{u}_{t+j|t} = \left[1 - e^{-j(f_t+s_t)}\right] u_t^* + e^{-j(f_t+s_t)} u_t. \tag{3.5}$$

If the hazard rates are persistent enough, equation 3.5 will provide reasonable forecasts.[6]

However, relying solely on current labor force flows constrains our approach to near term forecasts, because the steady state to which the actual unemployment rate converges also changes over time as the underlying flows evolve. As figure 3.4 shows, the hazard rates do evolve, and with them the conditional steady-state unemployment rate and the speed of convergence. Thus, we forecast the underlying labor force flows using a time-series model and feed those forecasts into our law of motion to generate unemployment forecasts at longer horizons.

After generating forecasts of the hazard rates, we obtain j-period-ahead forecasts of unemployment by iterating on

$$\hat{u}_{t+j|t} = \hat{\beta}_{t+j} \hat{u}^*_{t+j|t} + \left(1 - \hat{\beta}_{t+j}\right) \hat{u}_{t+j-1|t}, \tag{3.6}$$

[6] In our empirical evaluation of the model –section 3.5.3–, we consider a forecast based only on the convergence to the steady-state unemployment rate.

with

$$\hat{u}^*_{t+j} = \frac{\hat{s}_{t+j|t}}{\hat{s}_{t+j|t} + \hat{f}_{t+j|t}} \tag{3.7}$$

and

$$\hat{\beta}_{t+j} = 1 - e^{-\left(\hat{s}_{t+j|t} + \hat{f}_{t+j|t}\right)}. \tag{3.8}$$

With quarter $t + j$ forecasts of the flow rates in hand, we can forecast the quarter $t + j$ values of u^* and β. The quarter $t + j$ unemployment forecast is then obtained by taking a weighted average of the previous-period (quarter $t + j - 1$) unemployment rate and the current-period (quarter $t + j$) conditional steady-state unemployment rate, with the weights determined by the speed of convergence to steady state. In the rest of the chapter, we will refer to this model as the Steady-State Unemployment Rate model, or SSUR.

3.3 Theoretical forecasting performance

Our approach to forecasting unemployment rests on the convergence property of unemployment towards its steady-state value implied by the labor force flows. Intuitively, depending on the speed of convergence (in the order of months (as in the US case) or years (as in the continental Europe case), knowing the current values of the flows gives us information on the future level of unemployment, either over the next couple of months or years. This reasoning, and the bathtub analogy described in the introduction, form the cornerstone of our approach. However, the bathtub analogy does not explain why or when the SSUR model performs *better than* other standard models, such as the widely used AR (or more generally ARIMA) models that have been shown to perform particularly well. In this section, we theoretically explore the reasons behind the performances of SSUR over standard time series models. In particular, we identify four characteristics of the labor market that determine the relative performances of SSUR and the forecast-window over which SSUR dominates other models: (i) the magnitude of the flows, (ii) the volatility of the flows, (iii) the persistence of the flows, and (iv) the degree of heterogeneity in the time series properties of the flows.

3.3.1 The AR(1) representation of unemployment dynamics

First, we show that the law of motion of unemployment follows approximately an AR(1), thereby explaining why simple AR(1) models do so well at forecasting unemployment, but also why, and under what conditions, SSUR can perform better.

Recall that, at a given time frequency, next period unemployment is given by

$$u_{t+1} = \left(1 - e^{-(s_{t+1}+f_{t+1})}\right) \frac{s_{t+1}}{s_{t+1} + f_{t+1}} + e^{-s_{t+1}+f_{t+1}} u_t \tag{3.9}$$

with s_{t+1} and f_{t+1} the inflow and outflow rates.

Importantly, equation (3.9) holds at any frequency. Increasing the frequency of observations (say from quarters to months) only reduces the levels of the inflow and outflow rates. Without loss of generality, let us choose the lowest frequency for which s and f are close enough to zero such that equation (3.9) can be linearized with s_{t+1}, f_{t+1} around 0.[7],[8] A first-order Taylor expansion of (3.9) gives the law of motion for unemployment[9]

$$u_{t+1} \simeq (1 - f_{t+1} - s_{t+1})\, u_t + s_{t+1}. \tag{3.10}$$

Moreover, using the fact that $s \ll f$, which holds for all countries, we can further simplify and write

$$u_{t+1} \simeq (1 - f_{t+1})\, u_t + s_{t+1}. \tag{3.11}$$

Denoting $u = Eu_t$ and rearranging, we can write

$$\frac{u_{t+1} - u}{u} \simeq (1 - f_{t+1}) \frac{u_t - u}{u} + \frac{s_{t+1}}{u} - f_{t+1}$$

or

$$d \ln u_{t+1} \simeq (1 - f_{t+1})\, d \ln u_t + \varepsilon_{t+1} \tag{3.12}$$

with

$$\varepsilon_{t+1} = \frac{s_{t+1}}{u} - f_{t+1}.$$

Note that $E\varepsilon_{t+1} \simeq 0$ since $u = Eu_t \simeq \frac{Es_t}{Ef_t}$ and $s << f$, so that ε_{t+1} can be seen as a zero mean innovation. In other words, the law of motion for (log-)unemployment is approximately described by an AR(1) where the persistence term depends on the outflow rate and where the innovation ε_{t+1} depends on the inflow and outflow rates. Provided that movements in f_{t+1} are not too large compared to 1, an AR(1) can well describe the behavior of unemployment with

$$d \ln u_{t+1} \simeq \rho_u d \ln u_t + \varepsilon_{t+1} \text{ with } \rho_u = (1 - f)\,. \tag{3.13}$$

Thus, (3.13) helps explain why simple AR models, or more generally ARMA models since ε_{t+1} can be autocorrelated, perform so well in forecasting unemployment.

[7] Although the discussion is only theoretical at this point and increasing frequency comes at no cost, in practice, there is a trade-off between (i) using a higher frequency and hence obtaining an approximate AR representation and (ii) reducing the sample size and having greater measurement error.

[8] As can be seen from figure 3.1, for the US, a weekly frequency is required, but for EU countries, a monthly frequency is enough.

[9] Intuitively, $1 - e^{-\left(s_{t+1} + f_{t+1}\right)} \simeq (f_{t+1} + s_{t+1})\,.$

3.3.2 Performance relative to standard time series models

We now turn to the performance of SSUR relative to standard time-series models. The approximate law of motion for unemployment, (3.12), helps understand why and when SSUR can perform better than ARMA (or even VAR) models. Contrasting (3.12) and the approximate AR(1) representation (3.13), we can see that SSUR has two advantages over ARMA models: (i) SSUR can forecasts the innovations ε_{t+1} using data on the inflow and outflow rates, (ii) ARMA or VAR models are misspecified because they do not allow for the time-varying autocorrelation in u_t.

In this section, we study theoretically the determinants of the performance of SSUR relative to standard time series models, and discuss the evolution of these performance over the forecast horizon.

To capture the effect of forecasting the inflow and outflow rates on the performances of unemployment, let us assume that the inflow and outflow rates follow AR(1) processes given by[10]

$$\begin{cases} f_{t+1} = \rho_f f_t + \varepsilon^f_{t+1} \\ s_{t+1} = \rho_s s_t + \varepsilon^s_{t+1} \end{cases} \tag{3.14}$$

with ε^f_{t+1} iid, ε^s_{t+1} iid, $\sigma^2_s = E\varepsilon^s_t$, $\sigma^2_f = E\varepsilon^f_t$ and $E\varepsilon^f_t\varepsilon^s_t = 0$.[11]

We now discuss the two separate advantages of SSUR against alternative models: (i) Innovation forecasting using data on worker flows, and (ii) Misspecification of standard time-series models.

3.3.3 Innovation forecasting

To isolate the "innovation forecasting" aspect of SSUR, we first assume that fluctuations in f_t are small compared to 1 so that unemployment follows (3.13), i.e., that the behavior of unemployment only deviates from an AR(1) through the innovation term ε_{t+1}.

Average performance relative to an AR(1)

Guided by the approximate AR(1) representation of unemployment dynamics, we start with the simplest alternative to SSUR and consider a simple AR(1) model.[12]

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[10]As shown in the appendix 3.7, the behavior of the inflow and outflow rates are indeed well described by such simple AR(p) processes. In our empirical implementation of SSUR, we assume similar data generating processes when forecasting the flow rates. The choice of $p = 1$ is done for clarity of exposition.

[11]Assuming $E\varepsilon^f_t\varepsilon^s_t \neq 0$ would not change our main conclusions but would complicate the exposition, so we restrict ourselves to independent processes for s and f.

[12]Imposing one lag, i.e., using an AR(1) instead of an AR(p), is done for clarity of exposition. Using more lags would not change the conclusions.

Denote

$$dMSE_{t+j|t} \equiv E_t(\hat{u}^{AR}_{t+j|t} - u_{t+j|t})^2 - E_t(\hat{u}^{SSUR}_{t+j|t} - u_{t+j|t})^2$$

the difference in the Mean-Squared-Errors (MSE) of j-step ahead forecasts obtained with an AR(1) or SSUR. Assuming that $\rho_u = (1-f)$ is consistently estimated in the AR(1), we obtain the following result:

Proposition 1 *The difference in the MSEs of j-step ahead forecasts satisfies*

$$dMSE_{t+j|t} = Var(\frac{s_t}{u}) \left(\rho_s \frac{\rho_s^j - \rho_u^j}{\rho_s - \rho_u}\right)^2 + Var(f_t) \left(\rho_f \frac{\rho_f^j - \rho_u^j}{\rho_f - \rho_u}\right)^2. \tag{3.15}$$

Expression (3.15) highlights a number of interesting results regarding the performances of SSUR.[13]

Corollary 1 *There exists a unique j^* such that $\frac{\partial MSE_{t+j|t}}{\partial j} > 0$ for $j < j^*$ and $\frac{\partial MSE_{t+j|t}}{\partial j} < 0$ for $j > j^*$. Moreover, $dMSE_{t+j|t} \underset{j\to\infty}{\to} 0$.*

Corollary 1 states that the relative performance of SSUR increases initially with the forecast horizon until it reaches a maximum. Thereafter, relative performance declines and converges to 0, so that SSUR performs no better than an AR(1).

To understand the intuition behind this non-monotonicity result, recall that, while AR models assume $E_t\varepsilon_{t+1} = 0$ when making forecasts, the SSUR model uses time t information to forecast the inflow and outflow rates $\hat{s}_{t+j}$ and $\hat{f}_{t+j}$, and hence $\hat{\varepsilon}_{t+j}$. The non-monotonicity comes from two opposite forces. On the one hand, SSUR's "innovation forecasting" advantage over the AR model gets amplified with the forecast horizon: forecasting errors in the initial innovation (ε_{t+1}) get transmitted to next-period forecasts since both s_t, f_t (and hence ε_{t+1}) and u_t, are persistent. On the other hand, because unemployment and the hazard rates do mean-revert (ρ_u, ρ_s, $\rho_f < 1$), so that time t information becomes more and more irrelevant as the forecast horizon increases. This force brings down the relative advantage of SSUR as the forecast horizon increases.

Corollary 2 $\frac{\partial dMSE_{t+j|t}}{\partial \rho_s} > 0$, $\frac{\partial dMSE_{t+j|t}}{\partial \rho_f} > 0$ *and* $\frac{\partial dMSE_{t+j|t}}{\partial \rho_u} > 0$.

The relative performances of SSUR increase at all horizon with the persistence of the hazard rates ρ_s and ρ_f. Performances also increase with ρ_u, i.e., deteriorates with the level of the outflow rate f since $\rho_u = 1 - f$.

[13] Although j is discrete, we treat j as continuous in the following results for clarity of exposition.

Corollary 3 *The higher the level of the outflow rate f, the faster relative performances of SSUR converge zero as the forecast horizon increases.*

Proof: Note that for $\rho_u^A > \rho_u^B$, we have $dMSE_{t+j|t}(\rho_u^A) < dMSE_{t+j|t}(\rho_u^B)$, and combine with $dMSE_{t+j|t} \underset{j\to\infty}{\longrightarrow} 0$.

Using Corollaries 1-3, we can state three determinants of the performances of SSUR relative to AR models:

Condition 1: Level of the outflow rate

The levels of the flows, and specifically the level of the outflow rate,[14] determines the forecast horizon over which SSUR performs better than the AR model. The larger f, the faster the performances of SSUR deteriorates with the forecast horizon. Intuitively, with larger f, the relative advantage of SSUR over ARMA deteriorates faster with the forecast horizon because unemployment itself shows less persistence, i.e. is less forecastable. Using the analogy of the bath-tub, with a high f, unemployment converges faster to its steady-state and worker flows only bring information about the near future. This result has important implications for the relative performances of SSUR across countries. Depending on the lowest frequency that allows linearization and (3.12), the window over which SSUR outperforms AR models can vary across countries. In countries with large flows such as the US, we should expect, ceteris paribus, that SSUR would outperform other time series models only at short horizon. In contrast, in countries with small flows such as in Europe, SSUR would outperform other models mostly at much longer horizons.[15]

Condition 2: Volatility of the inflow and outflow rates

The more volatile are s_t and f_t, the larger the forecasting performances of SSUR relative to the ARIMA model. This result has interesting implications for the performances of SSUR over the business cycle. SSUR should perform especially well, relative to ARIMA models, during times of high volatility in the inflow and outflow rates, i.e., precisely during turbulent times when $Var(\frac{s_t}{u})$ or $Var(f_t)$ are high, so that the unemployment rate can move very rapidly. Interestingly, this is exactly the moment when forecasting the jobless rate is most valuable.[16]

Condition 3: Persistence of the inflow and outflow rates

The relative performance of SSUR depends on the persistence ρ_s and ρ_f (i.e., on the forecastability) of the inflow and outflow rates. The higher ρ_s and ρ_f, the higher the

[14]The level of s plays no role because $f >> s$.

[15]We confirm this theoretical prediction in the empirical section.

[16]We confirm this theoretical prediction in the empirical section.

forecastability of s and f, the better the relative performance of SSUR. In the extreme case where s_t and f_t are white-noise (ρ_s, $\rho_f = 0$), SSUR performs no better than an AR(1).

Average performance relative to ARMA models

While illustrative, using an AR(1) is a very naive approach. Indeed, it is clear from the data generating processes of f_t and s_t, that f_t and s_t are serially correlated so that ε_t is serially correlated. An ARIMA(1,0,1) would thus perform better than an AR(1). Indeed, the ARIMA would estimate the serial correlation in ε_t through

$$\varepsilon_{t+1} = \rho_\varepsilon \varepsilon_t + \upsilon_{t+1}$$

where ε_t is known at time t.

However, even in that case, SSUR will perform relatively better, because ρ_ε needs to summarize the persistence of two processes -s_t and f_t-. One can then expect that the relative performance of SSUR will depend on how different ρ_s and ρ_f are, and on the relative volatility of $\frac{s_t}{u}$ and f_t.

To clarify this intuition, we consider the relative performances of one-step ahead forecasts.[17] Assuming that ρ_u is the OLS estimate and $\rho_u = (1 - f)$, we can show the following result:

Proposition 2 *The difference in the MSEs of one-step ahead forecasts between SSUR and ARMA models satisfies*

$$dMSE_{t+1|t} = (\rho_s - \rho_f)^2 \frac{Var(\frac{s_t}{u})Var(f_t)}{Var(\frac{s_t}{u}) + Var(f_t)} \tag{3.16}$$

and the difference in j-step ahead forecasts

$$\begin{aligned} dMSE_{t+j|t} &= Var(\frac{s_t}{u}) \left(\rho_s \frac{\rho_s^j - \rho_u^j}{\rho_s - \rho_u} - \rho_\varepsilon \frac{\rho_\varepsilon^j - \rho_u^j}{\rho_\varepsilon - \rho_u} \right)^2 \\ &\quad + Var(f_t) \left(\rho_f \frac{\rho_f^j - \rho_u^j}{\rho_f - \rho_u} - \rho_\varepsilon \frac{\rho_\varepsilon^j - \rho_u^j}{\rho_\varepsilon - \rho_u} \right)^2 . \end{aligned} \tag{3.17}$$

Proposition 2 highlights two additional conditions under which SSUR will perform

[17]One must keep in mind that, the period considered (say "one month" or "one quarter") depends on the frequency considered. Indeed, the approximate AR(1) representation of unemployment requires a high enough frequency such that f is small enough to allow linearization.

better than ARMA models for one-step ahead forecasts:[18]

Condition 4: Heterogeneity in the time-series properties of the flow rates

The larger the difference between ρ_s and ρ_f, the better the forecasting performances of SSUR relative to the ARMA model. Intuitively, an ARMA can only capture the average property of ε_t, which is composed of two separate processes $\frac{s_t}{u}$ and f_t. The more similar the two processes, the better an MA term can capture the behavior of ε_t and the better the performances of the ARMA model. In the polar case where $\rho_s = \rho_f$, ARMA models may perform just as well as SSUR.[19]

Condition 2b: Volatility of the inflow and outflow rates

As in the case of the AR model, the more volatile s_t and f_t, the larger the forecasting performance of SSUR relative to the ARMA model. But here, in addition, the effect is magnified if movements in volatility in s_t and f_t are correlated.[20]

3.3.4 Misspecification

We now discuss the implications of the second advantage of SSUR. SSUR is based on the correct law of motion of unemployment. In contrast, linear time-series models such as ARMA or VAR models are misspecified, since they counterfactually impose that u_t has a constant autocorrelation.

Misspecification of ARMA models

ARMA models are misspecified because they impose a constant persistence term $1 - f$ in (3.13). In contrast, SSUR explicitly takes into account the correct law of motion for u_t, (3.12), and correctly incorporates the role of f_{t+1} when propagating unemployment movements forward. Intuitively, when forecasting $(1 - f_{t+1}) \ln u_t$, SSUR generates an error term with a magnitude in the order of $\sigma_f^2 E \ln u_t$. In contrast, an AR(1) generates an error term in the order of $sd(f_{t+1}) E \ln u_t = \frac{\sigma_f^2}{1-\rho_f^2} E \ln u_t$. As a result, and as in Condition 3 (although through a different channel), the larger the persistence in f_t, i.e., the more "forecastable" f_t, the better the relative performance of SSUR.

[18]Using Proposition 2, one can show that Conditions 1 to 3 (derived against AR models) are still valid against ARMA models. Moreover, a non-monotonicity result similar to Corollary 1 also emerges in the ARMA case.

[19]However, even in this case, SSUR can perform better, because the ARIMA model still remains misspecified, since it imposes a constant AR coefficient, unlike SSUR.

[20]The function $h(x, y) = \frac{xy}{x+y}$ is increasing in x and y, and satisfies $\frac{\partial^2 h}{\partial x \partial y} > 0$. The latter effect is relevant in practice because increases in hazard rates volatility are highly correlated (as we show in the empirical section), which further amplifies the performances of SSUR.

Misspecification of VAR models

A similar reasoning can apply to VAR models -for instance, a VAR with u_t, s_t and f_t- and can explain why a VAR, even if jointly forecasting unemployment and the flow rates and thus potentially addressing the first disadvantage of ARMA models ("Innovation forecasting"), need not to perform as well as SSUR.

While both the approximate law of motion for unemployment (3.11) and a VAR (u_t, s_t, f_t) come out of first-order approximations, the VAR relies on a much stronger assumption: A VAR in u, s and f comes out of a first order Taylor expansion of the dynamics of u_t, s_t and f_t for u_t, s_t and f_t around some constant value. In contrast, approximation (3.11) is only based on s_t and f_t close to some value (in our case, zero). Thus, the VAR also requires that u_t is close to some steady-state value u^*. This assumption is too strong: with $u_t \simeq u_t^* = \frac{s_t}{s_t+f_t}$, the level of unemployment u_t and its fluctuations can be large -and indeed are large in the data- even when s_t and f_t are small. Another way to see this is that our approximate law of motion (3.11) allows for an interaction term between f_{t+1} and u_t, which is not allowed for by the Taylor expansion in f, s, and u, i.e. by the VAR, which implies a law of motion for unemployment of the form

$$u_{t+1} \simeq a\,(u_t - u^*) + b\,(s_t - s^*) + c\,(f_t - f^*)$$

with a, b and c are constants. In other words, the VAR (just like the AR(1)) is misspecified. In our empirical section, we will to quantify the consequence of this misspecification, by comparing the MSEs of a VAR model with that of SSUR.

3.3.5 Measurement error and noise-to-signal ratio

As discussed in the previous subsections, there are benefits of directly forecasting the flows rather than the stock. In other words, forecasting the components of unemployment (in this case, the inflow and outflow rates) can generate better forecasting performances than directly forecasting unemployment. However, such disaggregation comes at a cost: the components of unemployment will have higher noise-to-signal ratios than unemployment itself, because the sample size used to determine the flows is smaller than that used to measure stock.[21]

Interestingly, since the sample size used to calculate the flow rates depends on the number of workers changing states each period, i.e. on the magnitude of the flows, the level of the flows affects the performance of SSUR through an additional channel than the one highlighted in **Condition 1**: the larger the flows, the lower the noise-to-signal ratios of the hazard rates and the better the forecasts of f_{t+j} and s_{t+j}, and hence the better the performances of SSUR.

[21] This discussion parallels a very general question in the forecasting literature; i.e., whether it is preferable to forecast directly the variable of interest (such as GDP) or to disaggregate that variable (and if so, to what level of disaggregation) and forecast its components.

3.4 Data

We construct quarterly transition rates series over the last 30 years across 5 OECD countries –France, Germany, Japan, Spain and the UK– using information on the stocks of unemployment and short-term unemployment following Shimer (2012) and Elsby et al. (2013). Because quarterly data are not always available, we rely on a combination of yearly duration data (as Elsby et al. (2013)) *and* quarterly transition rates measured from micro household survey data to construct quarterly flow rates measures.

This data construction exercise is a necessary step to estimate the model and evaluate its forecasting performances. However, for current forecasting purposes, it is important to note that quarterly unemployment duration data are available from the Eurostat website for all countries considered. Thus, our forecasting model can be easily used, in real time, for the OECD countries we considered.

To construct yearly transition rates series, we follow Elsby et al. (2013) and use information (available for many OECD countries) on the number of persons unemployed, U_t, and on the number of unemployed of less than d months, $U_t^{<d}$. Specifically, the probability of an unemployed worker exits unemployment within d months, F, can be calculated from

$$F_{t+1} = 1 - \frac{U_{t+1} - U_{t+1}^{<d}}{U_t},$$

with $f_{t+1} = -\ln(1 - F_{t+1})/d$ the monthly hazard rate associated with the probability that an unemployed worker at time t completes her spell within the subsequent d months. In practice, we use $d = 12$ months for Spain, France and Germany, and $d = 6$ months for the UK and Japan. The estimated outflow rates are very close to the ones reported by Elsby et al. (2013).

To construct quarterly transition rates, we proceed in two alternative ways, depending on data availability. When quarterly duration data are available, we follow Elsby et al. (2013) and use the stock of unemployed and short term unemployed. However, as shown in Table 3.1, quarterly duration data availability can be sparse and varies across countries. For instance, quarterly data start in 1987 for Spain but only in 2005 for Germany. When quarterly duration data are not available, we used annual duration data to expand the time coverage of quarterly series, except for Japan and Germany. In the latter cases, where quarterly duration data begins late in the sample, we use quarterly gross worker flows constructed from household survey data (Hertweck and Sigrist (2012), Lin and Miyamoto (2012)) in order to convert annual data to quarterly frequency[22].

[22]To infer the quarterly movements in f from movements in the quarterly transition rates, we posit that the outflow rate f behaves similarly to the unemployment outflow rate f_{alt} derived in a three labor market state model where $f_{alt} = \lambda^{UE} + \frac{\lambda^{UI} * \lambda^{IE}}{\lambda^{IE} + \lambda^{IU}}$ (Barnichon and Figura (2013)) with λ^{AB} the transition rate from A to B, with U unemployment, E employment, and I inactivity. Using f_{alt} as a proxy for the outflow rate, we can convert the annual series f to a quarterly frequency whenever quarterly duration data are unavailable. When both data sources overlap, f

The unemployment inflow rate, s, is then obtained by solving equation 3.1 forward over $[t, t+1]$ and finding the value of s_{t+1} that solves

$$U_{t+1} = \frac{\left[1 - e^{-(f_{t+1}+s_{t+1})}\right] s_{t+1}}{f_{t+1} + s_{t+1}} (U_t + E_t) + e^{-(f_{t+1}+s_{t+1})} U_t.$$

Note that in this accounting, given a value for the unemployment outflow rate (which also captures movements out of the labor force) and the stock of unemployed persons, the inflow rate is the rate that explains the observed stock of unemployed persons in the next month. As a result, the inflow rate incorporates all movements in unemployment not accounted for by the unemployment outflow rate.

3.5 Empirical forecasting performance

In section 3.3 we theoretically showed how and when SSUR could provide better forecasts than standard time series models. Moreover, we found that SSUR should perform especially well (relative to other models) during recessions and turning points.

In this section, we evaluate the empirical performances of SSUR by comparing its unemployment rate forecasts with alternative forecasts along two dimensions. First, we assess the RMSE of out-of-sample forecasts, considering forecast horizons ranging from one-quarter-ahead to two-year-ahead. Second, because it is harder, but especially valuable, to forecast the unemployment rate around recessions, we assessed our model's performance relative to a baseline time-series model over the business cycle.

3.5.1 SSUR specification

While SSUR is based on a structural law of motion for unemployment, it still relies on forecasts on the inflow and outflow rates. To generate such forecasts, we use a vector autoregression (VAR), where we include leading indicators of labor force flows, such as vacancy posting, claims for unemployment insurance, and GDP. Specifically, we consider a vector of the form[23]

$$\mathbf{y}_t = (\ln s_t, \ln f_t, \Delta \ln u_t, leading\ indicators\ _t)',$$

and we estimate the VAR

$$\mathbf{y}_t = c + \Phi_1 \mathbf{y}_{t-1} + \Phi_2 \mathbf{y}_{t-2} + .. + \Phi_n \mathbf{y}_{t-n} + \varepsilon_t \tag{3.18}$$

and f_{alt} are indeed highly correlated.

[23]Note that, given our timing convention for the flows, the hazard rates will effectively enter the VAR lagged by one period.

over a ten-year rolling window and using n lags.[24] Appendix 3.7 reports the final specifications of the VAR for each country.

3.5.2 Alternative forecasts

We consider four alternative forecasts of the unemployment rate. The first three alternatives forecasts are from time-series models. We consider a basic univariate ARIMA time-series model, that take no other information but the unemployment rate into account. We also consider the unemployment rate forecast derived from the law of motion for unemployment rate (equation 3.5) holding the inflow and outflow rates constant at their last known value. We refer to this model as the u^* model. Shutting down the evolution of the hazard rates isolates the contribution of the current conditional steady-state unemployment rate. Our last alternative is the unemployment rate forecast from a VAR that includes the labor force flows and the leading indicators. As discussed in section 3.3 by comparing our SSUR models against the VAR, we can directly evaluate the nonlinear relationship implied by the theory compared to an linear time-series model using the same information set. The three alternative time-series models are estimated over a ten-year rolling window.

Finally, as the professional forecasters we consider OECD forecasts. Batchelor (2010) shows OECD forecasts are a good benchmark compared to consensus forecasts (which the literature has generally shown to be the benchmark forecast), specially forecasting the unemployment rate for the G7 countries.

3.5.3 Forecast Errors

Table 3.2 and 3.3 report the Root Mean Squared Error (RMSE) of real-time forecasts for quarterly unemployment rates from the SSUR model over a two-year horizon (including a forecast of the current quarter, $t + 0$), and the relative RMSE of alternative forecasts to SSUR. To evaluate the statistical significance of our results, we report the $p-$values of the unconditional Giacomini-White (2006) predictive ability test statistic of equal predictive ability between our SSUR forecast and the comparison forecast.[25]

Table 3.2 reports the performance of SSUR against the time-series models. The univariate ARIMA model performs worse than SSUR at all horizons, confirming the

[24] A rolling window (in which the model is estimated over the previous K periods) yielded more accurate forecasts than a recursive window (in which the model is estimated over the entire observed history). The size of the window was restricted to data availability. We also considered lag lengths between 1 and 4 quarters.

[25] We use the Giacomini-White (2006) predictive ability test, because it is robust to both non-nested and nested models (as are the VAR, u^* and SSUR models), unlike the Diebold-Mariano (1995) test.

theoretical conclusions presented in section 3.3.[26]

The unemployment rate forecast from the VAR performs worse than SSUR at all horizons, showing that the misspecification present in linear time-series models is an important drawback.

Finally, the contribution of forecasting the flows is evident from comparing with u^* model, which reports the performance of a forecast based only on convergence to the conditional steady-state unemployment rate. This model performs worse than SSUR at all horizons (with the exception of Spain), indicating that time variation in the flow rates is, indeed, an important element of our model. In any case, it is remarkable that a forecast from the theoretical law of motion (3.3) that relies on only the last known value of u^* performs as well or better than estimated time-series models.[27]

Turning to professional forecasts, the OECD releases forecasts for many variables for OECD countries bi-annually: in June and December. The organization produces one-year and two-year ahead forecasts, using data available the previous month. We assume that SSUR has access to data from the previous quarter and annualize the quarterly forecasts of our model.[28]

Table 3.3 shows the RMSE of our annualized forecast from SSUR model, and the RMSE of OECD forecasts relative to SSUR. The notation here is different from the previous table. $t + 0$ is the forecast of the yearly unemployment rate for the current year made in December, i.e. the forecast for the current quarter, with information until the third quarter of that year. $t + 2$ is the yearly forecast of the unemployment rate made for the current year in June, with information until second quarter. Thus, the forecast made is of current quarter plus two quarters ahead of the current year. $t + 4$ is the forecast made in December for next year, while $t + 6$ is the forecast made in June for the next year. Finally, $t + 8$ is the forecast made in December for two-years-ahead.

SSUR outperforms the OECD forecast dramatically. As shown in table 3.3, SSUR's RMSE for two-quarter ahead forecasts are lower than OECD forecasts by 20% in Spain, 50% in the UK and even much lower in France and Germany. For one-year-ahead forecasts, the RMSE is more than 20% lower in Japan, 30% in Germany, 50% in France, and 60% in the UK. The improvements are statistically significant at the 10-percent level

[26] Appendix 3.7 presents a table with the ARIMA models estimated for each country.

[27] For France, even if point estimates indicate that SSUR is the best forecasting model, the three models based on labor flows (SSUR, VAR and u^*) have statistically the same predictive ability. For Spain, SSUR performs better than ARIMA and VAR but the difference is again not statistically significant. In fact, the u^* model does even better than SSUR, being statically significant, implying that a VAR does poorly forecasting the flows.

[28] Note that our approach is conservative. In countries, such as the UK, where releases of the unemployment rate are made at a monthly frequency, SSUR has a smaller information set than the OECD: While we assume that data are only available up to last quarter, the OECD can have information up last month when making their forecasts.

against SSUR in all countries, with the exception of Spain and France. [29]

3.5.4 Forecasting Performance over the Business Cycle

As discussed in section 3.3, **Condition 2** states that the relative forecasting performance of SSUR improves when the volatility of the flows is large, i.e during recessions and around turning points.

To test this idea and evaluate whether SSUR performs differently over the course of the business cycle, we use the Giacomini-Rossi (2010) predictive ability test in unstable environments. The test develops a measure of the relative local forecasting performance of two models and is ideal for testing whether the performance of our model varies over the cycle (compared to a benchmark model). We use as a benchmark the ARIMA model. We evaluate the local forecasting performance over a five-year window from quarterly forecasts.[30]

Figure 3.5 plots the Giacomini-Rossi (2010) fluctuation test for the year-ahead forecast, along with the corresponding 5 percent critical value. The unit of the y-axis is the (standardized) rolling difference in mean-squared-error between the two models. This is measure of the relative performance; a positive value indicates a superior performance of SSUR. The right y-axis shows the standard deviation of the inflow rate, ($\frac{s_t}{E(u_t)}$), and outflow rate, f.

SSUR performs especially well around recessions, when the volatility of f and s is high. It does particularly well during the deep last recession in 2007-08 in all countries, and during times of large and swift movements in the inflow rate.[31] In other words, SSUR yields the greatest improvement over a univariate model around turning points, precisely when accurate unemployment forecasts are the most valuable.

3.6 Concluding remarks

This chapter presents a nonlinear model for forecasting the unemployment rate based on labor force flows that dramatically outperforms basic times-series models, and professional forecasters' forecasts as far as one- to two-year ahead. Moreover, the model

[29] In Spain, SSUR only outperforms the OECD only for current quarter forecasts. As mentioned previously, the VAR used to forecast the flows performs poorly since the u^* model with constant flow rates performs better than SSUR.

[30] Although the professional forecasts would be an interesting benchmark, we use the ARIMA model because the Giacomini Rossi (2010) test is only valid for models estimated over rolling-windows. (Both models are estimated over a ten-year rolling window.)

[31] Even in Spain, where on average the SSUR model does not perform specially well compared to the ARIMA (see table 3.2), SSUR strongly outperformed the ARIMA model in the last recession for one-year ahead forecasts.

has the highest predictive ability during turbulent times, precisely when forecasts are especially valuable.

Our model is built on two elements: (1) A nonlinear law of motion describing how the unemployment rate converges to its conditional steady state -the rate of unemployment implied by the flows into and out of unemployment- and (2) forecasts of these labor force flows.

We theoretically study the properties of the model, and we identify two factors that underpin the superior performances of SSUR over standard time-series models: (i) misspecification of linear time series model, and (ii) innovation forecasting using data on worker flows. We then show that the model's forecasting performance relative to other models depends on four factors: (1) the magnitude of the flows, (2) the volatility of the flows, (3) the persistence of the flows, and (4) the heterogeneity of the time-series properties of the flows.

Tables

Table 3.1: Data availability

	France	Spain	UK
Quarterly data	Q1.1992-Q3.2012	Q1.1987-Q3.2012	Q2.1992-Q4.2012
Duration	$U^{<12}$, $U^{>12}$	$U^{<1}$,$U^{<3}$, $U^{<6}$, $U^{<12}$, $U^{>12}$	$U^{<6}$, $U^{<12}$, $U^{>12}$
Source	INSEE-Pôle emploi	INE-LFS	ONS-LFS
Annual data	1977	1977	1982
Source	OECD, Eurostat-LFS, Elsby et al. (2013)		
	Germany	**Japan**	
Quarterly data	Q1.2005-Q3.2012	Q1.2002-Q3.2012	
Duration	$U^{<6}$, $U^{<12}$, $U^{>12}$	$U^{<6}$, $U^{<12}$, $U^{>12}$	
Source	DeStatis-LFS	Stats Bureau-LFS	
Gross worker flows	M1.1984-M6.2009	Q1.1978-Q4.2009	
Source	Hertweck and Sigrist (2012)	Lin and Miyamoto (2012)	
Annual data	1985	1977	
Source	OECD, Eurostat-LFS, Elsby et al. (2013)		

Table 3.2: Unemployment Rate Forecasts.
RMSE of SSUR (percentage points) and Relative RMSE to SSUR

	Forecast horizon					
	t+0	**t+1**	**t+2**	**t+3**	**t+4**	**t+8**
			UK			
SSUR	**0.16**	**0.29**	**0.43**	**0.59**	**0.77**	**1.47**
VAR	1.34***	1.28***	1.14*	1.09	1.09	1.07
	(0.00)	(0.01)	(0.09)	(0.23)	(0.21)	(0.36)
u^*	1.22***	1.19***	1.14***	1.08	1.00	0.82*
	(0.00)	(0.00)	(0.01)	(0.15)	(0.76)	(0.06)
ARIMA	1.33***	1.35***	1.35***	1.30***	1.24**	1.11
	(0.00)	(0.00)	(0.00)	(0.01)	(0.03)	(0.31)
			Germany			
SSUR	**0.13**	**0.33**	**0.56**	**0.76**	**0.94**	**1.64**
VAR	1.45***	1.52***	1.52***	1.48***	1.43***	1.33***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
u^*	1.34	1.13	1.03	1.00	0.99	0.97
	(0.35)	(0.91)	(0.42)	(0.43)	(0.58)	(0.48)
ARIMA	1.98***	1.51***	1.32*	1.26	1.26	1.23
	(0.00)	(0.00)	(0.07)	(0.20)	(0.27)	(0.45)
			France			
SSUR	**0.19**	**0.34**	**0.50**	**0.67**	**0.82**	**1.22**
VAR	1.15	1.23	1.24	1.25	1.25	1.19
	(0.22)	(0.29)	(0.33)	(0.33)	(0.28)	(0.26)
u^*	0.99	1.05	1.07	1.07	1.09	1.08
	(0.21)	(0.42)	(0.56)	(0.59)	(0.50)	(0.68)
ARIMA	1.14**	1.21**	1.19*	1.13	1.10	1.01
	(0.03)	(0.05)	(0.07)	(0.17)	(0.24)	(0.99)
			Spain			
SSUR	**0.49**	**1.08**	**1.78**	**2.49**	**3.17**	**5.44**
VAR	1.11	1.06	1.05	1.09	1.13	1.39
	(0.43)	(0.94)	(0.81)	(0.57)	(0.44)	(0.30)
u^*	0.78**	0.77**	0.76**	0.76*	0.76*	0.77
	(0.04)	(0.02)	(0.04)	(0.07)	(0.08)	(0.14)
ARIMA	1.18	1.11	1.11	1.18	1.24	2.01
	(0.75)	(0.73)	(0.47)	(0.32)	(0.28)	(0.26)
			Japan			
SSUR	**0.16**	**0.22**	**0.30**	**0.38**	**0.46**	**0.88**
VAR	1.05**	1.08	1.07	1.09*	1.11*	1.09 *
	(0.05)	(0.15)	(0.17)	(0.10)	(0.08)	(0.10)
u^*	1.14**	1.30***	1.25**	1.28**	1.18	0.89
	(0.04)	(0.00)	(0.02)	(0.03)	(0.23)	(0.46)
ARIMA	1.18***	1.33***	1.28**	1.31**	1.28*	1.12
	(0.01)	(0.00)	(0.02)	(0.03)	(0.09)	(0.39)

Source: Authors' calculations. Notes: Rows starting with SSUR report the Root Mean Square in Error of SSUR forecasts in percentage points. All the other rows report relative RMSE of VAR, u^*, and ARIMA forecasts to SSUR. The evaluation of the models' forecasts is calculated from 77 forecasts over 1992q1−2010q4 (except for Germany 1995q2−2010q4). $t + 0$ denotes current quarter forecast. $p-$values of Giacomini–White test statistic for the comparison with SSUR are reported in parentheses. ***/**/* indicates statistically different from SSUR at 1/5/10 percent.

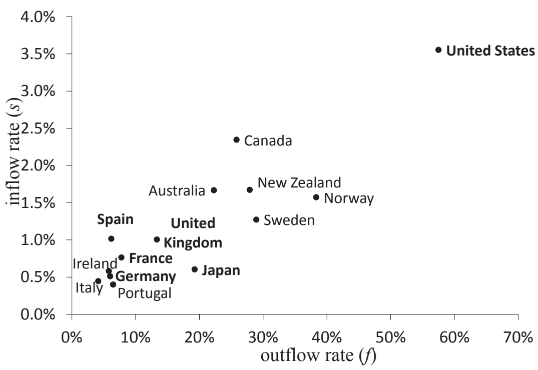
Table 3.3: Annual unemployment rate forecasts of SSUR and OECD.
RMSE (pp) of SSUR and Relative RMSE

	Forecast horizon-quarters				
	t+0	**t+2**	**t+4**	**t+6**	**t+8**
			SSUR		
UK	0.24	0.28	0.46	0.88	1.11
Germany	0.62	1.09	1.10	1.48	1.70
France	0.18	0.32	0.68	1.01	1.14
Spain	0.64	1.54	2.12	4.39	4.82
Japan	0.19	0.14	0.40	0.42	0.81
			OECD Forecasts		
UK	1.53	1.83**	1.64*	1.13	1.01
	(0.29)	(0.06)	(0.09)	(0.41)	(0.82)
Germany	2.04*	1.29*	1.32**	1.40***	1.23***
	(0.09)	(0.08)	(0.05)	(0.00)	(0.01)
France	5.41***	3.27***	1.54	1.20	1.02
	(0.01)	(0.00)	(0.17)	(0.29)	(0.80)
Spain	1.17	0.77	0.90	0.70*	0.77
	(0.71)	(0.39)	(0.50)	(0.08)	(0.17)
Japan	0.91	2.49**	1.16*	1.84***	0.91
	(0.87)	(0.04)	(0.10)	(0.00)	(0.68)

Source: Authors' calculations. Notes: First panel is Root Mean Square in Error of SSUR in percentage points. Second panel shows the RMSE of OECD forecasts relative to SSUR. The evaluation of the models' forecasts is calculated from 14 annual over the period 1997-2010. $p-$values of Giacomini–White test statistic are reported in parentheses. $***/**/*$ indicates statistically different from SSUR at 1/5/10 percent.

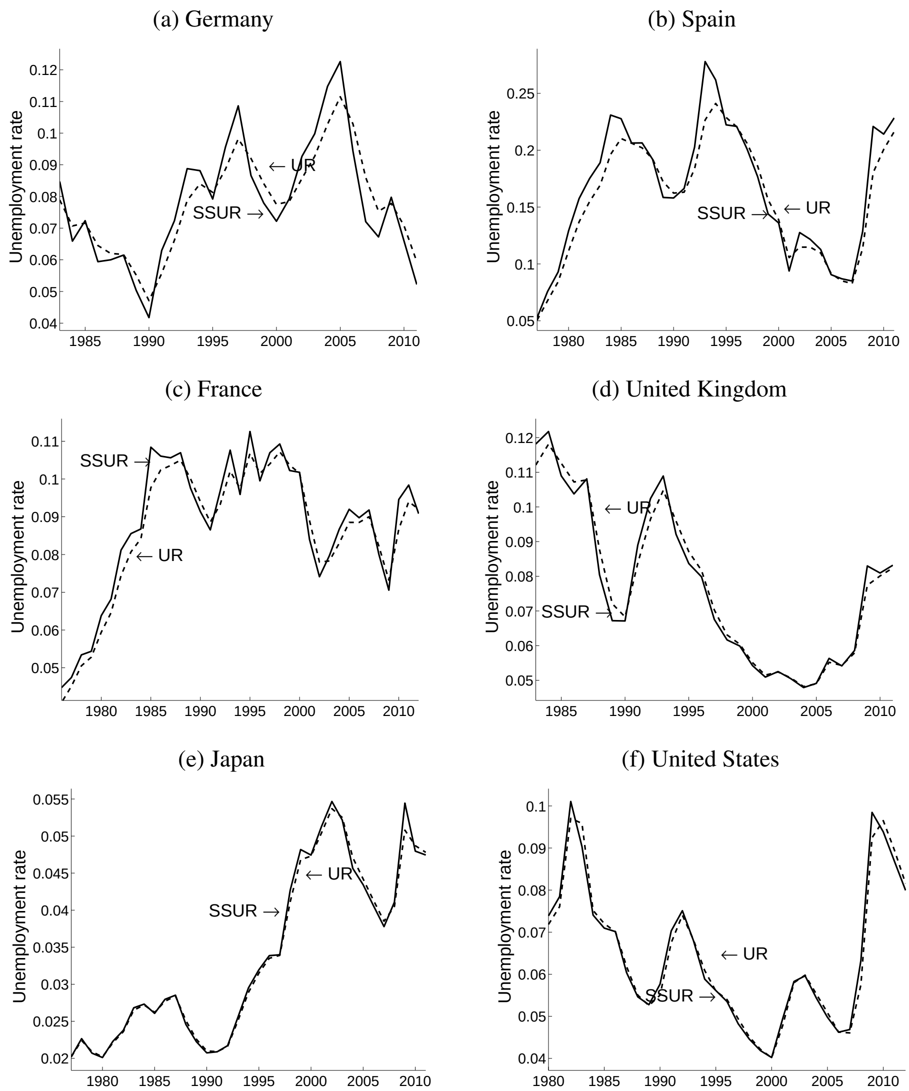
Figures

Figure 3.1: Average in - and outflow rates across countries



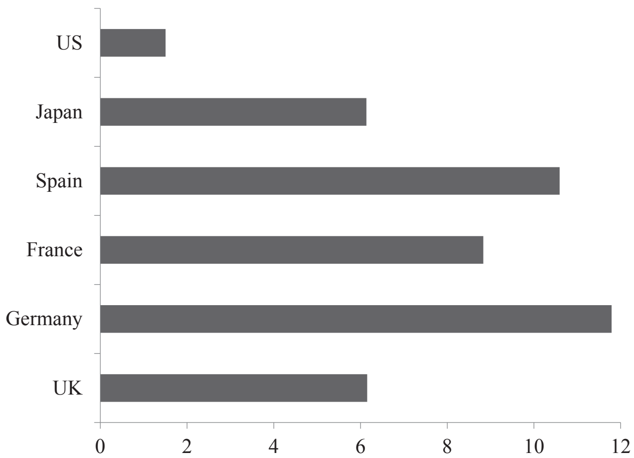
Source: Authors calculations based on Elsby et al. (2013). Notes: Average of monthly in- and outflows rates from unemployment. The starting year for the available series varies between 1968 (for the U.S.) and 1986 (for New Zealand and Portugal). For all countries, the data ends in 2009.

Figure 3.2: Unemployment rate and conditional steady state unemployment rate



Source: Authors calculations based on Elsby et al. (2013) and National Statistics Institutes data, and Barnichon and Nekarda (2012). Notes: The dashed line is the unemployment rate, and the continuous line is the steady state unemployment rate $u^* = \frac{s}{s+f}$. Average annual data.

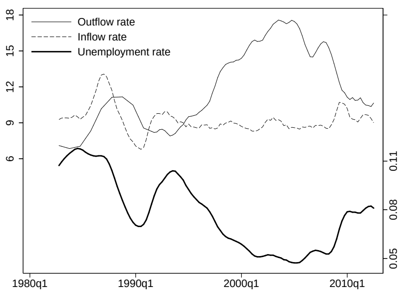
Figure 3.3: Convergence rates to the SSUR



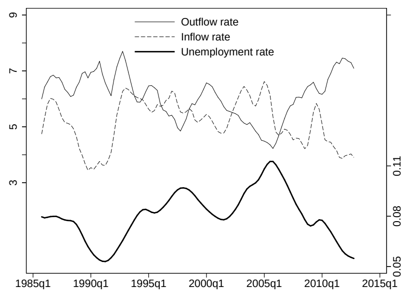
Source: Authors calculations based on Elsby et al. (2013) and National Statistics Institutes data, and Barnichon and Nekarda (2012). Notes: Time in quarters needed to close 90 percent of the gap with steady-state unemployment rate $u = \frac{s}{s+f}$. Averages over the period 1985-2012.

Figure 3.4: In and Outflows from unemployment

(a) United Kingdom

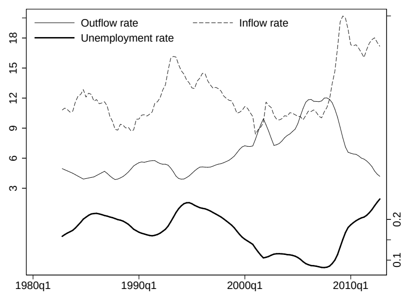


(b) Germany

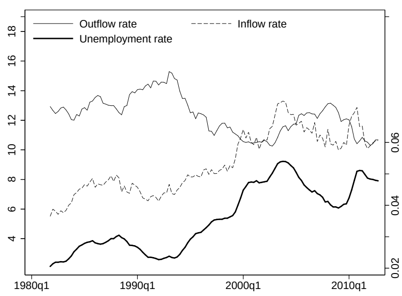


(c) France

(d) Spain

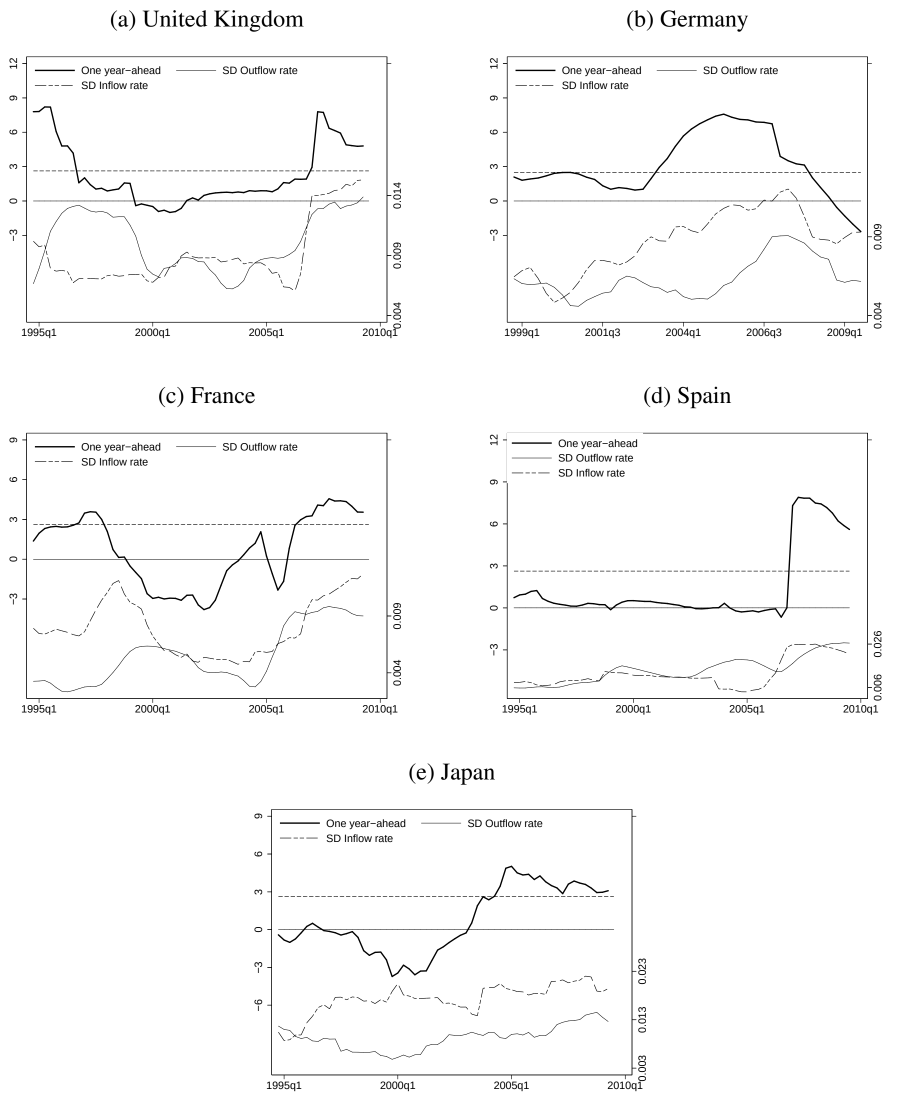


(e) Japan



Source: Authors calculations based on Hertweck and Sigrist (2012), Lin and Miyamoto (2012), Elsby et al. (2013) and National Statistics Institutes data. Notes: Quarterly data smoothed by a four-quarter moving average. The unemployment rate is in the right axis. The (rescaled) inflow rate is $s_t/E(u_t)$. s and f are quarterly averages of the monthly inflow and outflow hazard rates from unemployment. f and s are expressed in percent.

Figure 3.5: Giacomini-Rossi Fluctuation Test: SSUR vs ARIMA



Source: Authors' calculations. Notes: Relative performance in the left axis, and standard deviation of f and s in the right axis. Relative performance is the five-year rolling difference in MSE between forecasts from SSUR and ARIMA models. Standard deviation is calculated over five-year rolling. (Rescaled) inflow rate is $s = s_t/E(u_t)$. Both models are estimated over a ten-year rolling window. Dashed horizontal line indicates 5 percent critical value.

3.7 Appendix: Hazard rate time series properties and Model specifications

Table 3.4: Time series properties

	UK	**Germany**	**France**	**Spain**	**Japan**
			f_t		
E(X)	0.13	0.06	0.08	0.07	0.12
sd(X)	0.03	0.01	0.01	0.02	0.01
$\rho(X)$	0.97	0.91	0.94	0.96	0.74
R^2	0.97	0.80	0.93	0.95	0.55
			$s_t/E(u_t)$		
E(X)	0.13	0.06	0.09	0.08	0.13
sd(X)	0.01	0.01	0.02	0.02	0.03
$\rho(X)$	0.41	0.84	0.90	0.85	0.70
R^2	0.17	0.84	0.83	0.73	0.50

Table 3.5: ARIMA models for the UR

Country	Model
UK	ARIMA(2,0,0)
Germany	ARIMA(1,0,1)
France	ARIMA(1,0,1)
Spain	ARIMA(2,0,1)
Japan	ARIMA(2,0,1)

Table 3.6: VAR specifications

Country	Variables	Lags	Estimation period
UK	$\ln f_t, \ln s_t, \Delta \ln u_t, \Delta \ln v_t$ $\Delta \ln gdp_t, \Delta \ln ui_t$	1 lag	1982Q2-2012Q3
Germany	$\ln f_t, \ln s_t, \Delta \ln u_t, \Delta \ln v_t,$ $\Delta \ln gdpt, \Delta \ln ui_t$	1 lag	1985Q1-2012Q3
France	$\ln f_t, \ln s_t, \Delta \ln u_t, \Delta \ln gdp_t$	1 lag	1977Q1-2012Q3
Spain	$\Delta \ln f_t, \ln s_t, \Delta \ln u_t, \Delta \ln v_t,$ $\Delta \ln gdp_t, \Delta \ln const_t, \Delta \ln ere_t$	1 lag	1982Q1-2012Q4
Japan	$\ln f_t, \ln s_t, \Delta \ln u_t, \Delta \ln v_t$	2 lags	1980Q1-2012Q3

As leading indicators of the labor flows we used: ui, the number of claims for unemployment insurance each period, v the job openings or vacancies in each period, and $\Delta \ln GDP$ the growth gross domestic output.

Note that in the case of Spain we add more variables: GDP in the construction sector and ERE, in order to account in the VAR for the changes in labor market law in Spain. The GDP from the construction sector ($const_t$) helps explain the large turnover observed in Spain labor market and, ere is the the Employment Regulation. ERE (Record of employment regulation) is a procedure under the Spanish law by which a company in crisis seeks for authorization to suspend or layoff workers within a framework which guarantees certain rights of workers. This administrative procedure can be processed for the following reasons: collective dismissal based on economic, technical, organizational or productive reasons (the most usual reason); suspension or termination of the employment contract in case of superior force (like a natural disaster); termination of employment because of firm closure.

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