Essays on Labour Market Flows, Immigration and Persistence of Temporary Jobs

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A mis padres, Margarita y Federico. Siempre.
Por renunciar a todo por sus hijos
... y por tanto amor

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Abstract

In the last decades, the world economy experienced two striking transformations that shocked labour markets around the world, specially in developed economies. The first one is the boom in migration flows which caused an unprecedented increase in the labour force share of foreign-born workers in many countries. The second one is related to the emergence of the Great Recession in 2008, which had driven back the attention of macroeconomics to understand the impact of economic cycles in the evolution of unemployment and other macroeconomic aggregates. The rise in workers' heterogeneity that resulted from the increase in immigration is, interestingly, proven to be essential to fully comprehend this impact. This dissertation aims to understand the heterogeneous impact of economic cycles on the labour market outcomes of different workers' groups (natives/immigrants, private/public sector employees, temporary/permanent workers) and what are its implications on the overall impact of economic cycles on welfare and macroeconomic aggregates.

In the first chapter, '*Natives' Responses to Immigration and the Cyclicality of Wages and Labour Market Flows: Immigrants versus Natives*', I document a number of facts regarding the immigration experience in Spain for the period between 1999 and 2015. Using Labour Force Survey microdata, I examine the cyclicality of job-finding and job-separation rates for immigrants and natives over the long Spanish economic expansion and the sharp contraction. During the expansion (until 2008) the job-finding rate was higher for immigrants than for natives, but both rates converged to a lower level after the Great Recession took place in 2008. I also find that the impact of the crisis on the job-separation rate was twice as high for immigrants than for natives. Using longitudinal social security data, I find that wage cyclicality is higher for immigrants than for natives: a one percentage point increase in the unemployment rate is associated with a 0.65% and 0.95% drop in real wages for natives and immigrants respectively. However, these differences only occur among low-tenure workers. Using the skill-cell approach, I study whether immigration is correlated with natives' occupational upgrading or downgrading, regional mobility or changes in labour force participation. Immigration is positively correlated with natives' occupational upgrading, while none of the other adjustment's margins are significant. This study provides novel empirical

evidence to enrich macroeconomic theories on the interaction of economic cycles and the impact of immigration.

In the second chapter, '*The Role of Immigration in a Deep Recession*', I study the impact of foreign-born workers on the labour market during a recession. This is relevant as many economies experienced large immigrant inflows before the Great Recession took place. To this end, I use a random search model of the labour market featuring vacancy persistence, endogenous return migration and wage rigidity. Consistent with the Spanish data, in the model some immigrants leave the country in the event of a recession, so they free up jobs for natives. Yet, since immigrants and natives differ in their match quality draws, immigrants also affect the firms' job creation decision. While the return-migration channel is unambiguously positive for native workers, the calibration results for the Spanish economy suggest that the job-creation effect is negative. I find that immigrants smooth the recession and improve the welfare of natives. During the recession, the native unemployment rate would have been 2 percentage points higher in the absence of the pre-crisis immigration boom. Return-migration is the key channel since its short and long-run impact on natives' unemployment rate is 10 and 2 times as large as the sum of the impact of the other channels.

In the third chapter, '*Lifetime Job Instability over the Life-Cycle*', co-authored with Rubén Veiga-Duarte, we quantify the incidence of temporary jobs for workers late in their labour market career (at mid-career, defined as 30-35 years old). For that, we use Spanish administrative data from the "Continuous Sample of Working Histories", which allows us to track workers' entire labour marker history. We find that around 15 percent of workers spend more than 50 percent of their mid-career active time in temporary jobs. We also find a high degree of persistence in the time spent as temporary; workers spending most of their young-age (20-30 years old) employed in temporary jobs experience higher job-separation rates and find fewer permanent jobs later in their careers. Spending most of the young-time in temporary jobs is also associated with lower wages (around 10%) in permanent jobs, even at age 40. We then compare workers' labour market performance at young-age conditional on their time spent as temporary or permanent at mid-career. We find that both groups start their careers with similar job-finding and job-separation rates in permanent jobs, but differences increase as they age. Finally, while mid-career temporary workers have lower wages in permanent jobs than mid-career permanent workers right from the beginning of their career, this gap remains roughly constant over time. This empirical evidence will be used to develop a theory that could help us to disentangle the underlying mechanisms that explain the observed persistence in temporary employment.

In the forth chapter, '*Labour market flows: Accounting for the public sector*', co-authored with Idriss Fontaine, Pedro Gomes and Diego Vila-Martin, for the period between

2003 and 2018, we document a number of facts about worker gross flows in France, the United Kingdom, Spain and the United States, focussing on the role of the public sector. Using the French, Spanish and UK Labour Force Survey and the US Current Population Survey data, we examine the size and cyclicality of the flows and transition probabilities between private and public employment, unemployment and inactivity. We examine the stocks and flows by gender, age and education. We decompose contributions of private and public job-finding and job-separation rates to fluctuations in the unemployment rate. Public-sector employment contributes 20 percent to fluctuations in the unemployment rate in the UK, 15 percent in France and 10 percent in Spain and the US. Private-sector workers would forgo 0.5 to 2.9 percent of their wage to have the same job security as public-sector workers.

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Chapter 1

Natives Responses to Immigration and the Cyclicality of Wages and Labour Market Flows: Immigrants versus Natives

1.1 Introduction

As a consequence of large immigrant inflows in the last decades, foreign-born workers account now for a significant share of the labour force of many countries. In United States, the share of immigrants in the labour force increased from 9.3% in 1990 to 13.6% in 2005 and 15.3% in 2010. A similar growing trend is found in UK: while immigrants made up 4.3% of the labour force in 1990, by 2005 and 2010 that share was 5.9 and 8.3% respectively. A more striking example is Spain, where the share of immigrants rose from 2.9% in 2000 to 11.3% and 15.0% in 2005 and 2010.

The economic literature on immigration has shown that there are significant differences between immigrants and natives regarding both their employment probabilities and prospective wages, see for instance Baker and Benjamin (1994), Clark and Drinkwater (2008). Work on immigrants' assimilation have reached similar conclusions (Borjas (2015) or Izquierdo et al. (2009)). A related question that remains open is whether that differences are amplified or mitigated over recessions and expansions. In other words, are immigrants more vulnerable to the economic cycle?

This paper studies how differences in the labour market outcomes of immigrants and natives depend on the economic cycle. In particular, using data from the Spanish Labour

Force Survey (2005-2015), I first examine the cyclicality of job-finding a job-separation rates for immigrants and natives. Since the data starts in 2005, I can study the heterogeneity in transition flows of immigrants and natives during both an economic expansion (2005-2008) and a recession (2008-2015), which are particularly big boom and bust, making them a very interesting case of study. I compute labour market flows for immigrants and natives, both for the pool of workers and by fixing some job/worker characteristic (education, work experience, sector of activity, type of contract). Then I estimate a probit model to test whether the differential impact of the Great Recession on the probability of finding or losing a job for immigrants and natives also exists between comparable workers.

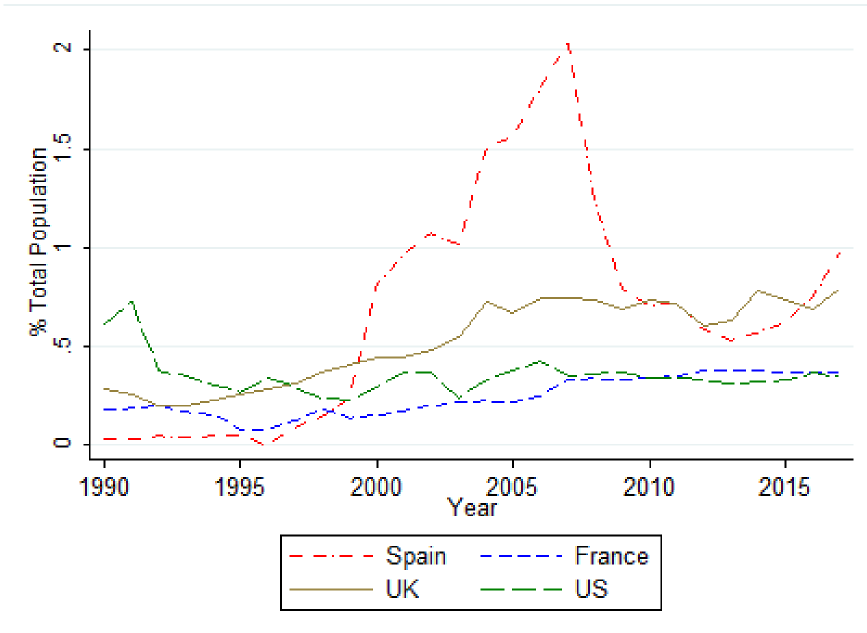
Second, I examine differences in real wage cyclicality between immigrants and natives, using a very rich administrative data from Spanish social security registers. Similar to the analysis on labour market flows, I start by documenting the evolution of real monthly wages from 1999 to 2015 for the pool of workers and fixing some job/worker characteristics, paying particular attention to the behaviour of the wage premium between immigrants and natives. I then follow De la Roca (2014) and study wage cyclicality by estimating a wage equation in a two-steps procedure, focusing on how wage cyclicality differs by nationality.

The Spanish economy is an interesting case of study for the purpose of the paper for two main reasons. Firstly, Spain experienced large foreign inflows in a very short span of time. As Figure 1.1 shows, immigration to Spain was close to zero before 1998. After that, immigrant inflows increased dramatically, reaching its maximum in 2007, where they made up to more than 2% of the total Spanish population. This increase is even more extraordinary when compared to other developed countries (Figure 1.1). As a consequence, the share of immigrants in the labour force surged from 2.9% in 2000 to more than 15% ten years later. Secondly, Spain experienced a sizeable employment destruction in the Great Recession. As Figure 1.3 shows, the increase in unemployment rate was higher for immigrants than natives, suggesting that the crisis hit harder immigrants than natives.

I also use the exceptional Spanish immigration process and the rich longitudinal data to study natives' responses to the immigration shock. The traditional approach to study the impact of immigration on the labour market consist in reduced-form estimates, which abstract from potential natives' adjustment responses to the migration shock (e.g by changing location or occupation). However, if these adjustments are relevant, the effect of immigration might be very different.

The first contribution of the paper is to provide direct empirical evidence on the impact of the Great Recession on wages, job-finding and job-separation rates for natives relative to immigrants. Regarding labour market flows, my analysis covers a long post-crisis period (2008-2015) which turns out to be relevant as the labour market's dynamics during the

Figure 1.1: Immigrant inflows



Source: OECD International Migration database

Great Recession are different on impact (right after the crisis emerges) and during the recessionary period. With respect to wages, my main contribution is to study differences in wage cyclicality between immigrants and natives. Importantly, the rich nature of the data allows me to analyse and show that wage cyclicality differences between immigrants and native disappear with workers' tenure.

The second contribution of the paper is to examine the relevance of three potential natives' adjustment to immigration (occupational upgrade, internal migration and labour force participation) in order to shed light on what ingredients a structural model aiming to quantify the impact of immigration should incorporate. For that, I apply the education-experience cell approach first used by Borjas (2003a).

I find that before the crisis (from 2005 to mid 2008) job-finding rates were higher for immigrants than for natives. However, after the crisis both rates converged to a lower level. Throughout all the period (2005-2015) job-separation rates are higher for immigrants than for natives, but the gap increased significantly after the Great Recession took place in 2008. These patterns hold even when fixing some worker and job characteristics. Given the nature of the Spanish crisis, results regarding the sector of activity are particularly relevant: I find that for all sectors (including construction), the job-separation rate increased more for immigrants than for natives. The probit estimation shows that *ceteris paribus* the impact of the crisis on the probability of losing a job was twice as high for immigrants than for natives. These results are consistent with those of Dustmann et al. (2010) for UK and Germany and Carrasco and García-Pérez (2015) for Spain, which found that immigrants are more sensitive than natives to changes in the economic conditions. I find that wage cyclicality is higher for immigrants than for natives: a one percentage point increase in the unemployment rate is associated with a 0.65% drop in native real wages, while for immigrants the decrease is 0.95%. My estimates are slightly higher than those reported by De la Roca (2014) and Font et al. (2015). However, overall they suggest a low degree of real wage sensitivity compared to other developed countries (Pissarides (2009)), as expected result given the well-known labour market duality and high rigidity of the Spanish labour market (Bentolila et al. (2012b), Bentolila et al. (2012a)). Importantly, when allowing for heterogeneity in the estimates by tenure, I find that wage cyclicality differences between immigrants and natives only occur among low-tenured workers (lower than 2 years of tenure in the establishment). Last, real wages were more responsive during the expansion (1999-2008Q2) than during the recession (2008Q3-2015), with higher wage cyclicality among immigrants in both phases of the business cycle. Regarding natives' adjustment to immigration, I find that immigrant inflows are positively correlated with natives' occupational upgrading, while none of the other adjustments' margins are significant.

Literature Review and Contribution

This paper relates to the extensive literature on economic assimilation of immigrants. Some examples are Baker and Benjamin (1994) for Canada, Borjas (2003a) and Card (2005) for U.S. or Dustmann and Fabbri (2003) and Clark and Lindley (2009) for U.K. Regarding the Spanish economy Amuedo-Dorantes and De la Rica (2007) use a single cross section for 2002 and show that immigrants face a higher unemployment rate (12.3 respect to 7% among natives in 2007). Izquierdo et al. (2009) uses administrative data from the Spanish social security registers (Continuous Sample of Working Histories), they analyse the earnings assimilation of migrants from outside the EU-15. They show that at time of arrival, immigrants' wages are significantly lower than natives', but immigrants reduce around half of the gap in the first 5 years after arrival. Other related work is Fernández and Ortega (2008) and Rodríguez-Planas and Nollenberger (2016). Using data from 2000 through 2011, Rodríguez-Planas and Nollenberger (2016) find that immigrants who arrived before the 2008 recession had little trouble finding work immediately but those who arrived after 2008 struggled to find work as Spanish unemployment rates increased. For the period 1996-2006, Fernández and Ortega (2008) find that immigrants face initially both a higher unemployment and temporary employment rate. A notable difference with these papers is that they use cross-sectional data, abstracting from exploiting the panel data dimension of the Spanish Labour Force Survey. Moreover, my data covers a longer post-crisis period. I add to this literature by focusing on differences between immigrants and natives regarding their labour market flows. In particular, my contribution is to show that a key source for the higher immigrants' unemployment rate is that their job-separation rate is higher regardless the macroeconomic conditions.

This paper is most closely related to the strand of the literature studying how immigrants respond to the economic cycle compared to natives. Dustmann et al. (2010) study unemployment and wage responses to economic shocks for immigrants relative to natives in Germany and the United Kingdom. They show that there are similar and significant differences in unemployment responses between immigrants and natives in both countries, even conditional on education, age, and location. They also find little evidence on differential wage responses. A close work to my study is that of Carrasco and García-Pérez (2015), who also uses longitudinal data from Spain (Continuous Sample of Working Histories) covering the expansionary and recession cycle. They investigate whether durations in unemployment and employment for immigrants and natives respond differently to changes in the economic conditions. They find that the effect of the crisis on these durations is higher for immigrants than for natives. Nonetheless, some relevant traits differentiate the two works: first, we focus on transition flows (i.e job-separation and job-finding rates) and how those changed with the cycle, instead of employment and unemployment durations; second, we cover a longer recessionary period, which is very relevant given the high persistence on the unemployment rates during the Great Recession. Therefore, my contribution to this literature is to provide direct evidence on how the Great Recession differently affected probabilities of finding and losing jobs for immigrants and natives.

My paper is also related with the literature estimating worker flows. Some of the most influential papers on this topic are Blanchard et al. (1990), Shimer (2012), Elsby et al. (2009) or Fujita and Ramey (2009), all for the U.S. economy. Several studies focus on European labour markets, for instance Gomes (2012) for UK, Fontaine (2016) for France or Hertweck and Sigrist (2015) for Germany. Using Spanish data, Silva and Vázquez-Grenno (2013) focus on the differences between permanent and temporary employment. While all these papers stress the relevance of accounting for the evolution of labour market flows to understand unemployment determination, they have ignored the potential differences between immigrants and natives. Therefore, I add to this literature by computing labour market dynamics by nationality.

Closely related to my work are the study of De la Roca (2014) and Font et al. (2015) that also use administrative data from the Spanish Social Security to examine real wage cyclicality. For the period 1988-2011, De la Roca (2014) finds evidence of weak real wage cyclicality, with a baseline estimate of a 0.4% increase in wages in response to a one percentage point decline in the unemployment rate. Focusing on how wage cyclicality differs in different phases of the business cycle, Font et al. (2015) finds that differences across expansions and recessions are significant, with an even lower real wage cyclicality in recessions. Some relevant traits differentiate my study from theirs. First, I focus on how wage cyclicality differs between immigrant and native workers. Second, I use data from a more recent period, which allows me to consider a longer post-crisis period. This is very relevant since, as stated before, the crisis affected more immigrants than natives in terms of employment destruction.

Finally, this paper draws upon the literature on natives' responses to immigration shocks. Natives' occupation/task specialization has been the most analysed margin of adjustment in the literature. Peri and Sparber (2009) showed that less educated foreign and native-born workers specialize in different production tasks (manual-intensive tasks vs communication-intensive tasks). Using a different approach, Llull (2014) found that immigrations inflows are correlated with changes in occupation from blue collar to white collar jobs. For the Spanish case, Amuedo-Dorantes and De la Rica (2011) found the same natives' specialization pattern as in the US, though in a lower magnitude. Some other adjustment margins has been investigated as well. Using Spanish data and the spatial correlation approach, Farré et al. (2011) showed that the recent immigration wave increased the labour supply of skilled native women. Last, natives' emigration response to an increase in immigration has also been studied (Borjas (2006)). I add to this literature by applying the education-experience cells approach for three different potential adjustment margins for natives (occupational upgrade, internal migration and labour force participation).

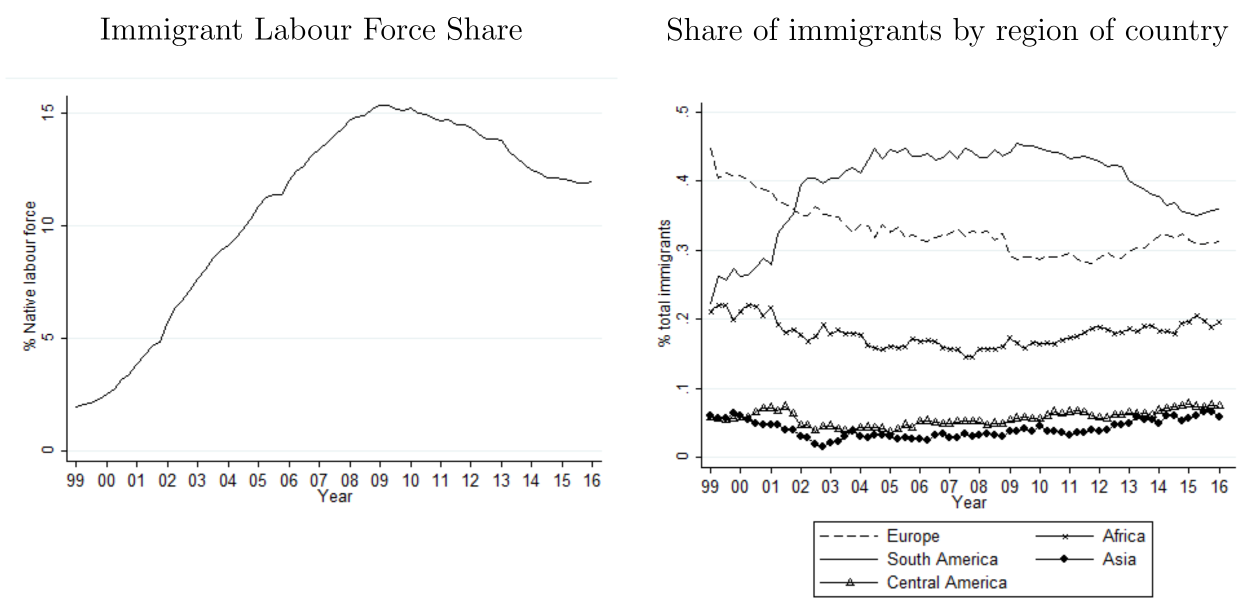
The rest of the paper is organized as follows. Section 1.2 summarizes some relevant features of the Spanish immigration process and legal environment. Section 1.3 examines the cyclicality of job-separation and job-finding rates for immigrants and natives. Section 1.4 studies the real wage cyclicality, and Section 1.5 performs the native responses analysis. Finally, Section 1.6 concludes.

1.2 Background

1.2.1 Migration to Spain

Immigration to Spain is a recent process. Throughout most of the 20th century Spain was a country of emigration, mainly to Europe (France, Germany and Switzerland)[1]. From the late 90's (around 1997-98), Spain experienced the largest inflow of immigrants among all developed countries. As Figure 1.1 shows, from 1998 to 2008, on average immigrant inflows made up 1.13% ot the total population per year. As a consequence, the number of immigrants in the labour force went up from 0.27 millions (1.6% of total population) in 1998, to 3.4 millions (15.0% of the total labour force) in 2010, as displayed in Figure 2.5. This notable immigration boom can be explained by a combination of factors. Bertoli et al. (2011) argue that the Latin American crisis had a lot to do with the Spanish immigration boom. Similarly, Bertoli and Moraga (2013) show that Spanish migration policies also played an important role, in particular a special migration arrangement with former colonies. Furthermore, the Eastern European expansion of the European Union can be also made responsible for a large part of the immigration flows over this period. Last, it has been argued that the Spanish economic boom enhanced the process.

Figure 1.2: Immigrant Share and Composition by Region of Country



Note: Share of foreign-born workers that are actively participating in the labour market. Source: Spanish Labour Force Survey.

[1]See Izquierdo et al. (2015a) for more a more exhaustive description of the historical migration process.

The right panel of Figure 2.5 displays the composition of immigrant workers by region of origin[2]. As we can see, the main regions of origin are South America (mainly Ecuador and Colombia, see Table 1.9 in Appendix D for details on the composition by country), Africa (Morocco) and Europe (mostly Romania). Focusing on how the composition evolved over time, two trends are observed. First, during the immigration boom (1999-2007), Romania and the South American countries experienced the highest rate of growth of immigrants, as their share in the total of immigrants increased from 1999-2004 to 2005-2007. On the other hand, the share of Africa remained quite constant. Second, South American immigrants' flows were also more sensitive to the crisis, as their share dropped from 2013 to 2016, due no only to a drop in the inflows but also an increase in south American immigrants' outflows, that decided to leave Spain to return to their countries of origin (Prieto et al. (2018)). Figure 1.22 in Appendix D plots the evolution of the stock of immigrant workers by region of origin.

1.2.2 Legal Environment

Given its late immigration experience, most of the migration legislation until the mid 80's focused on designing an appropriate framework for the emigration flows. Some unsuccessful attempts to legislate immigration were replaced by the approval of the Law 4/2000 on January of 2000. This law introduced new rights and integration policies which helped immigrants to regularize and formalize their status. Specifically, the law established a general principle of equality between foreign and natives. Among other aspects, it gave to foreigners the same rights as natives regarding access to the legal system and ideological/religious freedom. It also allowed full access to emergency assistance and to all other (basic) social services to those registered in the Municipal Registry (Padrón Municipal). Last, it only provided the rights to work, move freely or associate to those with legal residence permission. The law, which has been slightly modified, is still in force[3]. In the next section I study the cyclicality of labour market flows by using the Spanish Labour Force Survey. One important advantage that this survey has over other sources is that it collects information about national and foreign workers in the formal economy as well as in the informal economy. However, a relevant drawback in the analysis on real wages (Section 1.4) is that I use administrative data from the Spanish social security registers, which only includes legal workers. This could be an important limitation as I am missing some sectors where both the degree of informality and the presence of immigrants is high (Farré et al. (2011)), such as the agriculture or the household service sector (child and elderly care or household cleaning and cooking). See

[2]Results are constructed from the Spanish Labour Force Survey, and I am restricting my sample for immigrants that are actively participating the labour market.

[3]See Corella (2015) for an analysis of the main changes to immigrant integration policy in Spain

Farré Olalla and Bosch (2014) for an analysis on the size of the informal sector in Spain and its relationship with the Spanish immigration boom.

1.3 Cyclicality of Labour Market Flows: Immigrants versus Natives

1.3.1 Data

I use data from the Spanish Labour Force Survey-Flows (SLFS, *Estadística de Flujos de la Población Activa*), a quarterly representative survey of about 65,000 households, which is equivalent to around 180,000 individuals. The sample is divided into six waves (rotation groups) and every quarter one wave is replaced by a new one. The longitudinal structure of the SLFS allows us to match observations belonging to two consecutive surveys. Also, due to the structure of the database, we can track each individual for five successive quarters (one year and a half). Although the quarterly survey starts in 1999, I restrict my analysis to the period between 2005Q1 and 2016Q4, as the longitudinal dimension of the survey did not provide information about nationality before 2005.

The survey asks respondents about their labour market status and job characteristics (occupation, sector or type of contract) as well as personal and household characteristics (age, education or nationality).

Descriptive Statistics

This subsection provides an overview of the main characteristics of the Spanish labour force for the sample period considered here, focusing on the differences between immigrants[4] and natives. As in the next sections I divide the sample period, Table 1.1 displays the descriptive statistics by differentiating three phases: pre-crisis (from 2005Q1 to 2008Q2), crisis (2008Q3-2013Q2) and post-crisis (2013Q3-2016Q1)[5]. First, female workers represent a higher share among immigrants than natives, although differences decreased over time. Regarding the age structure, native workers are older than immigrants. Similar to gender differences, the average age gap decreased over time.

The third row of Table 1.1 shows the share workers with at most primary, secondary or

[4]Because the SLFS-Flows does not ask for country of birth, I identify immigrants as individuals with foreign nationality.

[5]I chose this span of time since 2008Q3 and 2013Q2 are, respectively first and last quarter with a negative quarterly growth rate of real GDP (ignoring two quarters in 2010 with slightly and temporarily positive rates).

Table 1.1: Immigrants and Natives Characteristics

	Natives			Immigrants		
	Pre-crisis	Crisis	Post-crisis	Pre-crisis	Crisis	Post-crisis
Male	58.27%	55.57%	54.03%	55.76%	53.56%	52.11%
Average age	31.66	36.12	38.88	31.96	34.38	36.80
Education						
Primary or less	20.72%	17.00%	11.00%	24.50%	24.00%	22.00%
Secondary	52.23%	53.05%	56.00%	54.67%	56.27%	55.93%
Tertiary	27.04%	30.00%	33.06%	20.42%	19.74%	22.07%
White Collar	58.13%	63.24%	66.06%	35.64%	40.18%	45.04%
Temporary rate	28.73%	22.12%	22.98%	56.70%	42.36%	37.30%
Unemployment rate	8.34%	19.13%	22.32%	12.36%	31.25%	33.04%
Sectors						
Agriculture	4.43%	3.76%	3.74%	6.34%	7.07%	8.06%
Industry	12.15%	10.54%	10.02%	8.89%	7.02%	8.06%
Construction	16.71%	12.50%	10.88%	25.15%	14.35%	9.47%
Services	66.70%	73.20%	76.15%	59.62%	71.57%	75.63%

Source: Spanish Labour Force Survey, INE.

tertiary education[6]. Three observations are worth highlighting. First, the share of tertiary educated workers is lower among immigrant workers, while the share of high-school drop-outs (primary education or less) is higher for them than for natives. Second, there are no significant differences regarding the share of secondary educated workers. Last, there is an upward trend on the share of highly educated workers for both immigrants and natives: the share of workers with tertiary education increased from 27.04% in 1999 to 33.06% in 2016 for natives, and from 20.42% to 22.07% for immigrants.

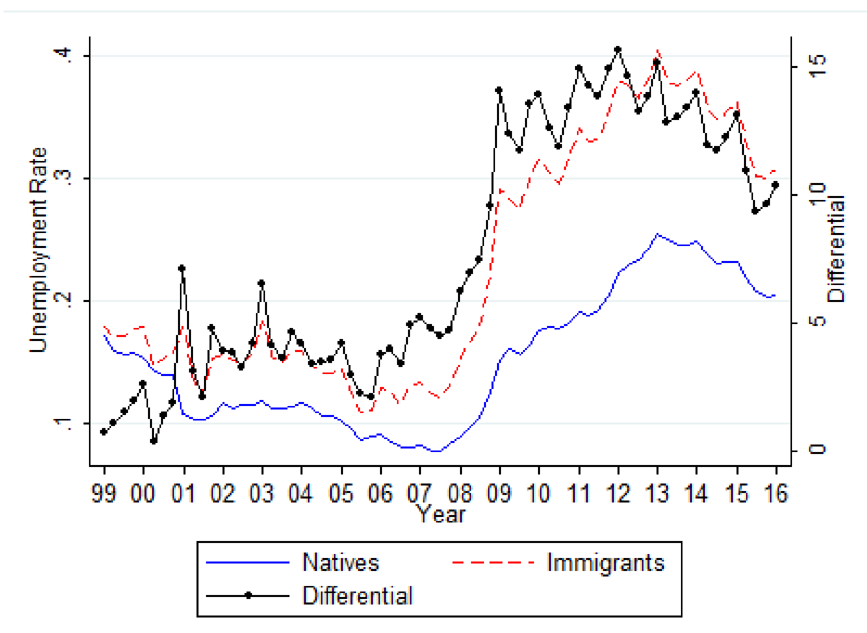
To analyse the occupation composition, I follow Llull (2014) and classify employed workers into two groups: blue and white collar, depending on their occupation (see Table 1.10 in Appendix D for details on the occupations included in each group). As we can see in the fourth row in Table 1.1, native employment is more concentrated among white collar occupations than immigrant employment. Also notice that the share of workers employed

[6]As Borjas (2003a) I classify individuals into four education groups: high school drop-outs or less (i.e primary studies or less), lower secondary education, higher secondary education and college degree. For the descriptive statistics I pool the two secondary education categories, as there are no big differences in those two educational levels between immigrants and natives.

in high skilled occupations increased for both groups after the Great Recession took place. The reason is that many workers employed in blue collar occupation lost their job during the crisis. Immigrant workers are also more concentrated among temporary jobs than natives. Specifically, during the pre-crisis period, the average temporary rate was 28.73% for natives and 56.70% for immigrants. As expected, temporary rate dropped for both groups with the arrival of the crisis, as most of the employment destruction was concentrated among workers with temporary contracts.

Table 1.1 also displays the sectoral composition of jobs. From the last two row one can see that the usual claim that most immigrants worked in the construction sector during the boom is a misleading statement. The vast majority of both immigrants and native are employed in the service sector. We can also see that during the pre-crisis period, immigrants were indeed more concentrated in the construction sector than natives (25% of immigrants versus 16.17% of natives), but the difference is less pronounced than one may think. The plunge in the construction sector employment with the Great Recession is salient: the share of immigrants employed in that sector dropped in 10 percentage points, while for natives the drop was 6 percentage points.

Figure 1.3: Unemployment Rate by Nationality



Source: Spanish Labour Force Survey, INE.

During all the period considered, the unemployment rate is higher for immigrants than for natives. Nonetheless, the unemployment rate gap between immigrants and natives skyrocketed after the Great Recession took place. Figure 1.3 displays natives' and immigrants' unemployment rates, as well as the difference between the two rates. We can observe that from 2001 to 2008 the unemployment rate gap fluctuated from its lower bound at 2.1 p.p. in 2005Q4 to its maximum of 6.5 p.p. in 2003Q1. However, with the crisis, the differential raised from 6 in 2008Q2 to more than 13 p.p. in 2013 and 15 p.p. in 2013Q1. Sectoral composition and differences in observables (education or age) can partially explain immigrants' higher unemployment rate.

In the next section, I disentangle the source of the unemployment rate gap between immigrants and natives from differences in job-finding and job-separation rates: are immigrants more time unemployed because the have a harder time finding jobs or because they lose their jobs more easily? Additionally, I examine whether the heterogeneity in the transition flows between the two groups still exists among comparable workers: is the unemployment gap and the differences in the labour market flows only due to composition effects? Last, I study if there are differences regarding cyclicality of job-finding and job-separation rates for immigrants and natives.

1.3.2 Methodology: Job-finding and Job-separation Rates

The longitudinal nature of the data allows us to examine labour market dynamics for immigrants and natives by using the transition rates approach (Elsby et al. (2009), Shimer (2012), or Silva and Vázquez-Grenno (2013) for Spain). In particular, I compute job-finding and job-separation rates from 2005Q1 to 2016Q1. In Appendix A, I compute job-to-job transitions with a change in employer[7]. As my goal is to understand differences in the probability of finding and losing jobs between immigrants and natives, I consider a three-state environment (employment, unemployment and inactivity). However, given the important role of the employment duality in the Spanish labour market[8], I will also compute job-separation rates by nationality and type of job (temporary versus permanent). I denote by $j = \{N, M\}$ the labour market dynamics of natives and immigrants, respectively. In order to analyse labour market dynamics, I use the following fundamental equations that describe the evolution of the stock of employed, unemployed and inactive workers (denoted as E_j, U_j and I_j,

[7] That is, transitions from employment to employment but with different employers.

[8] see Silva and Vázquez-Grenno (2013) for an analysis focused on the role of flows in and out of permanent and temporary employment in Spain

respectively):

$$\Delta E_{j,t} = \lambda_{j,t}^{UE} U_{j,t-1} + \lambda_{j,t}^{IE} I_{j,t-1} - (\lambda_{j,t}^{EU} + \lambda_{j,t}^{EI}) E_{j,t-1} \tag{1.1}$$

$$\Delta U_{j,t} = \lambda_{j,t}^{EU} E_{j,t-1} + \lambda_{j,t}^{IU} I_{j,t-1} - (\lambda_{j,t}^{UE} + \lambda_{j,t}^{UI}) E_{j,t-1} \tag{1.2}$$

$$\Delta I_{j,t} = \lambda_{j,t}^{UI} U_{j,t-1} + \lambda_{j,t}^{EI} E_{j,t-1} - (\lambda_{j,t}^{IE} + \lambda_{j,t}^{IU}) E_{j,t-1} \tag{1.3}$$

where $\lambda_{j,t}^{XY}$ is the transition probability of moving from state X in quarter $t-1$ to state Y in quarter t, for worker of nationality j, where $X, Y = \{E, U, I\}$. These transition probabilities (transition rates) are calculated as a fraction of the flows from X to Y and the total number of workers in state X at quarter $t-1$. In the next section I focus my analysis on the evolution of the transition rate from unemployment to employment (job-finding rate) and from employment to unemployment (job-separation rate). Using the definition stated above, these rates are computed as follows:

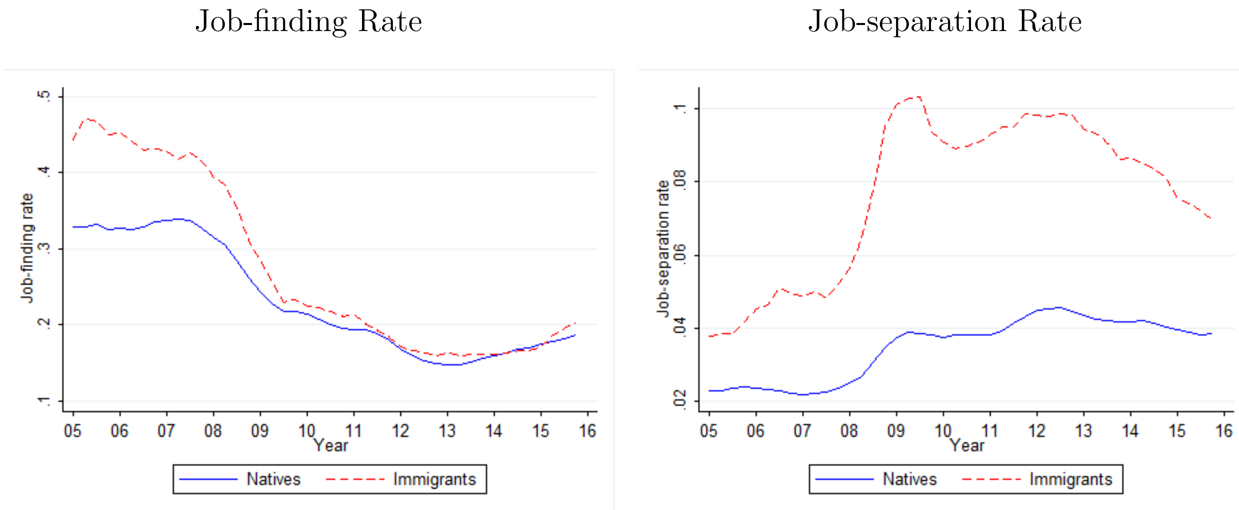
$$\text{Job-finding rate :} \quad \lambda_{j,t}^{UE} = \frac{N_{j,t}^{UE}}{U_{j,t-1}} = \frac{N_{j,t}^{UE}}{N_{j,t}^{UE} + N_{j,t}^{UU} + N_{j,t}^{UI}} \tag{1.4}$$

$$\text{Job-separation rate :} \quad \lambda_{j,t}^{EU} = \frac{N_{j,t}^{EU}}{E_{j,t-1}} = \frac{N_{j,t}^{EU}}{N_{j,t}^{EU} + N_{j,t}^{EE} + N_{j,t}^{EI}} \tag{1.5}$$

where $N_{j,t}^{XY}$ is the number of workers transitioning from state X to state Y at period t.

Figure 1.4 displays the evolution of immigrants and natives quarterly job-finding and job-separation rates. Before the crisis (from 2005 to mid 2008), the job-finding rate was higher for immigrants than for natives (45% and 35%, respectively). However, after the crisis both rates converged quickly to a lower level of around 20%. Regarding the evolution of job-separation, for all the period, those rates are higher for immigrants than for natives. However, the gap between the two increased significantly after the Great Recession took place in 2008. In particular, immigrants job-separation rate more than doubled from 2008 to 2009 (from 4.5% to 11%). For natives, the rate jumped from 2.3% to 3.8%. These two figures suggests a disruptive change in the workers' transition flows gap between immigrants and natives with the arrival of the Great Recession. Nonetheless, these figures should be viewed with caution as these differences may be just due to differences in experience, sector composition, or type of contract. As immigrants are younger, work more as temporary workers, and were more concentrated in the construction sector, the result that job-separation rate is higher for immigrants than for natives is far from being surprising. As a first attempt to disentangle how much of the observed differences in transition rates are due to differences in observables, in the next sections I examine the evolution of job-finding and job-separation rates keeping constant some individual characteristics (education, experience and sex) or job

Figure 1.4: Labour market transitions by nationality



Note: The transitions are seasonally adjusted using a 4-quarters moving average, constructed from the Spanish Labour Force Survey-Flows.

features (occupation, sector and type of contract).

Education

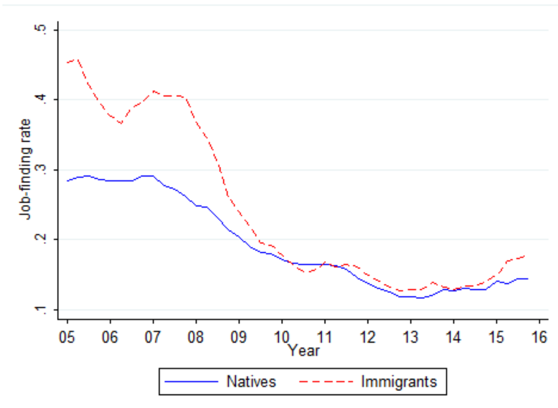
As the second raw of Table 1.1 shows, the share of workers with at most primary education is higher among immigrants than natives, whereas the share of highly educated workers is lower among them. Arguably, less educated workers are more vulnerable to the recession. Therefore, when comparing the impact of the crisis on the job-finding and job-separation rates for the two subgroups we should control for those differences in the education attainment.

Figure 1.5 plots the job-finding and job-separation rates by education attainment. The evolution of the job-finding rate (Panel A) for the lower qualification (primary educated and low-secondary graduates) displays a similar patter as when considering the entire pool of workers (in Figure 1.4). That is, before the crisis low skilled immigrants found jobs faster than natives. However, job-finding rates converged very fast after 2008. The Panel B shows that immigrants' job-separation rate increased more with the arrival of the Great Recession. The bottom panel of Figure 1.5 displays the results for tertiary educated workers. In this case, the evolution of the job-finding rate is slightly different. In fact, we can see that when considering highly educated workers, the pre-crisis differences in the job-finding rate between immigrants and natives disappear. However the same pattern is found regarding the job-separation rate: a large increase in immigrants' separations, steeper than for natives. Overall, differences persist within groups.

Figure 1.5: Labour market transitions by nationality and education attainment

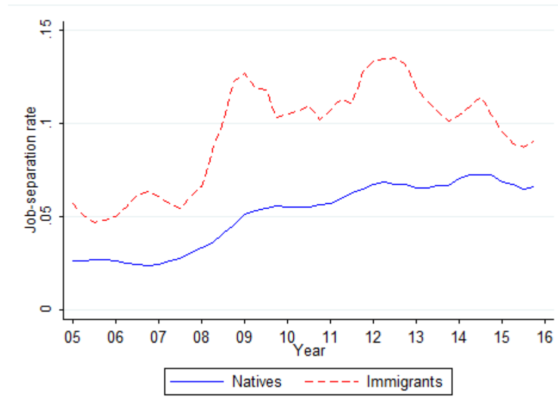
Panel A: Job-finding Rate

Primary or less

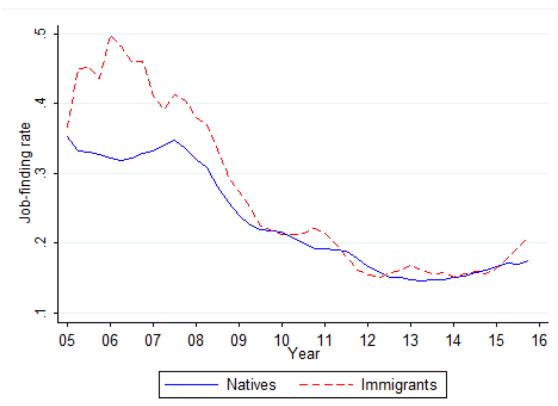


Panel B: Job-separation Rate

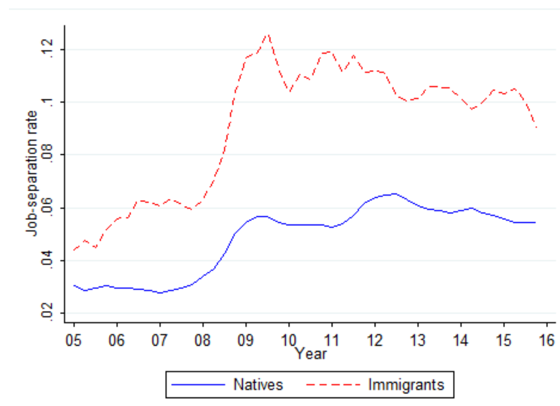
Primary or less



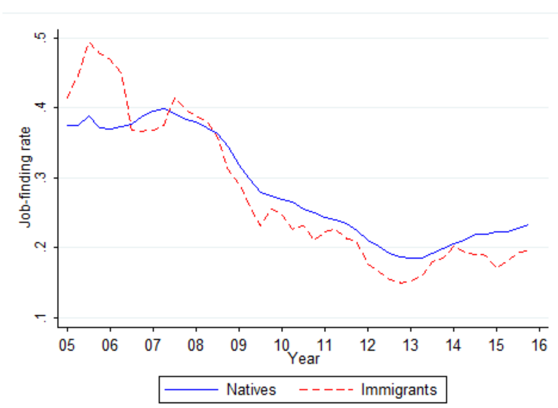
Low Secondary Graduates



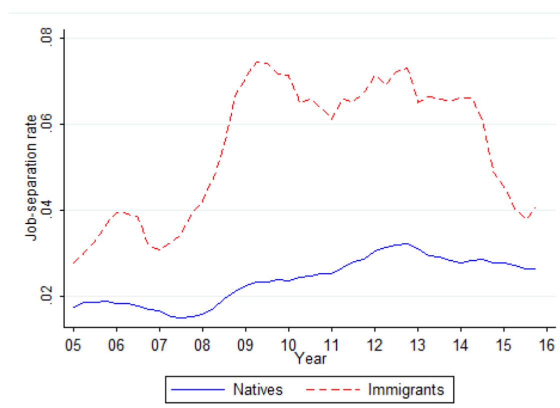
Low Secondary Graduates



College Graduates



College Graduates

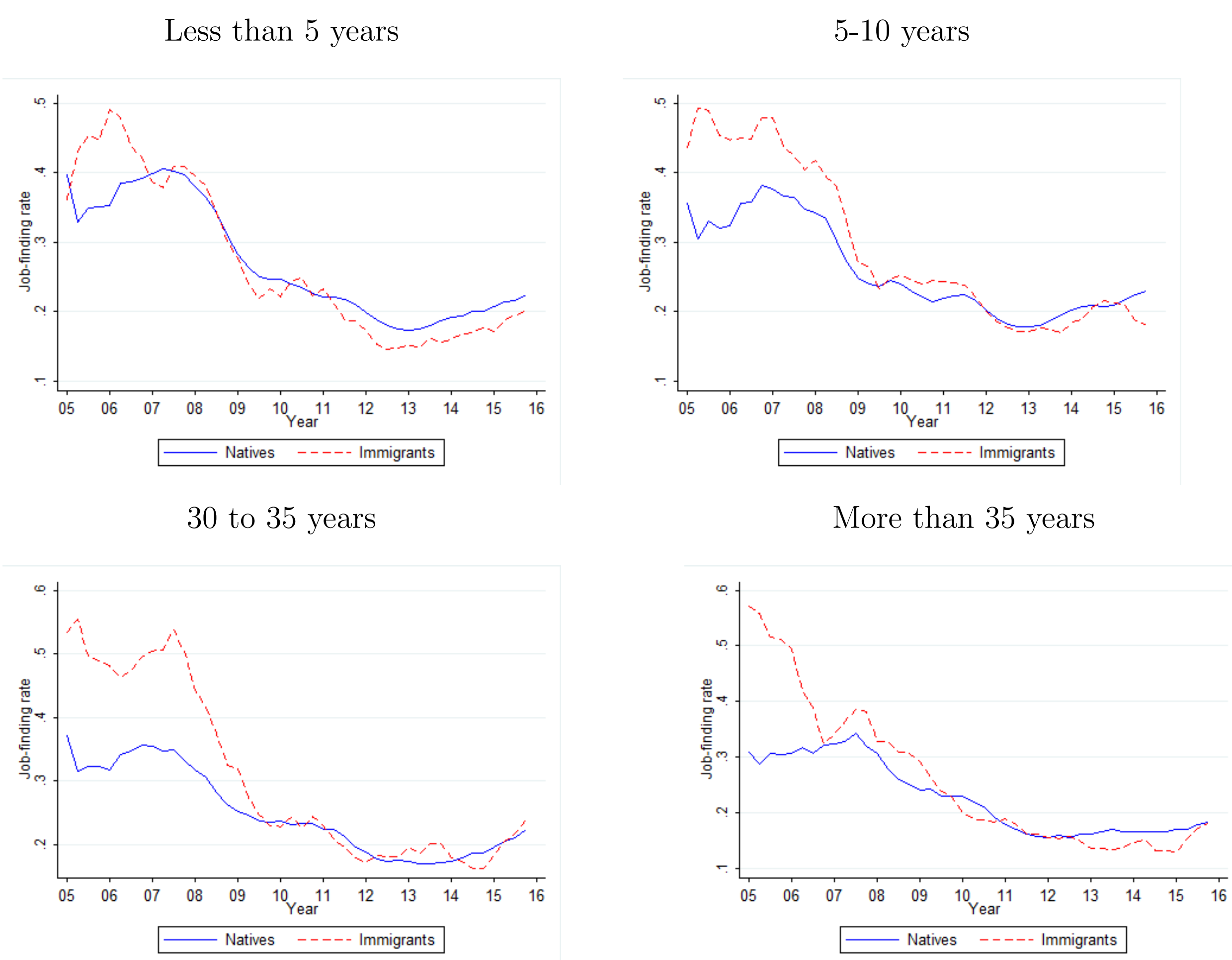


Note: The transitions are seasonally adjusted using a 4-quarters moving average, constructed from the Spanish Labour Force Survey-Flows.

Experience

Immigrants are younger and, therefore, have less work experience than natives, which could partially explain their labour market flows cyclical differences. To examine this hypothesis, I divide the sample into eight five-years experience groups and show that within each experience group, we again observe the previous patterns. One limitation of the data, common in the literature, is that it does not provide any measure of work experience. Following Borjas (2003a) and Ottaviano and Peri (2012), I approximate work experience by the difference between age and the age at which the individual finished her studies. Figures 1.6 and 1.7 plot the evolution of the job-finding and job-separation rates for four selected experience groups (the two lowest and the two highest), for immigrants and natives. Within each ex-

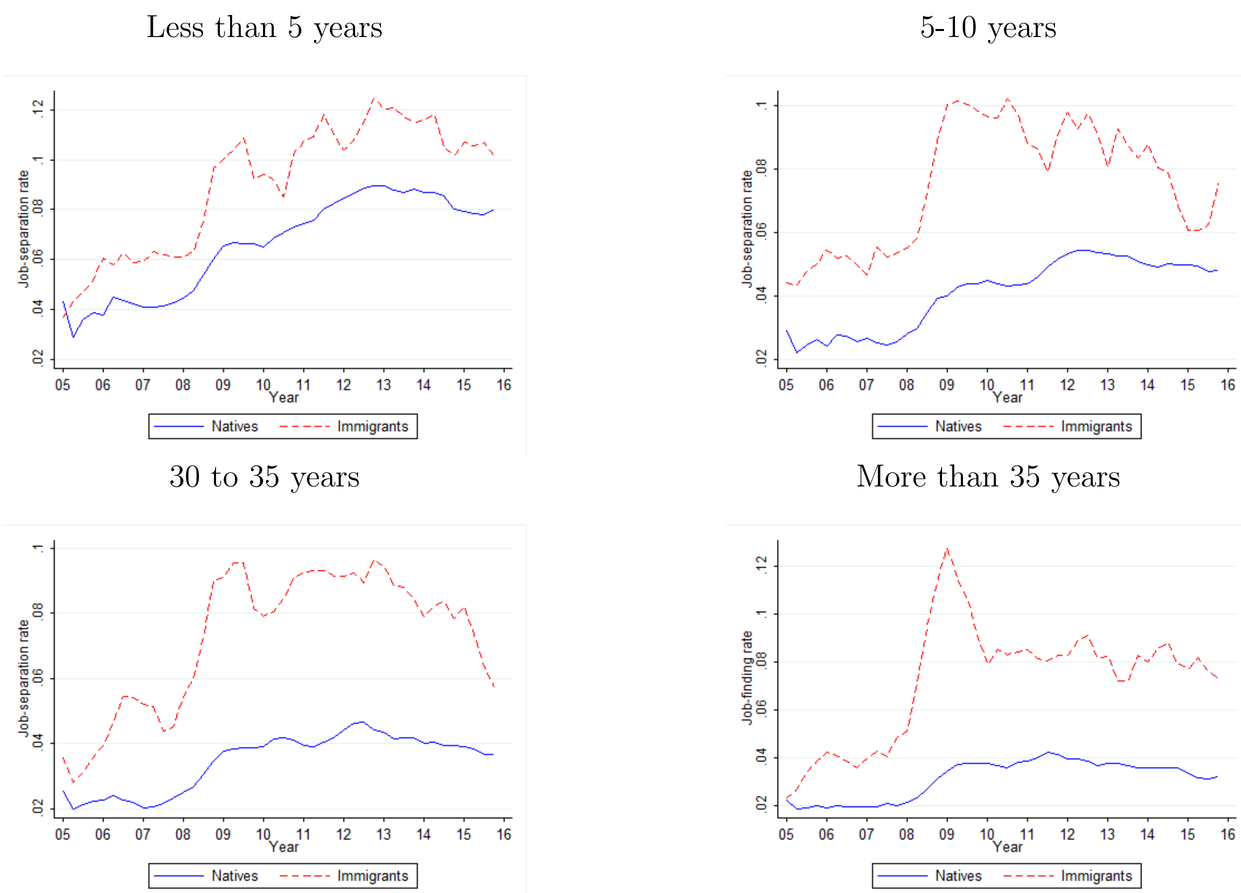
Figure 1.6: Job-finding rate by nationality and experience



Note: The transitions are seasonally adjusted using a 4-quarters moving average, constructed from the Spanish Labour Force Survey-Flows.

perience group, the job-finding rate (Figure 1.6) is higher for immigrants than for natives in the pre-crisis period. After 2008, we again observe that the job-finding rate gap between immigrants and natives vanished as both rates converge to a similar and low level during the recession. With respect to the job-separation rate, again we find a similar pattern for all groups of potential experience: higher job-separation rates for immigrants than for natives before the crisis, with a hike in that job-separation gap after the Great Recession took place in 2008. However, there are some differences among experience groups. The right bottom panel of Figure 1.7 suggests that the largest differences regarding the impact of the crisis on job-separation rates between immigrants and natives are found among workers with more than 35 years of experience. The impact of the crisis among the low-experience groups (top panel) is more similar between immigrants and natives: the job-separation gap between them did widen as much as in other experience groups after the Great Recession took place.

Figure 1.7: Job-separation rate by nationality and experience



Note: The transitions are seasonally adjusted using a 4-quarters moving average, constructed from the Spanish Labour Force Survey-Flows.

Sector

As discussed in subsection 1.3.1, immigrants' employment was more concentrated than natives' in the construction sector during the expansionary period. Arguably, this sector was the most affected by the arise of the crisis, and hence immigrants' concentration in construction could be a potential explanation for the steeper increase in the immigrants' job-separation relative to natives. Figures 1.8 and 1.9 display the evolution of the two transition flows for both immigrants and natives by sector of activity. One can see that in all sectors the job-finding rate was higher for immigrants than for natives during the pre-crisis period (Figure 1.8) . Also, we find the same fast drop in the gap after 2008. That is, patterns are very similar to those for low skilled (Figure 1.5) or for more experienced workers (Figure 1.6).

Figure 1.8: Job-finding rate by nationality and sector

Note: The transitions are seasonally adjusted using a 4-quarters moving average, constructed from the Spanish Labour Force Survey-Flows.

Regarding the cyclicality of the job-separation rate by sector of activity, Figure 1.9 shows that within the construction sector, for all periods the job-separation rate has been higher for immigrants than natives. Moreover, we find the same pattern as when pooling all workers: a large increase in the job-separation rate of immigrants, while for natives it increased by a smaller magnitude. The same pattern is found for the other sectors. Results therefore suggest that the story that immigrants were more affected by the crisis only because they were more concentrated in the construction sector is not supported by the data: in all sectors of activity, with the Great Recession the job-separation rate increased more for immigrants than for natives.

Figure 1.9: Job-separation rate by nationality and sector

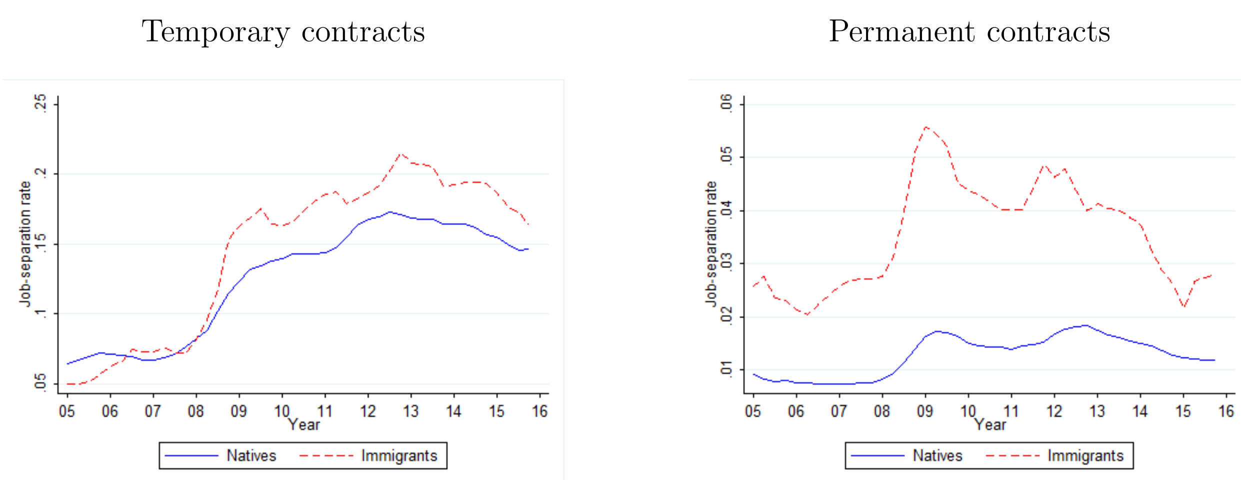
Note: The transitions are seasonally adjusted using a 4-quarters moving average, constructed from the Spanish Labour Force Survey-Flows.

Type of contract

The Spanish labour market is a well-known example of a dual labour market[9]. The main feature of such markets is the coexistence of open-ended (permanent) contracts and fixed-term (temporary) contracts. This segmentation is very relevant for unemployment volatility as job-security is much higher among workers with permanent contracts. Temporary contracts have a limited duration, and when they expire the firm must decide whether to keep the worker or dismiss her at not cost.

As Table 1.1 shows, immigrants are more concentrated in temporary jobs. As those jobs have higher job-separation rates, the fact that immigrants work more as temporary could partially explain the differences between immigrants and natives in the patterns of the overall job-separation rate. Figure 1.10 plots the evolution of the job-separation rate for immigrants and natives conditional on working as temporary or permanent[10].

Figure 1.10: Job-separation rate by nationality and type of contract



Note: The transitions are seasonally adjusted using a 4-quarters moving average, constructed from the Spanish Labour Force Survey-Flows.

As expected, job-separation rates are substantially higher among workers with temporary contracts. Regarding differences between natives and immigrants, the left panel of Figure 1.10 shows that before the crisis, the job-separation rate in temporary jobs was very similar for the two groups. After the crisis differences arise, as the increase in the job-separation rate is higher for immigrants than for natives. However, the figure suggests

[9]See Bentolila et al. (2019) for recent survey on the topic.

[10]As before, a job-separation is computed as a transition from employment to unemployment. In the case of temporary contracts, if the contract is renewed or another temporary contract follows an ending one, we do not have a separation.

that those differences are smaller than after controlling for other observables. Regarding the job-separation rate for permanent workers, the right panel of Figure 1.10 shows that for this jobs the patterns are more similar to the previous figures: during the pre-crisis period job-separation rates were already higher for immigrants than for natives. But the impact of the crisis seems to be higher for immigrants. Specifically, while the job-separation rate for permanent immigrants roughly triples (from 2% in 2007 to almost 6% in 2008), natives job-separation rate doubles (from 0.8% in 2007 to 1.8% in 2008).

1.3.3 Regression Approach

The previous section suggests that the immigrants' transition flows were more sensitive to the outset of the Great Recession. Moreover, findings suggest that even when controlling for some observables, the same pattern is found. In order to test whether the different impact of the crisis on the employment transitions of immigrants and natives also exists between comparable workers, I estimate the following regressions:

$$Pr\left(UE_{i,t}=1\right)=\Phi\left(\beta_0+\beta_1^m imm_i+\beta_1^c crisis_t+\beta_1^{mc} imm_i * crisis_t+\boldsymbol{\delta}_1\boldsymbol{X}_{i,t}^1\right) \tag{1.6}$$

$$Pr\left(EU_{i,t}=1\right)=\Phi\left(\beta_2+\beta_2^m imm_i+\beta_2^c crisis_t+\beta_2^{mc} imm_i * crisis_t+\boldsymbol{\delta}_2\boldsymbol{X}_{i,t}^2\right) \tag{1.7}$$

where $UE_{i,t}$ ($EU_{i,t}$) is a dummy variable defined only for the unemployed (employed) and takes value 1 if a job is found (lost) at time t and 0 otherwise; imm_i is a dummy variable that takes the value 1 if the worker is an immigrant and 0 otherwise[11]; $crisis_t$ is a dummy variable that takes the value 1 for the time interval 2008Q3-2013Q2 [12] and 0 otherwise; $\boldsymbol{X}_{i,t}^1$ is a vector of control variables that includes dummies for education, experience, marital status, age, gender, region of residence, sector of activity[13], type of contract (permanent or temporary), type of job (full or partial time) and year when the transition took place. Φ is the cumulative distribution function for the standard normal distribution, indicating that I will estimate probit models.

The coefficients of interest are $\beta_1^{mc}, \beta_2^{mc}$, which are associated with the interaction term of the variables imm_i and $crisis_t$. Their sign and magnitude will be used to test whether the probability of finding (losing) a job during the crisis differed among immigrant and native workers. The results of the estimation of Equations (2.1) and (2.2) are shown in Table 2.1.

[11]The survey does not provide the worker's country of birth, so we define immigrants as workers with foreign nationality.

[12]I chose this time span since 2008Q3 and 2013Q2 are the first and the last quarter with a negative quarterly growth rate of real GDP, respectively (ignoring two quarters in 2010 with slightly and temporarily positive rates).

[13]In case of unemployment, the sector of activity is the sector where the worker was last employed.

Results

Table 1.2: Probit estimation of UE and EU transitions

	(1) UE	(2) EU
Crisis (*crisis*)	-0.308***	0.190***
	(0.0456)	(0.0203)
Immigrant (*imm*)	0.0844	0.058**
	(0.0515)	(0.0208)
Immigrant*Crisis ($imm * crisis$)	-0.111**	0.104***
	(0.0553)	(0.02756)
Observations	108594	1385262
R-squared	0.033	0.156

Note: Regressions of dummy variables for the transition from unemployment to employment (UE, in column (1)) and from employment to unemployment (EU, in column (2)) on dummies for crisis, migration status and the interaction term of the last two. Both regressions includes controls for education, experience, marriage status, age, gender, region of residence, sector of activity, type of contract, type of job and year. Standard errors in parentheses. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Source: Spanish Labour Force Survey-Flows (2005-2015).*

As expected, the impact of the crisis on the probability of finding (losing) a job is negative (positive) and significant. More interestingly, the results in column (2) of Table 2.1 confirm the pattern seen in Figure 1.4: even for comparable workers, there is strong evidence that during the crisis the probability of losing a job increased more for immigrants than for natives. Regarding the UE transition, the results in column (1) suggest that the crisis also decreased by a larger amount the probability of finding a job for immigrants than for natives. Last, in the case of EU transitions I find that the immigration variable is positive and significant. That is, there is evidence that ceteris paribus immigrants are more likely to go to unemployment than natives.

Given the non-linear nature of the probit model, the estimated coefficients of Table 2.1 tell us little about the magnitude of the effect. To overcome this drawback, I compute both the adjusted predictions at mean (APMs) and the marginal effect (ME). The results are displayed in Table 2.2. Panel A shows the results for the model where the dependent variable is the transition from unemployment to employment (UE). The interpretation of the adjusted predictions goes as follows: according to the model, before the crisis the probability of finding a job for an average individual with native nationality was 21.9%, while if the same individual was immigrant that probability would be higher (23.5%). In other words, before 2008, *ceteris paribus*, the probability of finding a job was higher for immigrants than for natives. However, in the crisis, the job-finding probability is lower for immigrants than for natives: 12.7% and 14.0% respectively. The last column displays the marginal effect, which

Table 1.3: Adjusted Predictions and Marginal Effect

Panel A: Probability finding a job (UE)			
	crisis = 0	crisis = 1	Marginal Effect
Native	21.92	13.95	-7.97^{***}
Immigrant	23.46	12.67	-10.79^{***}
Panel B: Probability losing a job (EU)			
	crisis = 0	crisis = 1	Marginal Effect
Native	0.96	1.58	0.62^{***}
Immigrant	1.17	2.43	1.26^{***}

Note: Adjusted Predicted probabilities and Marginal Effects computed by the probit model. Panel A uses 108,594 observations. Panel B uses 1,385,262 observations. Significance level: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

is the change in the probability of finding a job for each of the two groups when the crisis hit. From the previous discussion we already know that the marginal effect is more negative for immigrants: -10.8 pp. for immigrants and -7.9 pp. for native workers.

Panel B of Table 2.2 shows the results regarding the job-separation rates. The model predicts that before the crisis the probability of losing a job for an average individual with native nationality was 0.96% while if the same individual was an immigrant that probability would be 1.17%. During the crisis, losing the job becomes more likely for both groups, but the increase is higher for immigrants than for natives: the probabilities of moving from employment to unemployment are now 1.58% and 2.43% for natives and immigrants, respectively. As the last column of Table 2.2 shows, the marginal effect of the crisis was twice as high for immigrants than for native workers.

1.4 Real Wage Cyclicality: Immigrants versus Natives

1.4.1 Data

Since the Spanish Labour Force Survey does not provide information on wages, in this section I use Spanish administrative data from the Continuous Sample of Working Histories

(*Muestra Continua de Vidas Laborales*, MCVL hereinafter) on earnings and working histories of workers. The MCVL consists of a 4% representative random sample of all workers affiliated (working, receiving a public pension or being registered as unemployed) with the social security administration in the year of the publication of the dataset. The data was released in 2004 and after that year it follows the same sample of individuals over time, adding new observations each year to replace exiting workers while keeping the sample representative of the population. Furthermore, the data provides retroactive information on the workers' entire labour market history. That is, as long as an individual registers one day of activity with social security in any year between 2005–2015 (which is the last year that I include in the analysis), her complete working life history can be recovered up to 1981.

Along with the job history, for each individual a large amount of information is available, including personal and demographic characteristics (age, gender, education, nationality, region of residence), firm information at the establishment level (location, size) and labour market information (industry, occupation, type of contract). The unit of observation in the data is any change in the individual's labour market status or any modification in job characteristics. Importantly, it also provides earnings data, in nominal terms. As explained in De la Roca (2014) wages are available for all workers but some observations are censored. I deflate wages using the consumer price index (base year 2011) provided by the Spanish Statistical Office (INE).

Sample restrictions

I construct a panel with monthly observations for the period 1999 to 2015. We start with the most updated version of the sample, which is the 2015 edition. After processing the social security and census records of individuals contained in the 2015 edition of the MCVL, we turn to the 2014 edition and extract the social security and census records of the individuals contained in this edition but absent from the 2015 edition. We do the same for the subsequent editions (2012 to 2005). The initial sample is a monthly data set of individuals who have worked at any time between January 1999 and December 2015. I restrict this sample to workers aged 20-60 during that period. Since I am interested in the wage behaviour, I focus on salaried employment, dropping from the sample unemployment spells and self-employed. Last, I restrict to workers who had worked the full month with the same establishment. These restrictions reduce the sample to 808,029 individuals and 71,552,530 monthly observations.

Descriptive Statistics

This section summarizes the main characteristics of the sample included in the MCVL, presenting the results for immigrants and natives. Again, I identify immigrants as workers with foreign nationality. In the sample, immigrants account for 20.34% of individuals, and 9.37% of the monthly observations[14]. As before, all statistics are displayed in Table 1.11 (in Appendix D) dividing the sample period in three phases: pre-crisis (1999Q1-2008Q2), crisis (2008Q3-2013Q2) and post-crisis (20013Q3-2016Q1)[15].

In the MCVL, I divide the eduction in three groups: low secondary education or less (i.e. primary education and lower secondary education), high secondary education, and college education[16]. Immigrants are more concentrated among the low educated groups and they are more time employed as temporary. Workers' sectoral composition is very similar to the sample of the Spanish Labour Force Survey, with most of workers employed in the service sector, and a higher share of immigrants working in construction, specially during the pre-crisis period (see Table 1.11 in Appendix D for details on the numbers).

I construct a variable specifying the number of days that a worker has been employed for a given establishment[17]. As De la Roca (2014) and Font et al. (2015), I classify employed workers into six tenure categories: (1) workers employed less than one year who came from unemployment or inactivity (newly-hired); workers employed less than one year who came from an employment spell (job-movers); (3) workers 1-2 years of tenure; (4) 2-4 years, (5) 4-6 years; and (6) more than 6 years of tenure. As we can see in Table 1.4, immigrant workers are more concentrated among the low-tenure groups than natives. During the pre-crisis period, 60% of employed immigrants were working in firms with less than one year of tenure, while that share was around 20% among natives. Similarly, natives are overrepresented in the highest group of tenure: during the whole sample period, 26% of employed natives are working in establishments with more than 6 years of tenure, for only 5% among immigrants.

[14]The difference between the two numbers is due to the fact that, on average, immigrants have shorter labour market career than natives (since they arrive late to Spain) and hence the sum of employment and unemployment spell must be lower.

[15]Notice that the pre-crisis period here is larger, as for the Spanish Labour Force Survey-Flows I had to restrict my analysis to the period 2005Q1, see Subsection 1.3.1.

[16]Unfortunately, these educational groups can not be directly compared with those of the Spanish Labour Force Survey, as the administrative data does not distinguish between primary graduates and low secondary education. And also this is the reason why the lower educational level is overestimated compared to Table 1.1

[17]This variable counts the number of days accumulated in an establishment throughout a worker's career. That is, if he leaves the establishment and then returns, the tenure starts from its former level. De la Roca (2014) also considers the alternative of counting every return as a new spell, and he founds very similar results. That is why I abstract from that case.

Table 1.4: Job tenure categories by nationality

	Natives			Immigrants		
	Pre-crisis	Crisis	Post-crisis	Pre-crisis	Crisis	Post-crisis
Tenure group						
Newly-hired	10.58%	9.17%	9.79%	13.38%	14.46%	15.71%
Job-movers	20.85%	12.15%	10.72%	46.18%	28.22%	22.71%
1-2 years	17.66%	14.12%	12.31%	20.91%	20.61%	20.39%
2-4 years	20.08%	19.69%	17.04%	13.65%	21.42%	20.55%
4-6 years	11.29%	13.64%	11.14%	3.76%	9.32%	8.77%
More than 6 years	19.55%	31.23%	39.00%	2.12%	5.97%	11.87%

Note: The new-hired group includes workers employed with less than one year of tenure that came from unemployment or inactivity. The job-movers group includes workers employed in with less than one year of tenure and came from an employment spell. Source: MCVL.

1.4.2 Monthly Average Wage

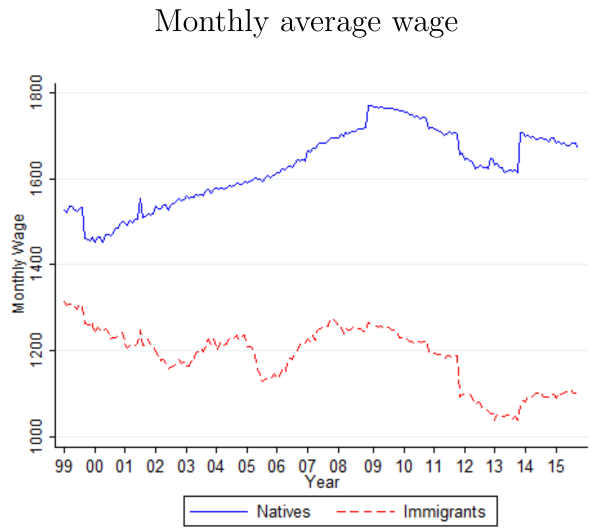
The left panel of Figure 1.11 plots the evolution of the monthly wage for immigrants and natives, while the right panel displays the wage premium[18]. First, monthly average wage is higher for natives than immigrants. Second, average wage of immigrants grew at a lower rate throughout the full period. In particular, in 1999 the average native wage was around 20% higher than for immigrants, while that difference increased to 30% in 2008 and more than 50% in 2012 and afterwards (right panel of Figure 1.11). Figure 1.11 also shows that with the arrival of the crisis (mid 2008), the average wage of immigrant stopped growing, while that of native workers was apparently less affected. As a consequence, the wage premium increased around 20% from 2008 to 2015.

Real wage heterogeneity by nationality could be partially or totally explained by differences in observables between immigrants and natives, as immigrants are more concentrated among low-educated and low-tenure groups, work more as temporary and were more concentrated in the construction section (see Table 1.4 and Table 1.11 in Appendix D). In particular, the literature has shown that tenure is a very important determinant of wage cyclicality (De la Roca (2014)[19]. Thus, the apparently higher wage sensitivity among immigrant workers could be due to the fact that immigrants are more concentrated among

[18] Throughout the paper I indistinctively use the term wage premium and wage gap to refer to the wage differential between immigrants and natives. It is computed as $(\bar{w}_{N,t}/\bar{w}_{M,t} - 1)$, where $\bar{w}_{j,t}$ is the monthly average wage for natives $j = N$ and immigrants $j = M$ at month t.

[19] As stated in De la Roca (2014), wages among newly-hired workers are more sensitive to changes in the aggregate economic conditions, as they are not as subject to re-negotiation agreements and other form of wage-bargaining rigidities. Similarly, from an employer point of view it seems easier to implement wage cuts among less-tenure employers

Figure 1.11: Monthly real wage by nationality

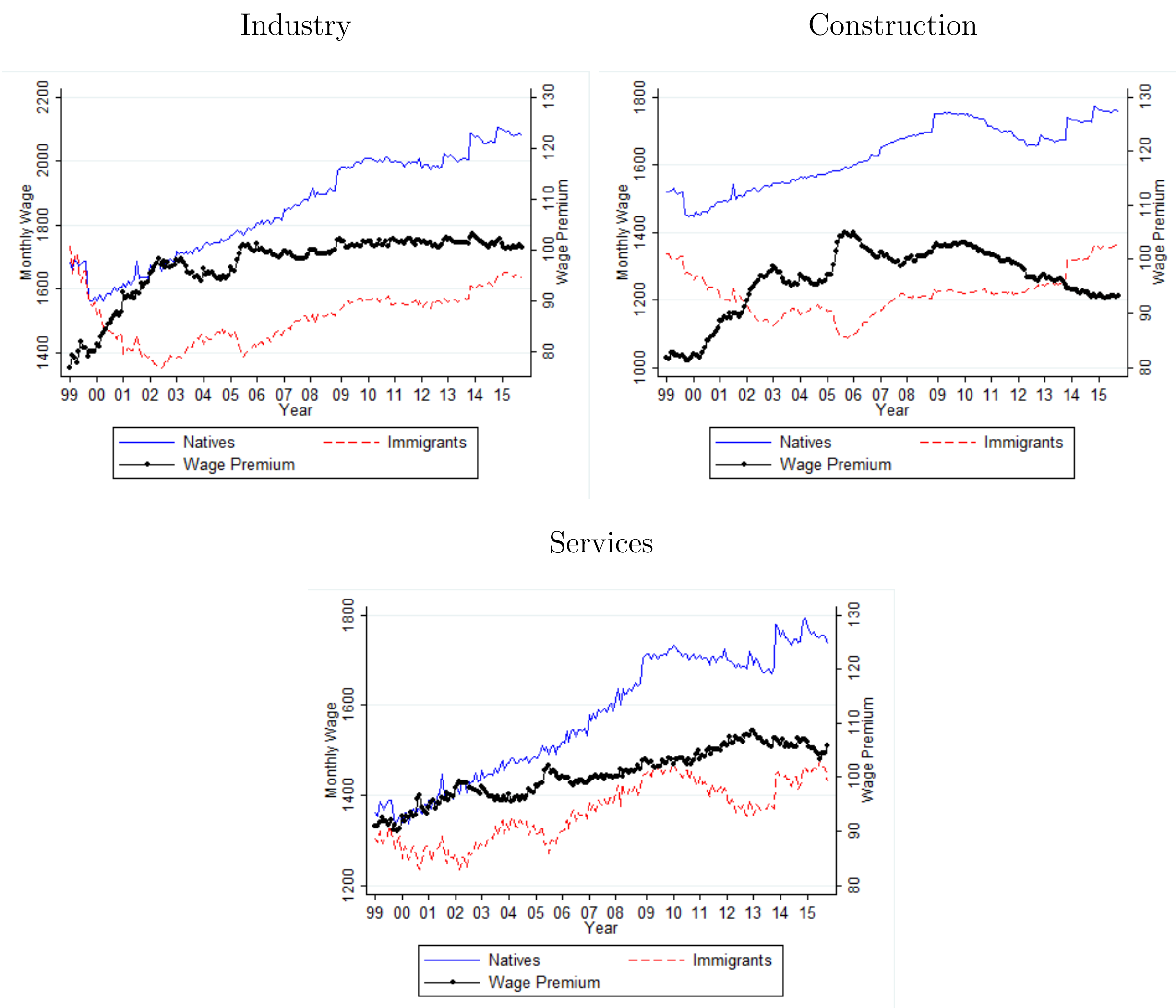


Note: The wage premium is computed as $(\bar{w}_{N,t}/\bar{w}_{M,t} - 1)$*, where* $\bar{w}_{j,t}$ *is the monthly average wage for natives* $j = N$ *and immigrants* $j = M$ *at month* t*. Wages are seasonally adjusted by taking out the coefficient of the monthly dummies from an OLS regression. Source: MCVL.*

low-tenure categories (newly-hired and job-movers). In Appendix B I try to provide empirical support for this hypothesis by comparing natives-immigrants monthly average real wage among workers who stayed employed in the same establishment from January 2007 to December 2012 (without any unemployment spell or change in employer). I find almost no differences in the cyclicality of wages between immigrants and natives (Figure 1.17 in Appendix B), suggesting that a significant part of the drop in the average wage of immigrants may be due to job-changers or newly formed jobs.

As an alternative attempt to disentangle how important are differences in observables to explain differences in the overall wage cyclicality, in Appendix C, I examine the evolution of real wages keeping constant some individual or job characteristics (education, sector, type of contract and gender). Overall, the figures suggest that wage sensitivity during the Great Recession (from 2007 to 2015), is not very different among native and immigrants once you control for differences in observables. For illustrative purposes I focus on the results for the sectoral composition. As we can see in Figure 1.12, the evolution of wages follows a similar pattern in all sectors: higher wages for natives than immigrants, with the gap growing during the expansion. After the Great Recession, the wage gap remained constant both in industry and construction sectors (where it actually dropped), and an small increase in services, where the drop in immigrant wages was higher than for natives, specially in the period 2009-2013 (bottom panel of Figure 1.12).

Figure 1.12: Monthly average wage by nationality and sector

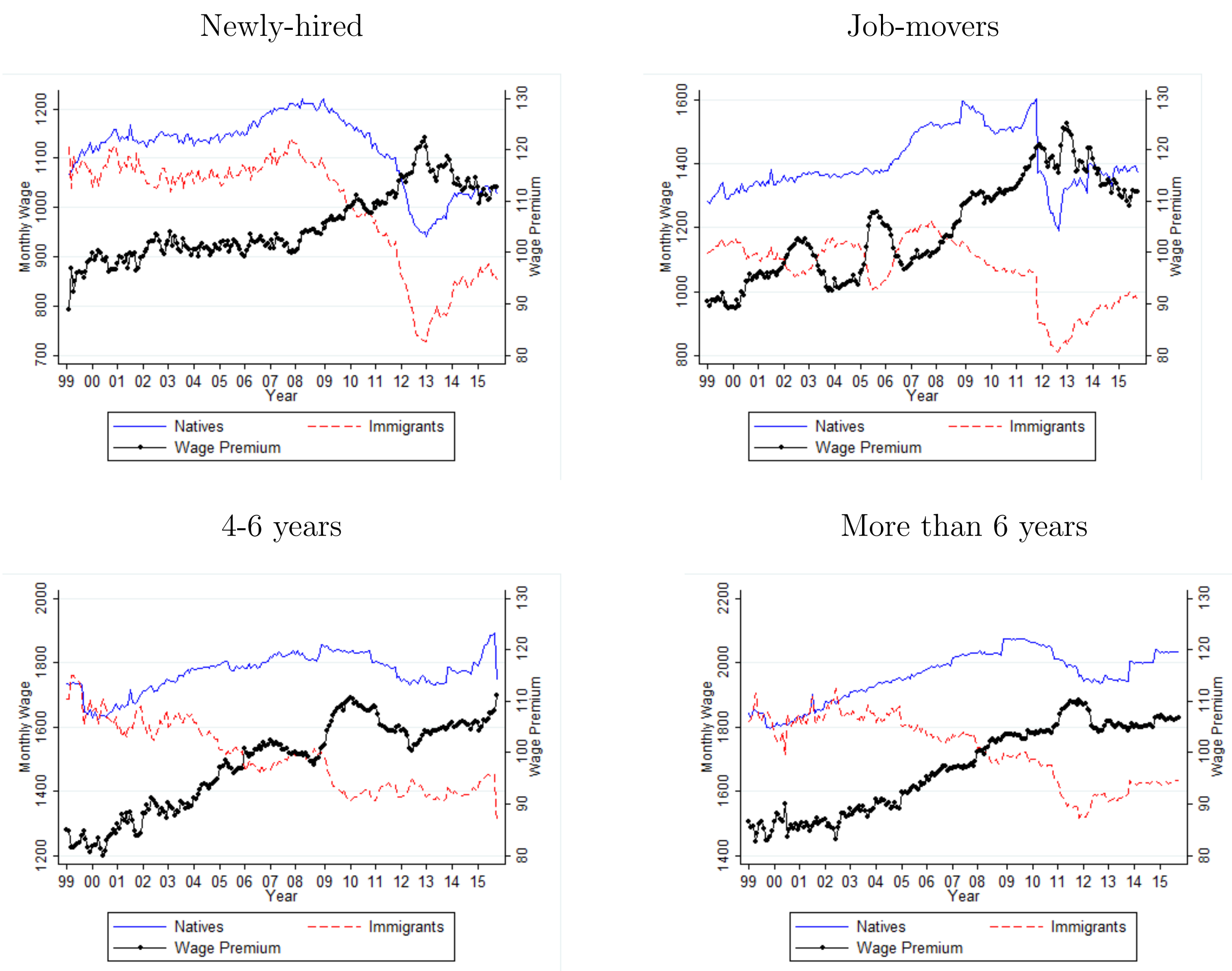


Note: The wage premium is computed as $(\bar{w}_{N,t}/\bar{w}_{M,t} - 1)$*, where* $\bar{w}_{j,t}$ *is the monthly average wage for natives* $j = N$ *and immigrants* $j = M$ *at month* t*. Wage premium is normalized to 100 at* 2008Q1*. Wages are seasonally adjusted by taking out the coefficient of the monthly dummies from an OLS regression. Source: MCVL.*

Tenure

Given the key role played by tenure of work in shaping wage cyclicality, in this subsection I look at the evolution of wages by nationality within each tenure group. Figure 1.13 plots the time series of real wages for each tenure category defined in Subsection 1.4.1 and wage premium between immigrants and natives. As expected, wage sensitivity is higher among the low-tenure groups, specially during the Great Recession. For all the tenure categories we find that the average wage gap between immigrants and natives was close to zero in 1999

Figure 1.13: Monthly average wage by nationality and tenure



Note: The wage premium is computed as $(\bar{w}_{N,t}/\bar{w}_{M,t}-1)$, where $\bar{w}_{j,t}$ is the monthly average wage for natives $j = N$ and immigrants $j = M$ at month t. Wage premium is normalized to 100 at 2008Q1. *Wages are seasonally adjusted by taking out the coefficient of the monthly dummies from an OLS regression. Source: MCVL.*

but it widens over the expansionary period (1999-2007). Last, Figure 1.13 also suggests that during the Great Recession, differences regarding average wage drop between immigrants and natives are higher among the low-tenure groups. This can be seen by looking at the evolution of the wage premium: we see a significant acceleration of this indicator from 2007 among the low-tenure groups, specially for job-movers (top right panel) and workers with 1-2 years of tenure (middle left panel). On the opposite, among the high-tenure groups (bottom panel) we observe fewer differences between immigrants and natives after the Great Recession. Somehow striking is the evolution of the wage premium for workers with 2-4 work tenure, as it remained almost constant from 2007 to 2013, and it suddenly increased by around 20% in only one year.

1.4.3 Regression Approach

The previous section suggests that wage cyclicality is not much different among immigrant and native workers once one takes into account differences in observables (education, sector of work, type of contract, and specially job-tenure). In order to test this hypothesis, I estimate a monthly wage equation of the following form:

$$\ln\, w_{i,t} = \alpha_i + \boldsymbol{\delta}_1 \boldsymbol{X}^1_{i,t} + \gamma_1 U_t + \gamma_2 T + \varepsilon_{i,t} \tag{1.8}$$

where ln $w_{i,t}$ is the log real monthly wage of worker i in period t (where t is a year-month pair); α_i is a worker fixed effect; $\boldsymbol{X}^1_{i,t}$ are worker and job characteristics; U_t is the cyclical variable (which is the unemployment rate); T is a linear time-trend and $\varepsilon_{i,t}$ is the error term with zero mean and constant variance. Worker fixed effects are introduced in order to address the workforce composition bias that originates along the different phases of the business cycle (Solon et al. (1994)). As discussed by De la Roca (2014), the most standard approach to overcome the composition bias is to estimate the wage equation in first differences (Bils (1985), Solon et al. (1994), Devereux and Hart (2006) Gertler et al. (2016)). However, I follow De la Roca (2014) and run the model in levels in order to include in the regression also workers who just moved from unemployment to employment in a given month.

The coefficient γ_1 of Equation (1.8) identifies changes in our cyclical variable (in this case the unemployment rate) with changes in wages. However, since in a given month all workers are exposed to the same level of unemployment, the standard error of the coefficient of γ_1 would be underestimated in the presence of time-specific errors (Moulton (1986)). To overcome that issue, I follow De la Roca (2014) by taking a two-steps procedure to transform Equation (1.8) into the following two equations:

$$\ln\, w_{i,t} = \alpha_i + \boldsymbol{\delta}_1 \boldsymbol{X}^1_{i,t} + \sum_{t=1}^{T} \beta_t D_t + e_{i,t} \tag{1.9}$$

$$\hat{\beta}_t = \phi_0 + \phi_1 U_t + \phi_2 t + \eta_t \tag{1.10}$$

In the first stage I estimate Equation (1.9), which includes a dummy for each year-quarter combination[20]. As the goal is to track down differences in the wage cyclicality by worker nationality, this first stage equation is estimated separately for the sample of immigrants and

[20] Wages are observed monthly, but unemployment rate is calculated quarterly.

natives workers[21]. The estimated set of coefficients $\hat{\beta}_t$ captures variations in wages that are free from observed characteristics and time-invariant unobserved individual heterogeneity. In my estimations, the vector of time-varying worker and job characteristics $\boldsymbol{X}^1_{i,t}$ includes the age, the square of the age, the type of contract, tenure, the square of tenure, and dummies for sector. To account for heterogeneity in the wage sensitivity between immigrants and natives among different tenure groups, I also estimate Equation (1.9) by including an interaction term between tenure groups and the year-quarter combinations.

In the second stage, Equation (1.10), I regress the estimated year-quarter coefficients $\hat{\beta}_t$ on the cyclical variable, which is the yearly-lagged quarterly unemployment rate[22], and linear trend T. Therefore, the standard error of the new coefficient of interest ϕ_1 is now free from the aggregate bias present in Equation (1.8) (De la Roca (2014)). The coefficient ϕ_1 captures the semi-elasticity of wages with respect to the unemployment rate: the higher and more negative its value, the more pro-cyclical real wages are. On the other hand, a positive value would imply that real wages are counter-cyclical.

Results

The first row of Table 1.5 displays the estimation results of the coefficient of interest ϕ_1 for immigrants and natives. Wage cyclicality is higher for immigrants than for natives: a one percentage point increase in the unemployment rate is associated with a decrease 0.62% decrease in native real wages, while for immigrants the decrease is 0.97%. My results are slightly higher than those reported by De la Roca (2014) and Font et al. (2015). The main reason is that their sample is restricted to years before 2011 and 2013, respectively and from subsection 1.4.2 we show that much of the action in real wages is observed after 2012. Nevertheless, overall my results suggest a very low degree of real wage cyclicality, specially compared to developed countries, where estimates tend to find semi-elasticities above 1 (see Pissarides (2009) for a summary of most available studies for U.S, France, Germany, U.K, Portugal or Italy).

I follow De la Roca (2014) and estimate wage sensitivity differences between immigrants and natives within tenure categories. For that, I modify Equation (1.9) by including an interaction term between the year-quarter combinations and a dummy for the tenure cat-

[21] An alternative is to modify Equation (1.9) by including an interaction term between the year-quarter combinations and a dummy for the worker nationality and estimate the equation for the entire pool of native and immigrant workers. Given the large size of the sample of both immigrants and natives, both approaches deliver very similar results (See Table 1.12 in Appendix D).

[22] This is standard in the literature. As argued in Font et al. (2015), wages are usually not able to adjust contemporaneously to cyclical shocks as most wages are set one year in advance. This is particularly relevant in Spain, where firm-level indexation is widespread (Bentolila et al. (2012a), Babecky et al. (2010)).

Table 1.5: Wage cyclicality for selected samples

	Natives	**Immigrants**
All workers	-0.623***	-0.971***
Newly-hired	-1.508***	-1.900***
Job-movers	-1.234***	-1.650***
1-2	-0.694***	-1.081***
2-4	-0.196	0.152
4-6	-0.219*	-0.112*
More than 6	-0.284***	-0.266***
Observations (first stage)	60,005,705	5,514,405

Note: Estimation results of the coefficient ϕ_1 in Equation (1.10). Each coefficient is a separate second stage regression of the estimated year-quarter coefficients on the yearly-lagged quarterly unemployment rate. All second stage regressions have 67 quarterly observations (1999:1 to 2015:4) and include a constant term, a linear time trend and quarter indicators. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Source: MCVL.*

egory. Now, the second stage Equation (1.10) regresses the estimated year-quarter indicator coefficients β_t for each tenure group on the yearly-lagged quarterly unemployment rate U_t and the linear time-trend T. Again, we run these two-steps procedure differently for our sample of immigrants and natives.

The lower panel of Table 1.5 shows the cyclicality of each tenure group for natives and immigrants. As expected, real wage cyclicality is higher among low-tenure groups. In particular, the newly-hired workers is the group with the highest coefficient: for natives, a one percentage point increase in the unemployment rate is associated with a 1.49% decrease in newly-hired real wage. Regarding differences by nationality, we see that wage cyclicality is higher for immigrants than for natives only in the low-tenure groups (newly-hired, job-movers and workers with 1-2 years of tenure). Among workers with more than 2 years of work tenure in the establishment, wage cyclicality is actually higher for natives than for immigrants.

Last, I investigate the existence of wage sensitivity asymmetries along the business cycle regarding. In particular, I want to test: (1) whether real wage is more sensitive to positive or negative changes in the unemployment rate; and (2) if we observe differences in real wage sensitivity before and after the Great Recession. To test for those two hypothesis, in the second stage of the estimation I interact the yearly-quarter unemployment rate with:

(1) a dummy that equals 1 if changes in unemployment rate are positive; (2) a dummy that equals 1 if t$\geq 2008Q3$.

Table 1.6 shows the results for each of the specifications. I find small differences regarding the wage sensitivity to positive and negative changes in the unemployment rate (among natives, semi elasticity of -0.585 to negative changes and -0.617 to positive change, top panel of Table 1.6). Moreover, as before, real wage sensitivity is higher among immigrants in both cases.

Table 1.6: Wage cyclicality along the business cycle

	Natives	**Immigrants**
Negative changes in UR	-0.585***	-0.867 ***
Positive changes in UR	-0.617***	-0.956***
Expansion	-0.884***	-1.107***
Crisis	-0.655***	-0.988***
Observations (first stage)	60,005,705	5,514,405

Note: Estimation results of the coefficient ϕ_1 in Equation (1.10). Each coefficient is a separate second stage regression of the estimated year-quarter coefficients on the yearly-lagged quarterly unemployment rate. All second stage regressions have 67 quarterly observations (1999:1 to 2015:4) and include a constant term, a linear time trend and quarter indicators. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source: MCVL.

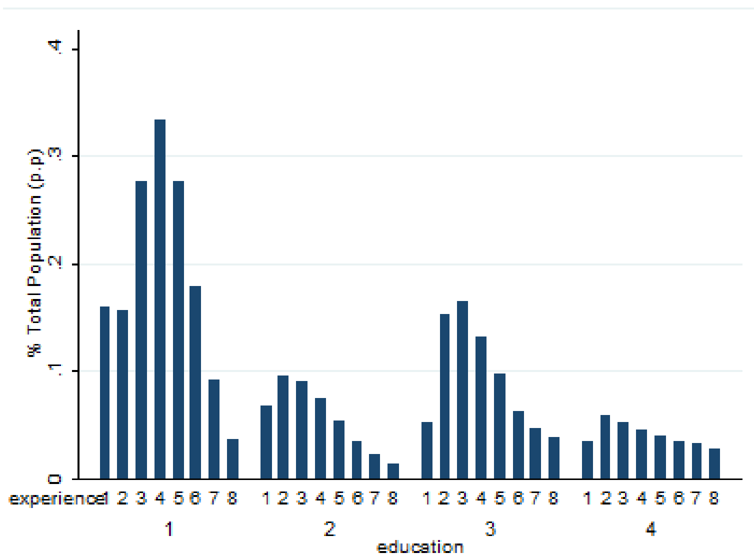
Bottom panel of Figure 1.6 shows that real wages were more responsive during the expansion than after the Great Recession, for both immigrants and natives (bottom panel of Figure 1.6), suggesting the existence of certain degree of downward wage rigidity during the last recession.

1.5 Natives' Responses to Immigration

In this section I study natives' responses to the immigration shock. From the labour economics point of view, an increase in the number of immigrants in a country is equivalent to a supply shock that in the simplest model would depress the equilibrium price (wage). Therefore, the possibility that natives adjust in some ways after an increase in immigration seems reasonable. In particular, in this Section I examine whether immigrant inflows are correlated with three potential natives' adjustment margins: occupational upgrading, regional mobility and changes in labour force participation.

For each of the three margins, I apply the education-experience cells approach first used by Borjas (2003a). It consists in defining education-experience cells as closed labour markets and then exploiting the variation in supply shifts across those cells in order to estimate the impact of immigration. This identification strategy alleviate (though it does not overcome completely) the main drawback of the spatial approach (that exploits geographical variation), which is the tendency of immigrants to move to places with better economic conditions. Following Borjas (2003a), I classify individuals into four education groups[23] and eight 5-years experience categories to define cells. Each of those 32 cells will be treated as a closed market. This means that workers with the same education level but different experience will not be substitutes. Figure 1.14 displays the average proportion of immigrants in each cell over the whole period. My identification strategy relies on the observed variation in the immigration share across-cells.

Figure 1.14: Share of immigrants by education-experience cell



Source: Own calculations based on the Spanish Labour Force Survey-Flows, INE.

1.5.1 Occupational Upgrading or Downgrading

In this section I assess whether immigration is correlated with changes in natives' occupation. Although the most intuitive margin of adjustment regarding an occupational change is an upgrading, I allow for downgrading (i.e transitions from high-skilled to low-skilled occupations). As explained in Subsection 1.3.1, workers are divided in two groups depending

[23] See Section 1.3.1 for more details about education levels in each group.

on their occupation: blue and white collar[24]. Similarly to Borjas (2003a), I estimate the following regression:

$$BW_{i,j,t} = \beta_1 imm_{i,j,t} + \alpha_i^1 + \delta_j^1 + \tau_t^1 + (\alpha_i^1 \times \delta_j^1) + \varepsilon_{i,j,t} \tag{1.11}$$

$$WB_{i,j,t} = \beta_2 imm_{i,j,t} + \alpha_i^2 + \delta_j^2 + \tau_t^2 + (\alpha_i^2 \times \delta_j^2) + \varepsilon_{i,j,t} \tag{1.12}$$

where $BW_{i,j,t}$ ($WB_{i,j,t}$) is the share of blue (white) collar workers in cell defined by education i and experience j that moves to a white (blue) collar occupation at quarter t; $imm_{i,j,t}$ denotes the share of immigrants in the education-experience cell i, j at quarter t; α_i is a vector of fixed effects indicating the cell education attainment; δ_j is a vector of fixed effects indicating the cell years of experience and τ_t denotes times fixed effects.

The coefficient of interest are β_1 and β_2, which are associated with the variable $imm_{i,j,t}$. Their sign and magnitude will be used to test whether immigrant arrivals are correlated with natives occupational upgrading (downgrading). The baseline estimation includes the full sample of workers from 16 to 65 years old but I also report the results when restricting the sample to male workers. The estimated coefficients from Equation (1.11) and (1.12) are displayed respectively in columns (1) and (2) of Table 1.7. First, results suggest that immigration is positively correlated with blue-to-white collar transitions (occupational upgrade). In particular, I find that one percent point increase in the immigration share in a given cell is associated with a 0.07 percentage point increase in the blue-to-white collar transition share [25]. The results are consistent with the estimates found by Llull (2014) for the US. Second, notice that the effects are higher when restricting to male workers.

Regarding natives' downgrading, the estimates in column (2) of Table 1.7 shows that an increase in immigration is associated with a decrease in the white to blue collar transition probability. The estimation is only significant at 5% and it is not statistically significant when restricting the sample to males. All together, the results from Table 1.7 suggest that the immigration is correlated with a natives' specialization pattern to move toward more skilled occupations (upgrading). This result points out the importance of controlling for both time and cells fixed effects when evaluating the impact of immigration. In order to interpret the

[24] See Table 1.10 for details about the classification.

[25] Average blue-white transitions proportion is 3.48%.

Table 1.7: Occupational Change: estimated coefficients

All workers	(1) BW	(2) WB
imm	0.0698***	-0.0720*
	(0.0135)	(0.0364)
Observations	1376	1376
Only males	BW	WB
imm	0.0781***	-0.0474
	(0.0142)	(0.0603)
Observations	1408	1376

Note: Regressions of the share of workers in an education-experience cell moving from blue collar to white collar jobs in a given quarter (BW, in column (1)) and moving from white collar jobs to blue collar jobs (WB, in column (2)) on the share of immigrants in that cell. Both regressions include education, experience and time fixed effects. Standard errors in parentheses. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Source: Spanish Labour Force Survey-Flows (2005-2015).*

magnitude of the coefficient, I compare an economy with the observed immigrant inflows from 2005Q1 to 2008Q1 with a counterfactual economy without immigrant inflows during that period. The evolution of white and blue collar workers is driven by these two difference equations:

$$B_{t+1} = (1 - \eta_t^{BW})B_t + \eta_t^{WB} W_t \tag{1.13}$$

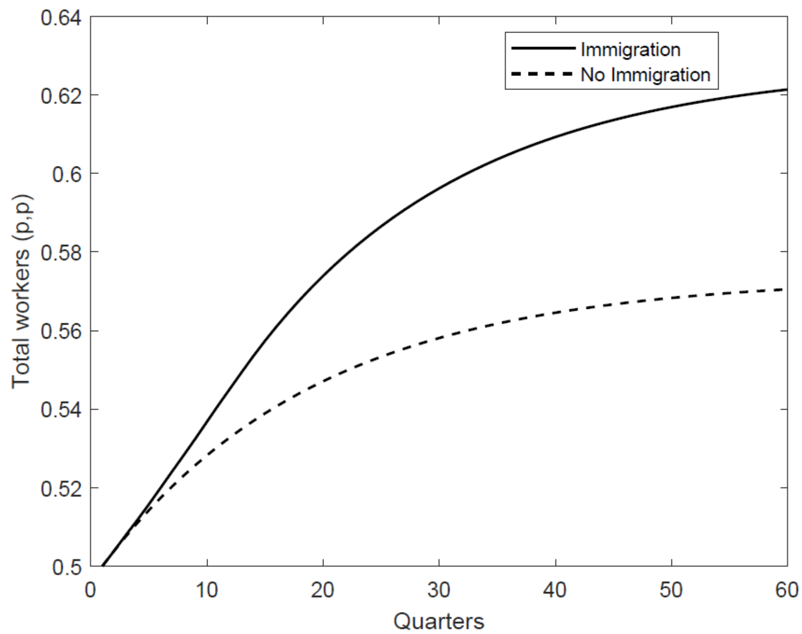
$$W_{t+1} = (1 - \eta_t^{WB})W_t + \eta_t^{BW} B_t \tag{1.14}$$

where η_t^{BW} (η_t^{WB}) denotes the probability of changing from a blue (white) collar occupation to a white (blue) occupation at quarter t. The estimation results from Table 1.7 imply that, according to my model, the probabilities η_t^{BW} and η_t^{WB} are affected by immigration in following fashion:

$$\eta_{t+1}^{BW} = \eta_t^{BW} + 0.0698 \times (imm_{t+1} - imm_t) \tag{1.15}$$
$$\eta_{t+1}^{WB} = \eta_t^{WB} - 0.0720 \times (imm_{t+1} - imm_t) \tag{1.16}$$

Figure 1.15 plots the transition toward the new steady state for the two economies. It suggests that, taking into account successive periods large immigrant inflows, the estimated coefficients from Table 1.7 imply a big change in the white collar proportion.

Figure 1.15: Share of white collar workers: Baseline VS No immigration



Note: The simulation assumes that, initially, workers are uniformly distributed among occupations. The initial probabilities η_0^{BW} and η_0^{WB} are set equal to the whole sample (2005Q1-2015Q4) average BW and WB transitions proportion (0.03 and 0.0223 respectively).

1.5.2 Regional Mobility

The effect of the immigration arrivals on native displacement has been broadly studied in the literature. Many of these studies have focused on the US and on the impact of immigration on residential segregation (Saiz and Wachter (2011)). Why is internal migration a channel we should take into account? Again, we can think of an immigration inflow as an increase in the labour supply in a specific area (region, city, community...). If that increase in the labour supply lowers wages in that area, natives may find it optimal to move to another place. In particular, in this section I test whether immigration is associated with natives' regional mobility. For this purpose I estimate the following regression:

$$emig_{i,j,t} = \beta_1 imm_{i,j,t} + \alpha_i + \delta_j + \tau_t + (\alpha_i \times \delta_j) + \varepsilon_{i,j,t} \tag{1.17}$$

where $emig_{i,j,t}$ is the share native workers in cell defined by education i and experience j that change their region of residence at quarter t; $imm_{i,j,t}$ denotes the share of immigrants in the education-experience cell i,j at quarter t; α_i is a vector of fixed effects indicating the cell education attainment; δ_j is a vector of fixed effects indicating the cell years of experience and τ_t denotes times fixed effects. As before, the coefficient of interest is β_1 which is associated with the variable $imm_{i,j,t}$. The main drawback of the data is that individuals' residence information is limited to regions (*Comunidades Autónomas*) and hence I am not capturing within region movements.

The estimated coefficient from Equation (1.17) is displayed in column (1) of Table 1.8. I find that the correlation between share of immigrants and native internal mobility is not statistically significant. Although the data limitation must be taken into account and robustness checks must be carried out, preliminary evidence points out that internal mobility seems not to be the main natives' adjustment margin to immigrant inflows.

Table 1.8: Internal Migration and Activity: estimated coefficients

All workers	(1) emig	(2) IA	(3) AI
imm	-0.00115	-0.0185	-0.00833
	(0.00259)	(0.0350)	(0.0174)
Observations	1376	1376	1376

Note: Regressions of the share of workers in an education-experience cell moving from changing region of residence in a given quarter (emig, in column (1)); moving from inactivity to activity (IA, in column (2)); and moving from activity to inactivity (AI, in column (3)) on the share of immigrants in that cell. All regressions include education, experience and time fixed effects. Standard errors in parentheses. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Source: Spanish Labour Force Survey-Flows (2005-2015).*

1.5.3 Labour Force Participation

Last, I examine whether immigration is associated with changes in natives' labour force participation. As Farré et al. (2011) point out, the huge increase in the household services supply thanks to the female immigration allowed many Spanish women to take up a job. My analysis, based on the cells approach, is particularly interested in understanding whether their findings can be generalized to a broader framework (since I do not restrict to female workers). I evaluate the correlation between immigration and both activity-to-inactivity (AI) and inactivity-to-activity (IA) transitions through the following two fixed effects regressions:

$$AI_{i,j,t} = \beta_1 imm_{i,j,t} + \alpha_i^1 + \delta_j^1 + \tau_t^1 + (\alpha_i^1 \times \delta_j^1) + \varepsilon_{i,j,t} \tag{1.18}$$

$$IA_{i,j,t} = \beta_2 imm_{i,j,t} + \alpha_i^2 + \delta_j^2 + \tau_t^2 + (\alpha_i^2 \times \delta_j^2) + \varepsilon_{i,j,t} \tag{1.19}$$

where the dependent variable $AI_{i,j,t}$ ($IA_{i,j,t}$) is the share of active (inactive) workers in the cell defined by education i and experience j that move from activity (inactivity) to inactivity (activity) at quarter t. The regressors are defined as in Subsection 1.5.1 and the results are displayed in columns (2) and (3) of Table 1.8. Both estimates are negative but they are not statistically significant, suggesting that immigration is not correlated with natives' changes in their labour force participation.

1.6 Conclusions

This paper documents a number of facts regarding the immigration experience in Spain for the period between 1999 and 2008. Using the Spanish Labour Force Survey-Flows, and administrative data from social security registers, I examine the cyclicality of real wages, job-finding and job-separation rates for immigrants and natives. I find that before the Great Recession (pre-2008) job-finding rates were higher for immigrants than for natives, but after the crisis both rates converged to a lower level. Data shows that job-separation rates were always higher for immigrants than for natives, but the gap increased after the Great Recession. I show that these patterns hold when fixing for worker/job characteristics: ceteris paribus the impact of the Great Recession on the probability of losing a job was twice as high for immigrants than for natives. I find that wage cyclicality is also higher for immigrants: a one percentage point increase in the unemployment rate is associated with a 0.65% drop in natives' real wages and with a 0.95% drop for immigrants. However, differences only occur among low-tenure workers (less than 2 years of tenure in the firm). Overall my results suggest a low degree of real wage sensitivity compared to other developed countries.

The empirical literature studying labour market outcomes of immigrants has commonly highlighted the existence of a gap between immigrant and native workers in terms on employment probabilities and prospective wages. My results confirm this findings. However, they also reveal that the gap can be significantly amplified during a recession, specially regarding unemployment hazard. The literature has also overlook on the sources explaining the unemployment differential between immigrants and natives. Taking the transition rates approach, I present new empirical evidence showing that the differential is mainly due to differences in the job-separation rate.

The empirical evidence provided in this paper might be also useful for policymakers to design targeted policies aimed at mitigating the effect of economic crisis on the unemployment prospect of immigrants, arguably one of the most vulnerable group of workers. In particular, my results confirm that the last recession came along with a dramatic increase in job-separations (and hence unemployment rate) while wages were less sensitive. This apparent dichotomy is specially striking among immigrants. To the extent that a major goal of policymakers is minimizing workers' unemployment risk, promoting wage flexibility or providing firms with an effective tool for adjusting production to economic downturns (which could prevent them from resorting to employment reductions) could be adequate before a new crisis occurs.

This paper is a step forward in understanding the interaction between economic cycles and the impact of immigration. The finding that immigrants were highly sensitive to the last recession may have implications on the overall labour market effect of immigrants. Further research is needed to assess and identify the underlying mechanisms explaining the heterogeneous impact of economic cycles on the labour market performance by nationality, and the implications of this heterogeneity on: (1) the impact of the economic cycle on unemployment and other macroeconomic aggregates; (2) the overall impact of immigrant inflows on natives' labour market outcomes.

1.7 Appendix

Appendix A. Job to Job Transitions

Re-write Equation (3.2), describing the evolution of the stock of employed workers, as:

$$E_{j,t} = \lambda_{j,t}^{UE} U_{j,t-1} + \lambda_{j,t}^{IE} I_{j,t-1} - \underbrace{(1 - \lambda_{j,t}^{EU} + \lambda_{j,t}^{EI})}_{\lambda_{j,t}^{EE}} E_{j,t-1} \tag{1.20}$$

where $\lambda_{j,t}^{EE}$ is the transition probability of moving from employment in quarter $t-1$ to employment in quarter t, for worker of nationality j. We can split this transition probability:

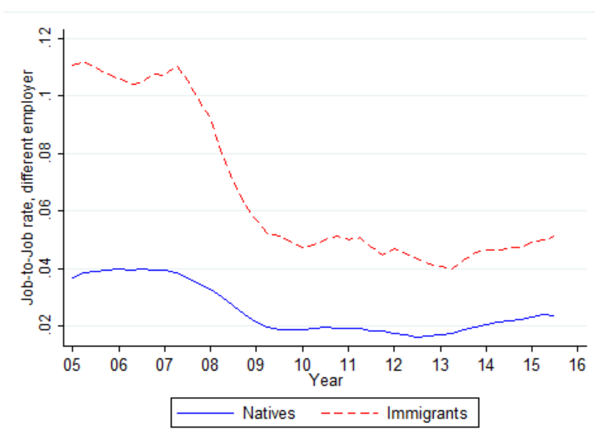
$$\lambda_{j,t}^{EE} = \lambda_{j,t}^{EE_{sf}} + \lambda_{j,t}^{EE_{df}} \tag{1.21}$$

where $\lambda_{j,t}^{EE_{sf}}$ ($\lambda_{j,t}^{EE_{df}}$) is the transition probability of moving from employment in quarter $t-1$ to employment in quarter t with the same (different) employer. Similar to Equation (1.5), these rates are computed as:

$$\text{Job-to jo rate, different employer}: \quad \lambda_{j,t}^{EE_{df}} = \frac{N_{j,t}^{EE_{df}}}{E_{j,t-1}} = \frac{N_{j,t}^{EE_df}}{N_{j,t}^{EU} + N_{j,t}^{EE} + N_{j,t}^{IE}} \tag{1.22}$$

where $N_{j,t}^{XY}$ is the number of workers transitioning from state X to state Y at period t and $N_{j,t}^{EE_{df}}$ is the number of workers transition from employment to employment but with a different in the employer.

Figure 1.16: Job-to-Job transition rate, different employer



Notes: The transitions are seasonally adjusted using a 4-quarters moving average, constructed from the Spanish Labour Force Survey-Flows.

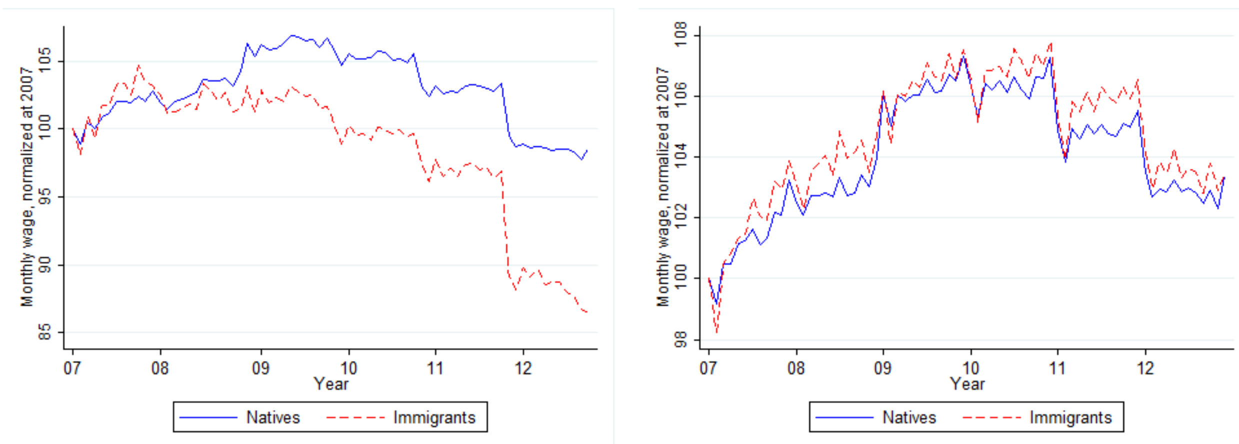
Appendix B. Wage Cyclicality: job-stayers vs rest

I compute the monthly average wage for workers who worked for the same establishment from January 2007 to December 2012, without any unemployment spell or change in employer. The idea is to check whether the drop in the aggregate average wage among immigrant workers also occurred among job-stayers.

Figure 1.17: Normalized monthly real wage by nationality, aggregate vs job-stayers (2007-2012)

Monthly average wage, all workers

Monthly average wage, only job stayers



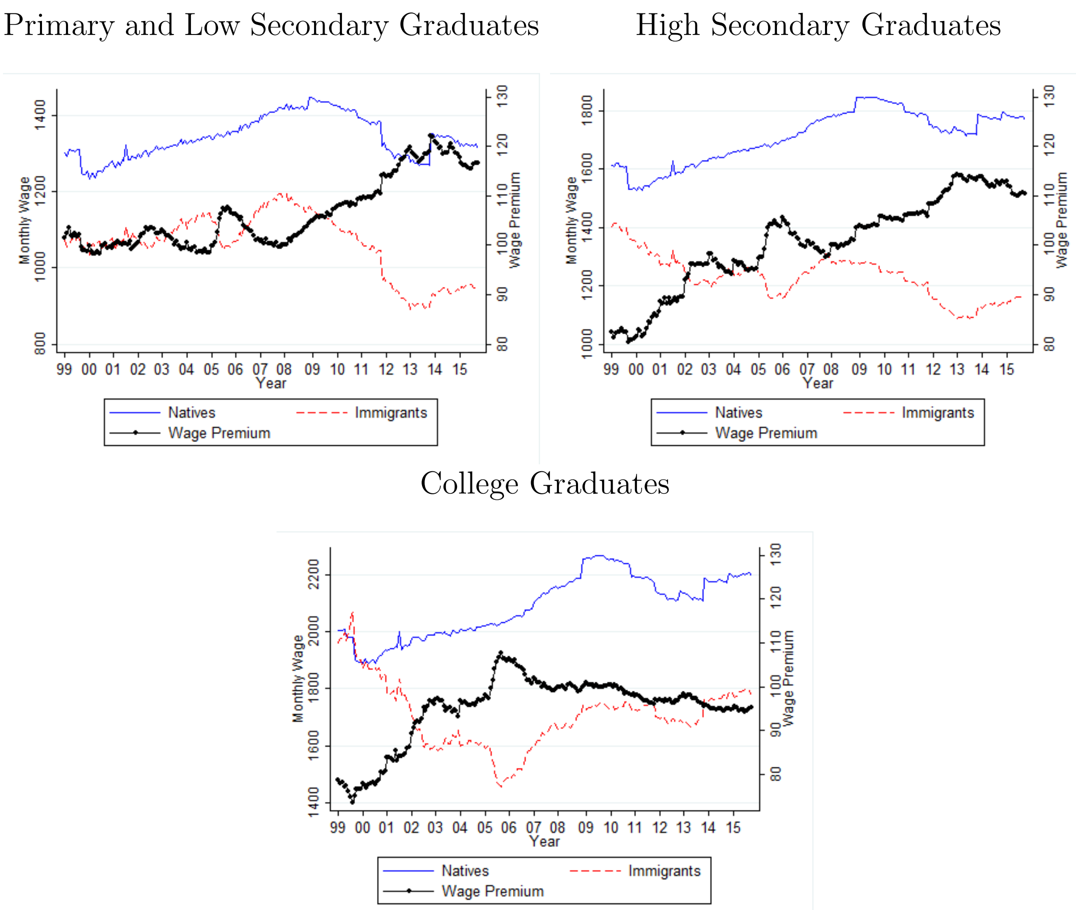
Note: The monthly wages are normalized to 100 at January 2007. Source: MCVL

Figure 1.17 plots the evolution of the monthly average wage for all workers and for job-stayers, from January 2007 to December 2012. For the seek of comparison, I normalize all time series to 1000 at January 2007. From the figure we can see clearly that among job-stayers, average wage of immigrant and natives grew at a very similar rate during the period considered (first years of the Great Recession). In other words, it seems that the drop in the average wage of immigrants is mostly due to job-changers os newly formed jobs.

Appendix C. Wage Cyclicality by worker/job characteristics

Figure 1.18 shows that natives' average real wage is higher than immigrants' for all education groups. The evolution of wages for the two lower educational levels is similar to the aggregate wage. But differences arise among college graduates: (1) the wage premium is lower, around 30% for the period 2002-2015 (Figure 1.24 in Appendix D)); (2) wages reacted less to the Great Recession than on aggregate, as both immigrant and native average wage continued growing after 2008. This can be seen in the bottom panel of Figure 1.18, as the wage premium remained almost constant (it decreased slightly) during the last recession (mid 2008 to 2015), while for the other education groups (top panel) it increased.

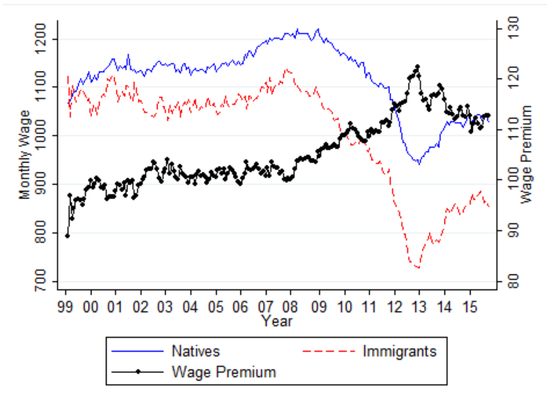
Figure 1.18: Monthly average wage by nationality and education attainment



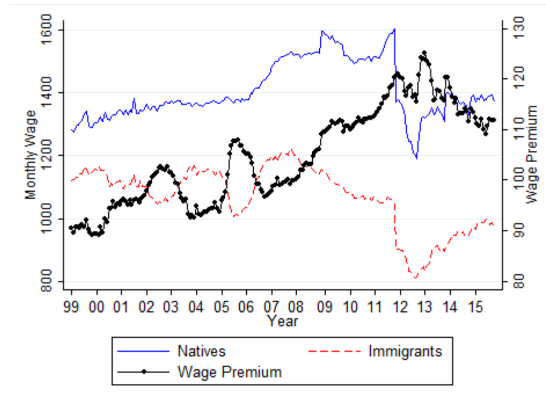
Note: The wage premium is computed as $(\bar{w}_{N,t}/\bar{w}_{M,t}-1)$, where $\bar{w}_{j,t}$ is the monthly average wage for natives $j = N$ and immigrants $j = M$ at month t. Wage premium is normalized to 100 at 2008Q1. Wages are seasonally adjusted by taking out the coefficient of the monthly dummies from an OLS regression. Source: MCVL.

Figure 1.19: Monthly average wage by nationality and tenure

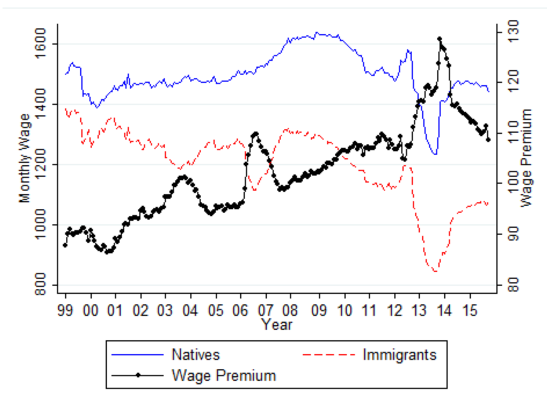
Newly-hired



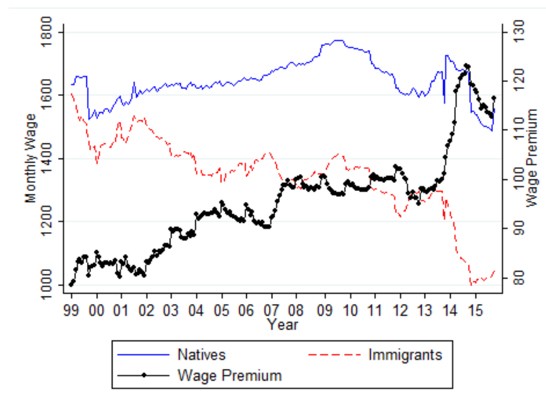
Job-movers



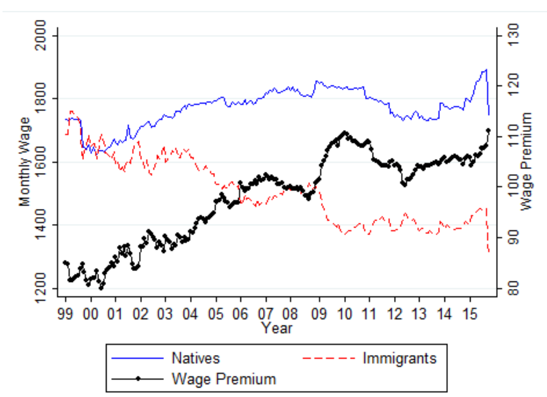
1-2 years



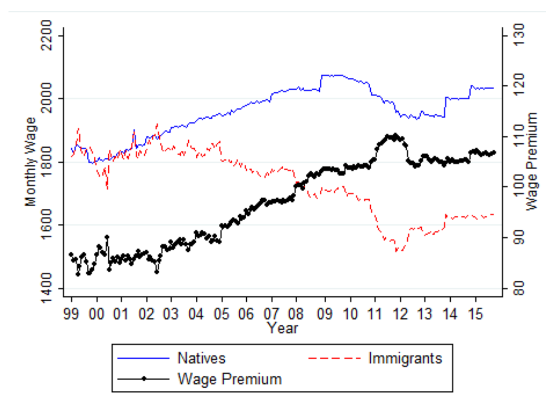
2-4 years



4-6 years



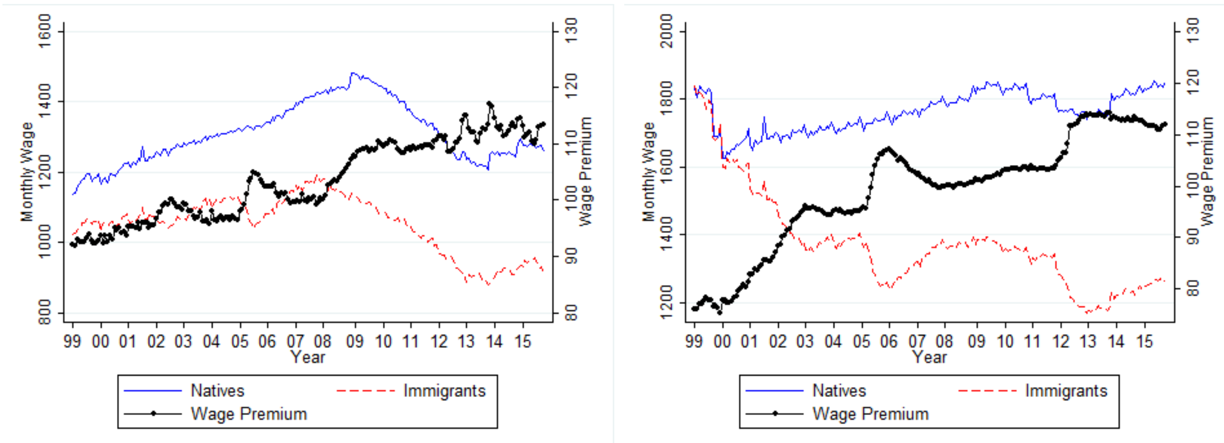
More than 6 years



Note: The wage premium is computed as $(\bar{w}_{N,t}/\bar{w}_{M,t}-1)$, *where* $\bar{w}_{j,t}$ *is the monthly average wage for natives* $j = N$ *and immigrants* $j = M$ *at month* t. *Wage premium is normalized to 100 at* 2008*Q*1. *Wages are seasonally adjusted by taking out the coefficient of the monthly dummies from an OLS regression. Source: MCVL.*

Figure 1.20: Monthly average wage by nationality and type of contract

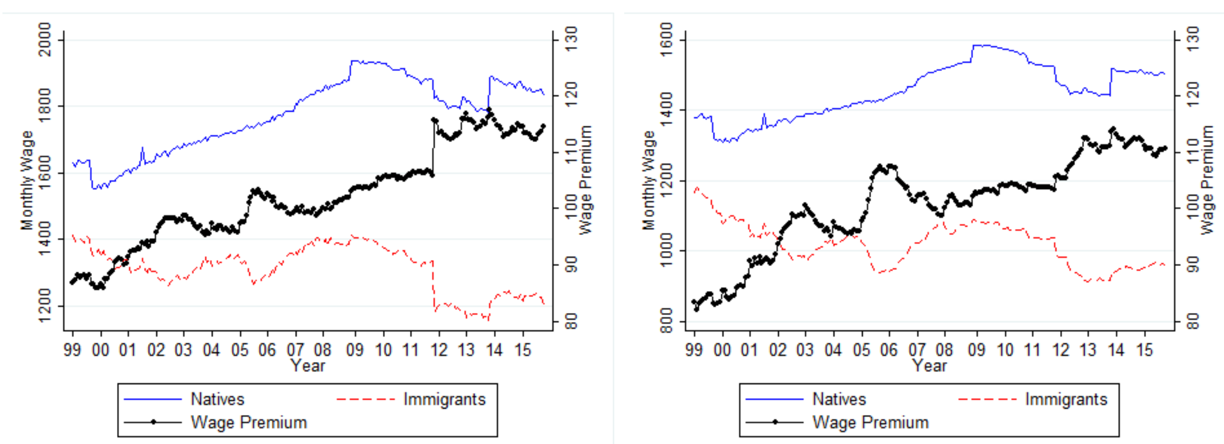
Temporary contracts Permanent contracts



Note: The wage premium is computed as $(\bar{w}_{N,t}/\bar{w}_{M,t} - 1)$*, where* $\bar{w}_{j,t}$ *is the monthly average wage for natives* $j = N$ *and immigrants* $j = M$ *at month* t*. Wage premium is normalized to 100 at* 2008Q1*. Wages are seasonally adjusted by taking out the coefficient of the monthly dummies from an OLS regression. Source: MCVL.*

Figure 1.21: Monthly average wage by nationality and gender

Male Female



Note: The wage premium is computed as $(\bar{w}_{N,t}/\bar{w}_{M,t} - 1)$*, where* $\bar{w}_{j,t}$ *is the monthly average wage for natives* $j = N$ *and immigrants* $j = M$ *at month* t*. Wage premium is normalized to 100 at* 2008Q1*. Wages are seasonally adjusted by taking out the coefficient of the monthly dummies from an OLS regression. Source: MCVL.*

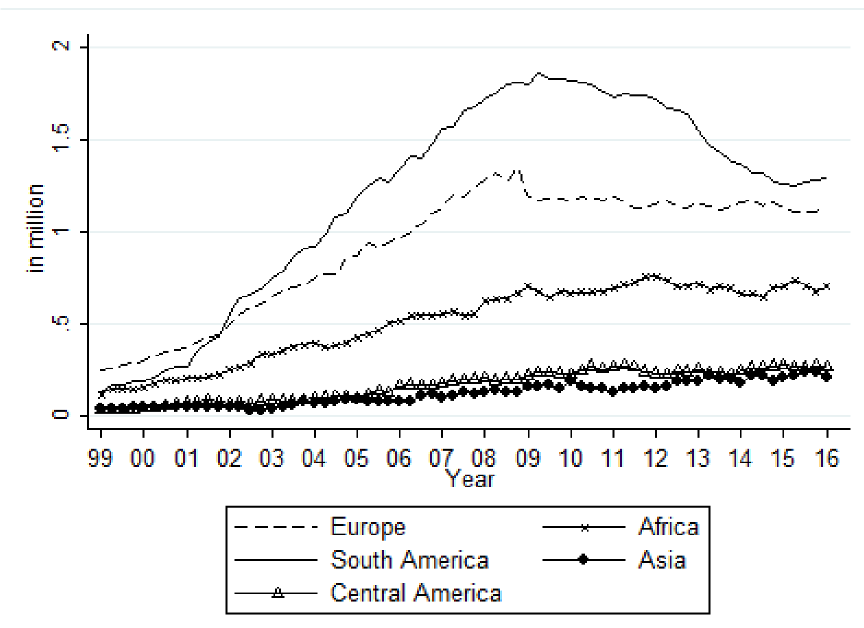
Appendix D. Other Figures and Tables

Table 1.9: Immigrant Workers by Country

	1999-2004	2005-2007	2008-2013	2014-2016
Country				
Morocco	14.55%	12.35%	11.45%	12.59%
Romania	2.49%	8.35%	11.96%	11.01%
Ecuador	7.30%	9.60%	7.30%	6.85%
UK	6.10%	5.81%	5.90%	4.59%
Colombia	5.35%	6.01%	5.56%	5.79%
Argentina	5.12%	5.56%	4.44%	4.11%
Germany	7.48%	4.31%	3.80%	3.01%
France	7.89%	4.13%	3.48%	3.32%
Bolivia	0.65%	3.00%	3.33%	2.79%
Peru	2.38%	2.54%	2.90%	3.01%
China	1.41%	2.07%	2.32%	2.88%

Note: Country of foreign-born workers that are actively participating in the labour market. Source: Spanish Labour Force Survey.

Figure 1.22: Stock of Immigrant Workers by Region of Country



Source: Spanish Labour Force Survey.

Table 1.10: Blue Collar - White Collar Classification

A. Blue Collar
Skilled agricultural and fishery workers
Craftsmen
Plant and machine operators and assemblers
Elementary occupations
B. White Collar
Legislators, senior officials and managers
Professionals
Technicians and associate professionals
Clerks
Service workers and shop and market sales workers

Note: groups are based on the International Standard Classification of Occupations (ISCO-88)

Table 1.11: Immigrants and Natives Characteristics

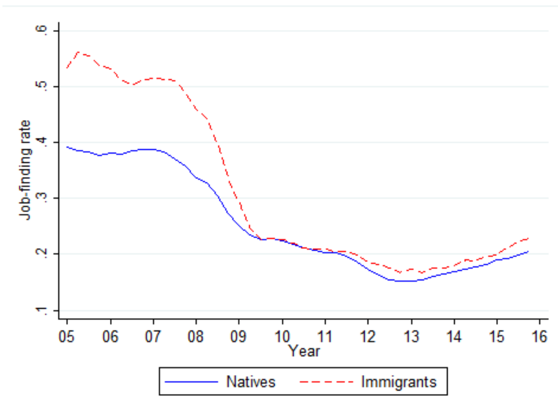
	Natives			Immigrants		
	Pre-crisis	Crisis	Post-crisis	Pre-crisis	Crisis	Post-crisis
Male	56.23%	51.36%	50.86%	59.97%	53.30%	52.33%
Average age	39.62	40.62	41.40	34.52	35.74	37.32
Education						
Primary and low Sec	47.58%	45.11%	44.56%	65.48%	64.23%	66.11%
High secondary	31.57%	30.11%	29.42%	24.98%	22.72%	20.02%
Tertiary	20.85%	24.78%	26.02%	10.54%	13.05%	13.88%
Temporary rate	42.05%	29.76%	29.87%	62.32%	47.13%	42.94%
Sectors						
Agriculture	0.80%	0.71%	0.68%	1.49%	1.36%	1.69%
Industry	17.15%	14.63 %	14.98%	12.31%	10.78%	12.04%
Construction	11.47%	7.08%	4.43%	22.74%	12.12%	6.59%
Services	70.58%	77.59%	79.91%	63.46%	75.73%	79.68%
Monthly Wage	1614.38	1710.06	1711.39	1244.10	1172.99	1101.82

Source: MCVL

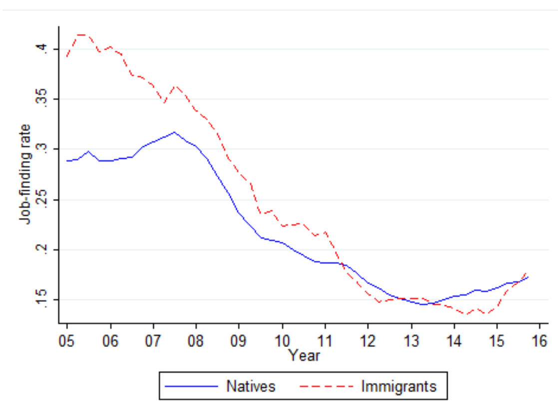
Figure 1.23: Labour market transitions by nationality and gender

Panel A: Job-finding Rate

Male

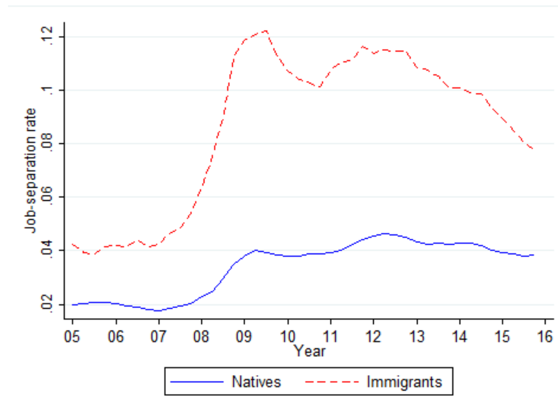


Female

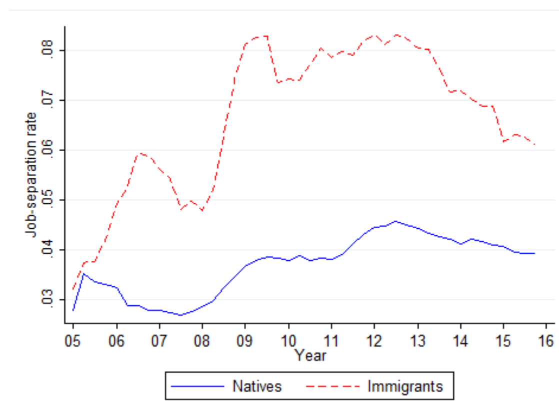


Panel B: Job-separation Rate

Male

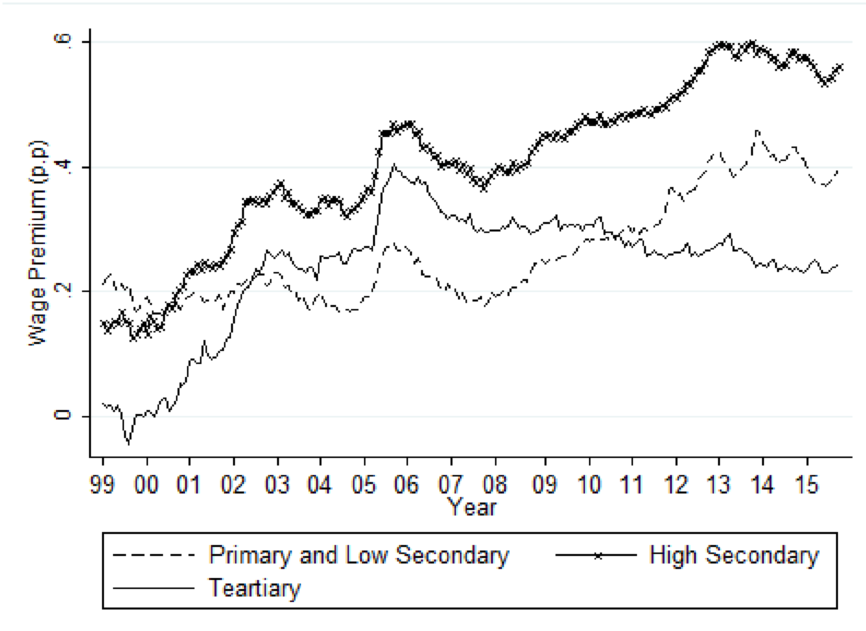


Female



Note: The transitions are seasonally adjusted using a 4-quarters moving average, constructed from the Spanish Labour Force Survey-Flows.

Figure 1.24: Wage premium by education attainment



Note: The wage premium is computed as $(\bar{w}_{N,t}/\bar{w}_{M,t} - 1)$*, where* $\bar{w}_{j,t}$ *is the monthly average wage for natives* $j = N$ *and immigrants* $j = M$ *at month* t*. Source: MCVL*

Figure 1.25: Wage premium by tenure group

Low-tenure groups

High-tenure groups

Note: The wage premium is computed as $(\bar{w}_{N,t}/\bar{w}_{M,t} - 1)$*, where* $\bar{w}_{j,t}$ *is the monthly average wage for natives* $j = N$ *and immigrants* $j = M$ *at month* t*. Source: MCVL*

Table 1.12: Wage cyclicality for selected samples, single regression with a dummy for nationality

	Natives	**Immigrants**
All workers	-0.640***	-1.107***
Newly-hired	-1.509***	-2.010***
Job-movers	-1.227***	-1.785***
1-2	-0.757***	-1.188***
2-4	-0.208	0.105
4-6	-0.248*	-0.125*
More than 6	-0.339***	-0.354***
Observations (first stage)	60,005,705	5,514,405

Note: Estimation results of the coefficient ϕ_1 in Equation (1.10). Each coefficient is a separate second stage regression of the estimated year-quarter coefficients on the yearly-lagged quarterly unemployment rate. All second stage regressions have 67 quarterly observations (1999:1 to 2015:4) and include a constant term, a linear time trend and quarter indicators. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source: MCVL.

Chapter 2

The Role of Immigration in a Deep Recession

2.1 Introduction

The increase in the foreign-born population is one of the main socio-economic changes in many developed countries in the last decades. In the United States, the share of foreign-born population increased from 9.2% in 1990 to 14.3% in 2010. More striking examples can be found in Europe. In Italy, over the same time span, the share of foreign residents rose from 2.5% to 9.7%, whereas in Spain it increased from 2.1% to 14.4%. In these economies the Great Recession took place in such context of large immigrant inflows. Resulting from rigid labour markets, in Spain or Italy the contraction of economic activity triggered by the Great Recession led to a large increase in unemployment instead of wage reductions. Many papers have tried to estimate the impact of immigration on the labour market outcomes of the host country (some examples include Borjas (2003b), Card (2005), Ottaviano and Peri (2012), Chassamboulli and Palivos (2014), Battisti et al. (2017), Dustmann et al. (2017))[1]. However, most of these papers either abstract from search frictions or focus on stationary environments and, consequently, little is known on how this impact depends on the economic cycle.

This paper studies the impact of a high share of foreign-born workers on rigid labour markets during a recession. I document two empirical facts for the Spanish economy. First, I provide evidence that the Great Recession affected job-finding and job-separation rates differently for immigrant and native workers. In particular, I find that the effect of the crisis on the probability of losing a job was twice as high for immigrants than for natives.

[1] See Kerr and Kerr (2011) or Edo (2019) for recent surveys.

Second, I document that foreign outflows were very responsive to the Great Recession as many immigrants left the country. Then, I build a random search model of the labour market featuring vacancy persistence, endogenous return migration[2] and downward wage rigidity[3] that captures these empirical facts. I use the model to quantify by how much the native unemployment rate would have increased during the Great Recession in the absence of the pre-crisis immigration boom. I also use the framework to understand the underlying channels explaining the results.

The first contribution of the paper is to quantify the impact of immigration on the labour market using a frictional search model with out-of-steady state dynamics. By incorporating the study of immigration in non-stationary environments, I allow this impact to depend on the economic cycle. Two ingredients are key to generate effects of immigration on the native unemployment rate during a recession. The first ingredient is vacancy persistence: in the model, if an employed worker leaves the country or she is fired, her job will continue to exist and the firm could post it again. The second ingredient is the heterogeneity between immigrants and natives, coming from three sources: (1) representing the large foreign outflows, immigrants can leave the country at every period; (2) immigrants' unemployment flow payments are lower; (3) immigrants and natives draw their match quality from different distributions. In the model, production is given by the sum of aggregate productivity and a match quality component, which is drawn after a firm meets a worker. I allow the distribution of match quality draws to differ for immigrants and natives in order to pin down both the native wage premium and the job-separation gap between them. With these two ingredients (vacancy persistence and immigrants-natives heterogeneity), the model embeds three channels through which immigration affects the native unemployment rate during a recession. The first is the *job-creation effect*: as search is random and there is heterogeneity between immigrants and natives, the share of immigrants among job-searchers affects firms' job creation decisions. The second is the *return-migration effect*: unemployed immigrants' return migration affects firms' job-creation whereas employed immigrants' return migration increases the stock of existing jobs. The third is the *match-destruction effect*: since the impact of the recession on job-separation is higher for immigrants than for natives, the share of immigrants among the employed affects the stock of existing jobs on impact. A quantitative exercise in a calibrated model determines the sign and magnitude of each of the channels.

[2]Throughout the paper I indistinctly use the terms return migration and foreign outflows to refer to the flow of foreign-born workers leaving the country.

[3]There is large evidence of downward wage rigidity in the Spanish labour market. For instance, Font et al. (2015) and De la Roca (2014) find that real wages are weakly pro-cyclical in Spain, specially in recessions. Gálvez-Iniesta (2020) also finds small wage responses during the Great Recession for both immigrants and natives. In Section 2.8.1 I show that relaxing partially this assumption does not change the main results of the paper.

The second contribution of the paper is introducing vacancy persistence (Pries and Rogerson (2005)) into a model with endogenous return migration, which turns out to be key for the quantitative results. By incorporating a notion of capital in the model, vacancy persistence allows us to distinguish between worker and job-turnover and helps the model to deliver realistic dynamics of the job-finding rate during the Great Recession. These dynamics would not be captured in the standard model with free-entry condition where vacancies adjust immediately to a negative shock. Importantly, it makes the effects of immigration long-lasting: the employed immigrants' *return-migration* and *match-destruction* channels of immigration would be ignored in the standard model.

Although the methodology could be extended to other economies, I specialize the discussion to the Spanish case for three main reasons. On the one hand, as the left panel in Figure 2.1 shows, Spain experienced large foreign inflows during the expansion, raising the foreign-born population share from barely 4% at the end of the 90's to more than 14% only ten years later[4]. On the other hand, with the economic slowdown foreign inflows dramatically decreased while foreign outflows steadily increased[5]. Lastly, Spain experienced a sizeable employment destruction in the Great Recession that was even higher for the immigrant population (see right panel of Figure 2.1). In sum, the emergence of a deep recession in the context of a large immigrant share makes the Spanish economy a particularly interesting case of study for the purpose of the paper.

I calibrate the model for the low-skilled segment of the Spanish labour market[6]. The focus on this segment is motivated by two facts. First, immigrants are concentrated among the low-skilled, which implies that the potential effects of immigration should be quantitatively larger in that segment. Second, return migration was also higher among the low-skilled. I show that the model's performance in the Great Recession is consistent with the previously mentioned empirical facts, as the model captures: (1) the higher increase in the job-separation rate for immigrants than for natives; (2) the drop of the immigrant share by delivering realistic immigrants' outflows. On top of that, it also generates the observed smooth decrease of the job-finding rate.

In the first part of the quantitative analysis I use the model to quantify by how much the native unemployment rate would have increased during the Great Recession in the absence of the pre-crisis immigration boom. For that aim, the model is first solved in two

[4]See Izquierdo et al. (2015b) for a recent exhaustive description of the historical migration process.

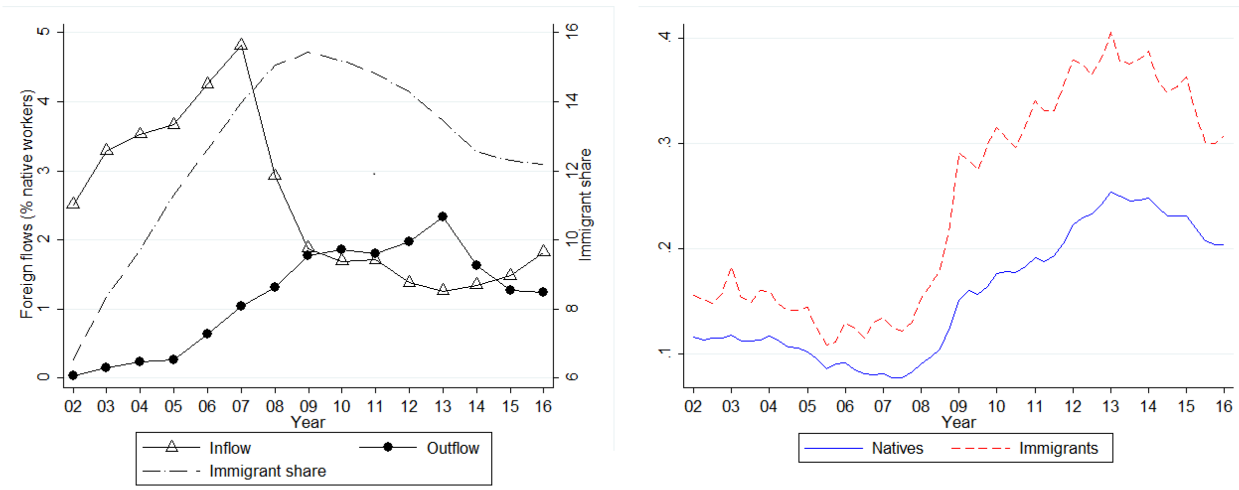
[5]Prieto et al. (2018) already described the immigrants' internal and international migration responses during the Great Recession. They study how different forms of international migration (return migration and remigration) depend upon the demographic characteristics of the immigrant. However, because of data limitations they abstract from education heterogeneity.

[6]Following Battisti et al. (2017) and Krusell et al. (2000), high-skilled labour is defined as requiring college completion (or equivalent) or above.

Figure 2.1: Trends in the Spanish Immigration Experience

Foreign Flows and Immigrant Share

Unemployment Rate



Source: Unemployment rates from the Spanish Labour Force Survey. Foreign flows and immigrant share from the Spanish Migration Statistic.

steady-states. In the first one, aggregate productivity is high and wages are Nash-bargained. At the final state, aggregate productivity is lower and wages cannot be adjusted. I then compute the transition path between steady-states, where again wages cannot be changed, for two economies: (1) baseline economy, with the observed pre-crisis immigration boom; (2) counterfactual economy, without foreign inflows during the pre-crisis period.

I find that the native unemployment rate would have been substantially higher in this counterfactual scenario of no immigration, compared to the baseline economy. The largest difference is reached three years after the shock, when the natives' unemployment rate is three percentage points higher in the counterfactual economy than in the baseline. The reason is that the drop of the job-finding rate is more moderate in the baseline than in the no immigration economy. The model also predicts that unemployed native workers are the ones who benefit most from the presence of immigrants, as they are more directly affected by the higher job-finding rate.

I also use the framework to disentangle the relative importance of each of the channels by which immigrants affect the labour market during the crisis. The model suggests that the job-creation effect is negative but small. This is a calibration outcome: in order to pin down the native wage premium and the job-separation gap between immigrants and natives, the calibration implies that match quality draws are more concentrated and have a lower mean for immigrants than for natives. Yet, a decomposition analysis reveals that return-migration and match-destruction effects are positive and dominate the job-creation effect, implying overall welfare gains for native workers. In fact, I find that immigrants' return-migration is quantitatively the most relevant channel: in the short-run and long-run, the impact of return-migration is 10 and 2 times as large as the sum of the impact of the other two channels.

Finally, I conduct some robustness checks. First, I investigate the role of wage rigidity in explaining the results. I show that introducing a certain degree of wage flexibility does not affect the model' performance in the Great Recession. Moreover, the predictions of the main counterfactual are unaffected. Second, I explore the validity of the results when conducting an alternative calibration strategy. In particular, following Battisti et al. (2017) or Albert (2019), I assume that the native wage premium is pinned down by differences in the workers' bargaining power instead of by differences in the mean of the distribution of match quality draws. I find that in this case the sign of the job-creation effect of immigration becomes positive. This is intuitive, as now firms can extract a higher share of the match surplus out of immigrant workers. However, the results shows that magnitude of the job-creation effect is small and thus the quantitative results of the main counterfactual experiment still hold.

Literature Review and Contribution

This paper primarily relates to the literature that estimates the impact of immigration on the labour market in a frictional environment. My contribution to this literature is incorporating the study of immigration in a frictional model with out-of-steady state dynamics. In a model with search frictions, Chassamboulli and Palivos (2014) study the effect of a skill-biased immigrant inflow, allowing for heterogeneous effects for low and high-skilled natives. They find that skill-biased immigration raised the overall net income to natives. Also, while unskilled native workers gain in terms of both employment and wages, skilled natives gain in terms of employment but may lose in terms of wages. Using a similar framework, Battisti et al. (2017) add a welfare state and analyse the welfare effect of a marginal increase in immigration. They conduct their quantitative analysis for a large set of countries. They find welfare gains for both skilled and unskilled native workers in two thirds of the countries. Interestingly, for Spain they find welfare losses for the unskilled native workers when the marginal increase of immigration is all made up of unskilled immigrants. Other related work, such as Chassamboulli and Peri (2015) or Albert (2019), highlights the importance of the different effect of documented and undocumented immigration. In Chassamboulli and Peri's (2015) model, immigrants (especially illegal ones) have a worse outside option than natives, so their wages are lower. Hence, their presence boosts firms' job creation. They find that tightening border control weakens low-skilled labour markets, increasing the low-skilled native workers' unemployment. Albert (2019) introduces non-random hiring in his model. This gives rise to a competition effect of immigration which implies that the wage difference between natives and immigrants determines whether immigration is beneficial for natives or not. He finds that documented immigration reduces natives' employment, whereas undocumented immigration generates gains in terms of both employment and wages for native workers. While all these papers stress the relevance of accounting for labour market frictions when analysing the effect of immigration, they focus on steady-state comparisons. As stated above, I add to this literature by embedding the analysis of immigration in a context of recession. Moreover, my paper also contributes by incorporating wage rigidity into the analysis.

My paper is also related to the literature studying whether immigrants' mobility smooths labour market adjustments. Cadena and Kovak (2016) use data on low-skilled Mexican-born immigrants in the US. They leverage the substantial geographic variation in labour demand during the Great Recession to identify migration responses to local shocks. They demonstrate that Mexican-born immigrants' high mobility reduced the incidence of local demand shocks on natives. With a similar identification strategy, Basso et al. (2018) use Euro Area data and also find that foreign workers' mobility (which is strongly pro-cyclical) reduces the variation of overall employment rates over the business cycle. My contribution is to incorporate this channel in a general equilibrium model and to quantify its impact at facilitating labour market adjustments[7].

Finally, the paper draws upon the literature on vacancy persistence. Fujita and Ramey (2007) emphasize the excessively rapid responses of vacancies to productivity shocks in the standard search and matching model with free entry, and show that the introduction of vacancy persistence improves the dynamics of the standard model[8]. More recently Acharya and Wee (2018) assume costly entry to study the issue of replacement hiring. I add to this literature by showing that the interaction between vacancy persistence and return migration can deliver very interesting implications regarding labour market adjustments during a recession. In particular, I show that due to vacancy persistence, immigrants leaving the labour market in a context of no-job creation (recession) have a positive effect on the evolution of the job-finding rate.

The rest of the paper is organized as follows: Section 2.2 documents the labour market

[7]Notice that those papers focus on local labour markets and therefore they analyse the role of regional mobility. Since here I model the labour market of the country as a whole, I focus on international mobility. Nevertheless the intuition and the mechanisms of the channels should be similar. See Conclusions for a broader discussion.

[8]See Elsby et al. (2015b) for a recent survey on the topic

and mobility behaviour of the immigrant population in Spain during the Great Recession. Section 2.3 outlines the quantitative model, which is solved and calibrated in Sections 2.4 and 2.5, respectively. Section 2.6 examines the model's performance, and Sections 2.7 and 2.8 describe the counterfactual experiments. Finally, Section 2.9 concludes.

2.2 Empirical Evidence

This section reviews the labour market and mobility behaviour of the immigrant population in Spain during the Great Recession. In particular, I document the following facts:

- Immigrant workers were more affected than natives by the onset of the crisis, mainly due to differences in the evolution of their job-separation rates: the increase in the job-separation rate was higher for immigrants than for natives.

- Migration flows were more responsive among immigrants than natives: foreign inflows dropped and foreign return migration increased with the advent of the crisis, whereas natives did not emigrate that much.

These two facts motivate the quantitative analysis of Section 2.3, and they will also be used for the calibration in Section 2.5.

2.2.1 The Data

I use data from the Spanish Labour Force Survey-Flows (SLFS-Flows) from 2005Q1 to 2016Q1. The Labour Force Survey is a quarterly representative survey of about 65,000 households, consisting of around 180,000 individuals. The sample is divided into six waves (rotation groups) and every quarter one wave is replaced by a new one. This allows us to track each individual for five successive quarters (one year and a half). The survey asks respondents about their labour market status and job characteristics (occupation, sector or type of contract) as well as personal and demographic information (gender, age, education, nationality, marital status, region of residence, etc.). See Silva and Vázquez-Grenno (2013) for more details on the survey. I use 2005 as the first year of the analysis since in the previous years the longitudinal dimension of the survey did not provide information about nationality[9]. Following Battisti et al. (2017) and Krusell et al. (2000), low skilled labour is defined as requiring less than college completion (or equivalent).

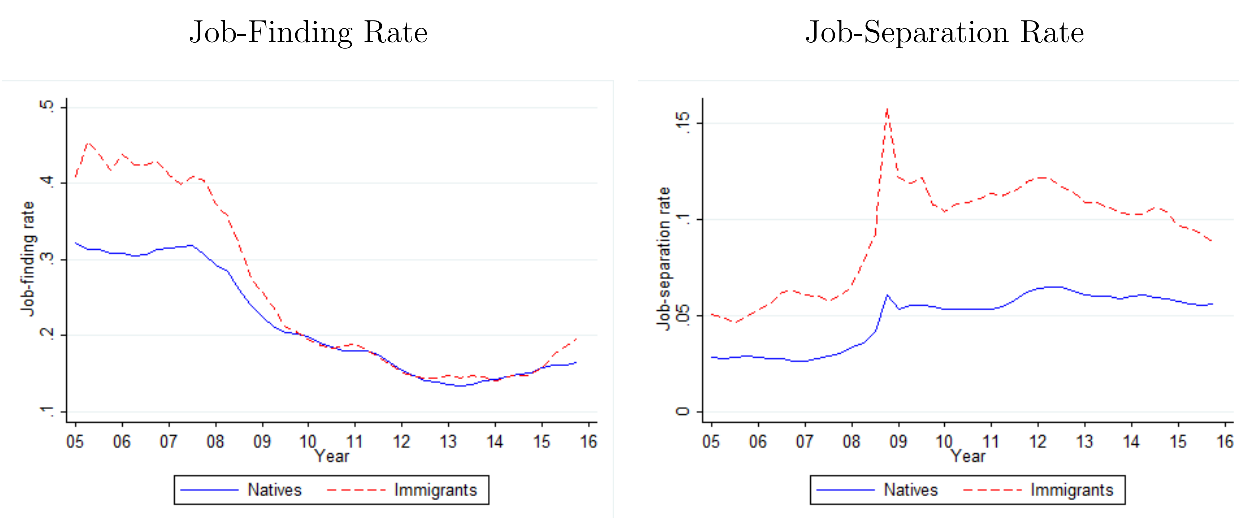
[9]The Spanish Labour Force Survey-Flows (SFLS-flows) is the longitudinal version of the standard cross-section version of the Spanish Labour Force Survey (SLFS). That is, the SLFS-Flows is contracted based on the cross-sectional SLFS. While the cross-section version provides both information on country of birth and nationality, the SPLS-Flows only provides the nationality.

2.2.2 Labour Market Transitions By Nationality

With this data, we can construct job-finding and job-separation rates by nationality[10]. The job-finding (separation) rate is defined as the quarterly probability of transiting from unemployment (employment) to employment (unemployment).

The left panel of Figure 2.2 plots the series of the low-skilled job-finding rate (UE transitions) for immigrant and native workers. Before the crisis, the job-finding rate was higher for immigrants than for natives. However, both rates converged very fast after 2008.

Figure 2.2: Transition rates of low-skilled workers



Note: The transitions are seasonally adjusted using a 4-quarters moving average, constructed from the Spanish Labour Force Survey-Flows.

Regarding the evolution of the job-separation rate (EU transition), the right panel of Figure 2.2 shows two interesting patterns. First, before the crisis immigrants already had a higher probability of losing their jobs than natives. Second, the differential substantially increased from 2008. These two figures suggest that the immigrants' transition probabilities were more sensitive to the outset of the crisis. Nonetheless, they should be viewed with caution as these differences may be just due to differences in experience, sector composition, or type of contract (as immigrants are younger, work more as temporary workers, and were more concentrated in the construction sector)[11].

[10]Rates are computed conditional on staying in the country. That is, if a worker transits from employment to unemployment and then moves out of the country within the same quarter, that job-separation does not add to the job-separation rate. Consequently, the constructed series of immigrants' job-separation rates can be seen as a lower bound of the actual job-separation rates.

[11]See Gálvez-Iniesta (2020) for an overview of the descriptive statistics of natives and immigrants. In

In order to test whether the different impact of the crisis on the employment transitions of immigrants and natives also exists between comparable workers, I estimate the following regressions:

$$Pr\left(UE_{i,t}=1\right)=\Phi\left(\beta_0+\beta_1^{m}imm_i+\beta_1^{c}crisis_t+\beta_1^{mc}imm_i*crisis_t+\boldsymbol{\delta}_1\boldsymbol{X}_{i,t}^{1}\right) \tag{2.1}$$

$$Pr\left(EU_{i,t}=1\right)=\Phi\left(\beta_2+\beta_2^{m}imm_i+\beta_2^{c}crisis_t+\beta_2^{mc}imm_i*crisis_t+\boldsymbol{\delta}_2\boldsymbol{X}_{i,t}^{2}\right) \tag{2.2}$$

where $UE_{i,t}$ ($EU_{i,t}$) is a dummy variable defined only for the unemployed (employed) and takes value 1 if a job is found (lost) at time t and 0 otherwise; imm_i is a dummy variable that takes the value 1 if the worker is an immigrant and 0 otherwise[12]; $crisis_t$ is a dummy variable that takes the value 1 for the time interval 2008Q3-2013Q2 [13] and 0 otherwise; $\boldsymbol{X}_{i,t}^{1}$ is a vector of control variables that includes dummies for education, experience, marital status, age, gender, region of residence, sector of activity[14], type of contract (permanent or temporary), type of job (full or partial time) and year fixed effects. Φ is the cumulative distribution function for the standard normal distribution, indicating that I will estimate probit models.

The coefficients of interest are β_1^{mc}, β_2^{mc}, which are associated with the interaction term of the variables imm_i and $crisis_t$. Their sign and magnitude will be used to test whether the probability of finding (losing) a job during the crisis differed among immigrant and native workers. The results of the estimation of Equations (2.1) and (2.2) are shown in Table 2.1.

As expected, the impact of the crisis on the probability of finding (losing) a job is negative (positive) and significant. More interestingly, the results in column (2) of Table 2.1 confirm the pattern seen in Figure 2.2: even for comparable workers, there is evidence that during the crisis the probability of losing a job increased more for immigrants than for natives. Regarding the UE transition, the results in column (1) suggest that the crisis also decreased by a larger amount the probability of finding a job for immigrants than for natives.

Given the non-linear nature of the probit model, the estimated coefficients of Table 2.1 tell us little about the magnitude of the effect. To overcome this drawback, I compute both the adjusted predictions at mean (APMs) and the marginal effect (ME). The results

there, I also perform an exhaustive analysis of the evolution of the job-finding and the job-separation rate of immigrants' and natives' workers by different categories (education, experience and sector). I show that the patterns described above hold for any category.

[12]The survey does not provide the worker's country of birth, so we define immigrants as workers with foreign nationality.

[13]I chose this time span since 2008Q3 and 2013Q2 are the first and the last quarter with a negative quarterly growth rate of real GDP, respectively (ignoring two quarters in 2010 with slightly and temporarily positive rates).

[14]In case of unemployment, the sector of activity is the sector where the worker was last employed.

Table 2.1: Probit estimation of UE and EU transitions

	(1) UE	(2) EU
Crisis (*crisis*)	-0.308***	0.190***
	(0.0456)	(0.0203)
Immigrant (*imm*)	0.0844	0.058**
	(0.0515)	(0.0208)
Immigrant*Crisis ($imm * crisis$)	-0.111**	0.104***
	(0.0553)	(0.02756)
Observations	108594	1385262
R-squared	0.033	0.156

Note: Regressions of dummy variables for the transition from unemployment to employment (UE, in column (1)) and from employment to unemployment (EU, in column (2)) on dummies for crisis, migration status and the interaction term of the last two. Both regressions includes controls for education, experience, marital status, age, gender, region of residence, sector of activity, type of contract, type of job and year. Standard errors in parentheses. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. *Source: Spanish Labour Force Survey-Flows (2005-2016).*

are displayed in Table 2.2. Panel A shows the results for the model where the dependent variable is the transition from unemployment to employment (UE). The interpretation of the adjusted predictions goes as follows: according to the model, before the crisis the probability of finding a job for an average individual with native nationality was 21.9%, while if the same individual was immigrant that probability would be higher (23.5%). In other words, before 2008, *ceteris paribus*, the probability of finding a job was higher for immigrants than for natives. However, in the crisis, the job-finding probability is lower for immigrants than for natives: 12.7% and 14.0% respectively. The last column displays the marginal effect, which is the change in the probability of finding a job for each of the two groups when the crisis hit. From the previous discussion we already know that the marginal effect is more negative for immigrants: -10.8 pp. for immigrants and -7.9 pp. for native workers.

Panel B of Table 2.2 shows the results regarding the job-separation rates. The model predicts that before the crisis the probability of losing a job for an average individual with native nationality was 0.96% while if the same individual was an immigrant that probability would be 1.17%. During the crisis, losing the job becomes more likely for both groups, but the increase is higher for immigrants than for natives: the probabilities of moving from employment to unemployment are now 1.58% and 2.43% for natives and immigrants, respec-

Table 2.2: Adjusted Predictions and Marginal Effect

Panel A: Probability finding a job (UE)	crisis = 0	crisis = 1	Marginal Effect
Native	21.92%	13.95%	-7.97^{***}
Immigrant	23.46%	12.67%	-10.79^{***}
Panel B: Probability losing a job (EU)	crisis = 0	crisis = 1	Marginal Effect
Native	0.96%	1.58%	0.62^{***}
Immigrant	1.17%	2.43%	1.26^{***}

Note: Adjusted Predicted probabilities and Marginal Effects computed by the probit model. Panel A uses 108,594 observations. Panel B uses 1,385,262 observations. Significance level: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

tively. As the last column of Table 2.2 shows, the marginal effect of the crisis was twice as high for immigrants than for native workers.

2.2.3 Immigrants' Mobility Responses

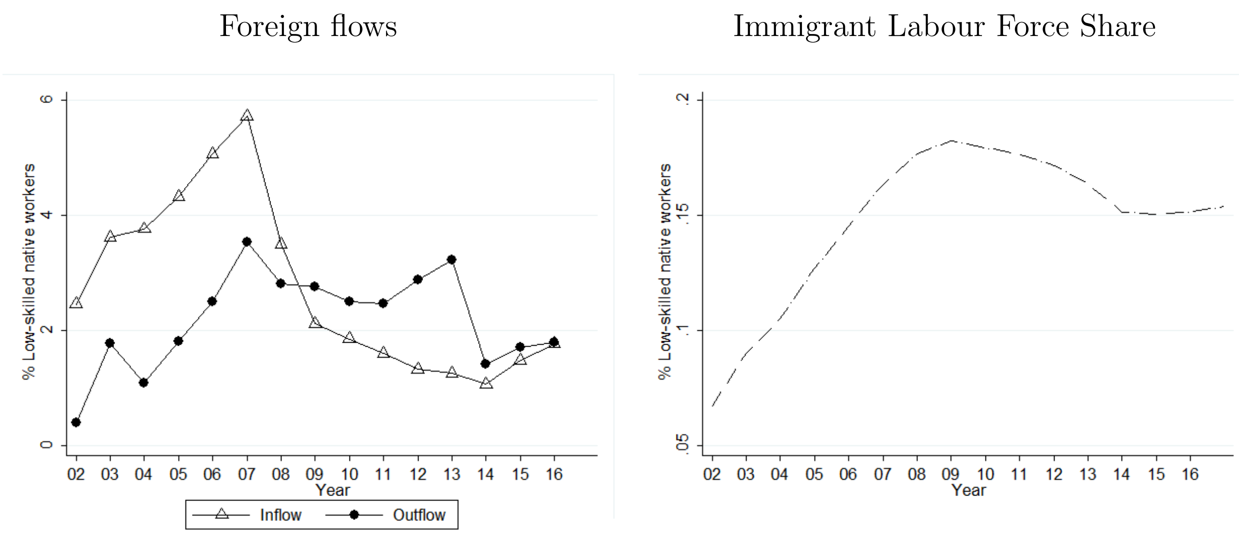
Using the Spanish Labour Force Survey and the Spanish Migration Statistic (which is based upon the Residential Variation Statistics), I construct the series of foreign inflows and outflows for low-skilled and high-skilled workers[15]. The left panel of Figure 2.3 plots the evolution of low-skilled foreign inflows and outflows from 2002 to 2016. Regarding the behaviour of foreign inflows, we can clearly observe that the Great Recession implied a sudden change in the trend: foreign inflows plummeted with the arrival of the crisis.

More interestingly, the figure also displays a steady increase in foreign outflows that started slightly before 2008. Specifically, we can see that from 2009 foreign outflows exceed the foreign inflows. Consequently, as the right panel of Figure 2.3 shows, with the outset of the Great Recession, the share of immigrant workers among the low-skilled workers declined. These mobility pattern during the crisis are in contrast with those of Spanish natives. As Figure 2.14 in Appendix E shows, natives' inflows and outflows were very low both during the pre-crisis period and after the Great Recession[16].

[15] The Residential Variation Statistics only provides aggregate data on foreign flows. However, the SLFS ask respondents about their years of residence in Spain. Therefore, by using the SLFS I can compute the share of newcomers that are high and low-skilled workers.

[16] Residential Variation Statistics presents some drawbacks regarding the coverage of emigration. As emigrants do not have incentive for cancellations, the emigration of natives (and hence also natives' return migration) may be underestimated. González Ferrer (2013) estimates that between 2008 and 2012 official figures on natives' outflows could be one third of the actual outflows. Two observations are worth highlighting.

Figure 2.3: Trends in low-skilled immigrants mobility



Source: Spanish Migration Statistic and Labour Force Survey.

The empirical evidence provided in this section lead us to suspect that the presence of foreign-born workers affects the behaviour of the labour market during a recession. In other words, we may think that there is a trade-off in the presence of immigrants in an economy during an economic downturn. On the one hand, immigrants are more mobile. In a context of no job creation (as in a deep crisis such as the Great Recession), this may contribute to moderate the drop in the job-finding rate for natives[17]. On the other hand, the finding that immigrants are *ceteris paribus* more likely to lose jobs than natives seems to suggest the existence of certain degree of unobserved heterogeneity between them. This would imply that a higher immigrant share will affect firms' job-creation incentives. Depending on the source and magnitude of the heterogeneity, this channel could be positive or negative for natives. In the next sections, I construct a random search model of the labour market with immigrants and natives, vacancy persistence, endogenous return migration and wage rigidity to be able to examine these alternative hypotheses.

First, even under that estimation, natives' outflows would still be quantitatively small with respect to foreign outflows. Second, as González Ferrer (2013) states, although we do not have information on the education level of the emigrated natives, we expect that the recent Spanish natives' emigration is mainly driven by high-skilled workers.

[17]In the simple version of the standard search and matching model of the labour market, the job-finding rate is a positive function of the market tightness (v/u). Suppose that the number of vacancies is fixed (firms are not posting new vacancies). Then, a decrease in the number of unemployed workers (e.g. due to higher unemployed immigrants' return migration) will lead to an increase in the job-finding rate (on impact).

2.3 Model

I build on the canonical search and matching model (Mortensen and Pissarides (1994)), but depart from that model by introducing vacancy persistence (Pries and Rogerson (2005) or Fujita and Ramey (2007)), endogenous return migration choices, and downward wage rigidity.

The model aims to rationalize the empirical facts presented in the previous section and it will be used to quantify by how much the native unemployment rate would have increased during the Great Recession in the absence of the pre-crisis immigration boom. For that purpose, I both solve the model in steady-states and compute equilibrium transition paths between states (see Section 2.4).

2.3.1 Environment

I consider an infinite horizon model in discrete time, $t = 0, 1, 2, \ldots$ The economy may be out of its steady-state equilibrium, and thus we keep track of calendar time t. There are two types of infinitely lived workers in the economy, natives and immigrants, indexed by $j = \{N, M\}$. Workers are risk-neutral and have a common discount factor β. The mass of native workers is constant and normalized to 1.

Every period there is an exogenous inflow m_M of immigrants[18] who enter the labour market as unemployed[19]. On the other hand, emigration is endogenous: every period all immigrant workers (employed and unemployed) choose between staying in the country or emigrating and obtaining an exogenously fixed life-time flow utility w_M^A[20]. In order to account for emigration that is not driven by economic reasons, a migration preference shock is introduced: every period workers draw an i.i.d. migration preference shock ε from a distribution with c.d.f. denoted by $G(\varepsilon)$. Consequently, the size of the immigrant population is endogenously determined by the equilibrium probability of return migration.

There is also an infinite mass of risk-neutral firms which may be either matched with a worker, unmatched or inactive. Firms can only be matched with one worker.

Matched firms produce $z + x$ units of output, where z is an aggregate productivity

[18] There are several reasons on why this is reasonable assumption. Bertoli et al. (2011) argue that the Latin American crisis had a lot to do with the Spanish immigration boom. Similarly, Bertoli and Moraga (2013) show that Spanish migration policies also played an important role. Last, the Eastern European expansion of the European Union can be made responsible for a large part of immigration flows over this period.

[19] The assumption that immigrants enter the labour market as unemployed is made for computational convenience and plays no role for the quantitative results.

[20] We can interpret this flow as the discounted lifetime wage that immigrants expect to obtain when working abroad.

component and x is an idiosyncratic match-specific component (match quality). The match quality $x \in [0, x^{max}]$ is drawn at the time the firm and the worker meet and remains constant for the duration of the match. Immigrants and natives draw x from a different distribution with c.d.f. denoted by $F_j(x)$. As will be explained in Section 2.5, I allow the mean of the match quality distribution of immigrants to be different from that of natives in order to replicate the wage gap observed in the data. Albert (2019) or Chassamboulli and Palivos (2014) take a different approach and assume no productivity differences between immigrants and natives of the same skill level. Instead, they introduce heterogeneity in the bargaining power parameter and unemployment flow payment respectively, in order to explain the wage gap. In Section 2.8.2, I follow Albert's (2019) calibration strategy and assume no differences in the mean productivity and allow the bargaining power to differ in order to explain the observed wage differences between natives and immigrants. I find that the results of the main counterfactual experiment are robust to this alternative calibration.

Unemployed search is costless, whereas employed workers cannot search; that is, there is no on-the-job search. Unemployed workers receive a flow payment b_j.

I introduce a simple learning mechanism regarding the match quality: when the worker and the firm first meet, the match quality is unknown. Once matched, agents discover the actual value of x with probability α every period. Employed workers earn a wage $w_j^*(x)$ when they are employed in a match of known quality. I denote the wage paid to employed workers when their match quality is unknown by $\widetilde{w}_j$. Following Pries and Rogerson (2005), I assume that when the match quality is unknown, the expected current-period production is given by the expected output $z + \bar{x}_j$[21]. This assumption ensures that the match surplus of jobs with unknown quality is always positive and hence all meetings lead to match formation.

Wage Setting

Initial steady-state

In the initial steady-state wages are set according to the Nash-bargaining solution. Formally, wages are given by these expressions:

$$w_{j,t}^*(x) = arg \max_{w_{j,t}(x)} \left(W_{j,t}^*(x) - U_{j,t}\right)^{\gamma} \left(J_{j,t}^*(x) - V_t^o\right)^{(1-\gamma)} \tag{2.3}$$

$$\widetilde{w}_{j,t} = arg \max_{\widetilde{w}_{j,t}} \left(\widetilde{W}_{j,t} - U_{j,t}\right)^{\gamma} \left(\widetilde{J}_{j,t} - V_t^o\right)^{(1-\gamma)} \tag{2.4}$$

[21]The intuition behind this assumption is simple. Think of a firm with several employers. If a new worker is hired, it will take some time to observe her actual productivity. During that time, it is reasonable to think that the firm will proxy the new worker's productivity by the average of the rest of (observably similar) workers.

where γ denotes the worker's bargaining power[22] In the above equations, $W^*_{j,t}(x)$ and $\widetilde{W}_{j,t}$ denote the value functions of workers employed in a match of known quality x and unknown quality, respectively; $U_{j,t}$ is the worker's value function when unemployed; $J^*_{j,t}(x)$ and $\widetilde{J}^*_{j,t}(s)$ denote the value functions of firms employing a worker in a match of known quality x and unknown quality, respectively; and V^o_t is the value of a firm with a previously created unfilled job.

Final steady-state and along the transition

Motivated by the large empirical evidence on wage rigidities in Spain (Font et al. (2015), De la Roca (2014), Gálvez-Iniesta (2020)) during the Great Recession, I introduce a simple form of downward wage rigidity into the model[23]. In particular, I assume that if a negative shock to the aggregate productivity is realized, wages cannot be adjusted, i.e. they are fixed to their initial steady state value (Hall (2003))[24]. Notice that this approach is equivalent to a stochastic framework with perfectly myopic agents: firms and workers expect to re-bargain wages if needed[25].

Matching technology

I assume that both nationality and match quality (upon discovery) are observable to the firm but only after the meeting takes place. The search process is then random: firms cannot direct their search towards a specific type of worker and there is only one labour market where both immigrant and native workers search for a job. The total number of matches between unemployed workers and posted jobs is determined by a Cobb-Douglas matching function:

$$m(v_t, u_t) = \xi v_t^{\delta} u_t^{1-\delta} \tag{2.5}$$

where ξ denotes the degree of matching efficiency, u_t is the number of unemployed workers, and v_t is the number of posted (advertised) jobs. At each period, posted jobs are given by:

$$v_t = k^n_t + k^{o,p}_t \tag{2.6}$$

[22]Section 2.8.2 introduces heterogeneity in this parameter so that $\gamma_M < \gamma_N$.

[23]This modelling assumption is not restricted to a framework aiming to resemble the Spanish economy. In fact, motivated by the lack of decline in real wages in the U.S. during the Great Recession, Ravn and Sterk (2017) also incorporate inflexible wages into a framework with search and matching frictions.

[24]Hall (2003) allows wages to be fixed but only within a bargaining set in order to improve the dynamics of the model. Our assumption about extreme wage rigidity is more closely related with Shimer (2004).

[25]Firms and workers are forward-looking agents as they need to form expectations about the future when making decisions (see value functions in 2.3.3 and 2.3.4). They are myopic regarding their incapacity to expect that they will not be allowed to change wages if there is a shock in the aggregate productivity z.

where k_t^n denotes the number of newly created jobs at t, and $k_t^{o,p}$ are the number of previously created unfilled jobs (i.e. jobs created before t that are unfilled) that are posted at t. (see Section 2.3.1). The probability that a worker matches with a firm is $p(\theta_t) = m(v_t, u_t)/u_t = \xi\theta_t^{\delta}$, where $\theta_t = v_t/u_t$ is the labour market tightness. The probability that a firm matches with a worker is $q(\theta_t) = m(v_t, u_t)/u_t = \xi\theta_t^{\delta-1}$.

Vacancy Costs

I follow Pries and Rogerson (2005) and assume that there is a constant fixed cost $\bar{K}$ of creating a new job[26]. On top of that, firms posting a job must pay a flow cost κ in order to fill empty job positions at each t. There are two key arguments for why the assumption on a fixed cost of creating a new job is reasonable given the purpose of the paper. First, it allows the framework to differentiate between worker and job turnover[27]. Second, the fixed cost $\bar{K}$ can be interpreted as the capital investment required to create a job. As a result of this sunk cost of job-creation, if a worker decides to emigrate, or she turns out to be not a good match for the firm, his job will continue to exist at the workers' previous firm[28]. Another important implication is that, as in Riegler (2019), my model allows for the possibility that during the transition some firms will fill jobs (i.e they will post jobs) even if they do not create new ones.

Consequently, in this setup we need to differentiate between the stock of unfilled jobs that are available to be posted, and the jobs that are indeed posted at each period t. The first stock is given by the sum of unfilled jobs created before t, denoted by k_t^o, and the new jobs created at t, denoted by k_t^n. At each t, firms then decide whether or not to post (advertise) their previously created unfilled jobs k_t^o. I denote as $k_t^{o,p}$ the number of previously created unfilled jobs that are posted at period t. I define an indicator function $\mathbb{I}_{post,t}$ that takes value 1 if firms with previously created unfilled jobs decide to post the job and 0 otherwise. Using this indicator function, we can then write the number of posted jobs at period t (v_t, Equation (2.6)) as follows:

$$v_t = k_t^n + k_t^{o,p} = k_t^n + \mathbb{I}_{post,t}k_t^o \tag{2.7}$$

Finally, I assume that job positions are exogenously destroyed at rate λ.

[26] See also Acharya and Wee (2018) or Riegler (2019).

[27] Studies by Michaels et al. (2017) or Mercan et al. (2019) among others have stressed the relevance of this distinction given the increasing importance of quit-driven replacement hiring among the posted vacancies. Using German data, Mercan et al. (2019) find that 56% of posted vacancies are associated to old unfilled jobs vacated by quits.

[28] As discussed in Fujita and Ramey (2007), due to the existence of a fixed creation cost and in contrast to the standard DMP model, in this setup previously created jobs are a predetermined variable and unfilled jobs have a positive value in equilibrium

Job Separations

Job separations can be either exogenous or endogenous. As noted above, exogenous separations occur with probability λ and are interpreted as the result of a process of job obsolescence. Therefore, firms would not attempt to rehire another worker following such separations and consequently the stock of jobs will shrink.

On the other hand, job separations may also occur endogenously. That is, for matches of known quality, firms and workers decide whether to continue to be matched or not each period. The match is preserved only if the two of them agree on this decision. In the initial steady-state, wages are Nash-bargained every period, and so there is no room for disagreement i.e. a match is preserved as long as the match surplus is positive. This is not the case when wages are fixed: since the firm cannot re-bargain the wage after an aggregate negative shock hits the economy, it could be possible that a match delivering total positive surplus is not profitable any more for the firm. In other words, when wages are not Nash-bargained every period, firms and workers will not always agree on preserving the match. For that purpose I define an indicator function $\mathbb{I}_j(x)$ that takes value 1 if both parties agree on continuing to be matched. In case that the match is dissolved, the worker becomes unemployed[29] and the job adds to the stock of previously created unfilled jobs, as in Pries and Rogerson (2005).

2.3.2 Timing

The timing of events within a period is assumed to be as follows:

- At the beginning of the period, aggregate productivity z is realized. Upon observing z, immigrant workers draw the migration preference shock ε, decide whether to emigrate or stay and emigration the takes place.

- Endogenous separations take place, jobs are destroyed exogenously with probability λ and agents learn their actual match quality x with probability α.

- At this point, firms decide whether they want to create new jobs at cost $\bar{K}$.

- Firms with previously created unfilled jobs decide whether they want to post those jobs.

- The matching process then takes place. Firms with unfilled posted jobs and unemployed workers meet and matches are formed.

[29] I assume that workers that become unemployed at period t cannot search for a job within that period. See 2.3.2 and law of motion (2.24) in Appendix A.1

- For preserved matches, production takes place, wages are paid, and unemployed workers receive b_j. Last, immigration takes place.

2.3.3 Workers' Problem

I formulate workers' and firms' decision problems in recursive form. This can be done since there is no aggregate uncertainty in the model. Moreover, this notation is convenient given that the model is solved not only in steady-state but also for transitions between states.

Unemployed workers

Every period unemployed workers choose between staying in the country as unemployed or emigrating[30]. For type-j workers, the value of staying in the country as unemployed $V_{j,t}^{U,stay}$ can be written as:

$$V_{j,t}^{U,stay} = b_j + \beta \left[p\left(\theta_t\right) \widetilde{W}_{j,t+1} + \left(1 - p(\theta_t)\right) U_{j,t+1} \right] \tag{2.8}$$

where $\widetilde{W}_{j,t}$ is the value of being employed in a job of unknown quality and $U_{j,t}$ is the value of being unemployed.

The value of staying in the country as unemployed can be decomposed into two terms. The first one is the flow payment b_j associated with unemployment. The second term is the next period expected discounted value: with probability $p\left(\theta_t\right)$ the unemployed worker finds a job of unknown quality[31]. With the complementary probability $1 - p(\theta_t)$ the worker remains unemployed, in which case she obtains the value of being unemployed $U_{j,t+1}$.

The value of emigrating is given by:

$$V_t^{mig} = W_j^A + \varepsilon_t \tag{2.9}$$

where the first term in (2.9) is the value of working abroad, which is the discounted sum of the life-time flow payment w_j^A:

$$W_j^A = w_j^A + \beta W_j^A \tag{2.10}$$

and the second term in (2.9) is the one-time migration utility shock ε_t that every period workers draw from the distribution $G(\varepsilon)$. After observing the realization of ε_t, the unem-

[30]For the sake of generality, I define all value functions for a generic worker type $j \in N, M$. However, as explained in 2.3.1 I abstract from native emigration. Therefore the decision to return migrate is only taken by $j = M$.

[31]As explained in Section 2.3.1, I assume that at the time the meeting takes place, the match quality is unknown.

ployed worker will emigrate if $V_{j,t}^{U,stay} \leq V_t^{mig}$. There exists a threshold value $\varepsilon_{j,t}^{u,*}$ such that $W_j^A + \varepsilon_{j,t}^{u,*} = V_{j,t}^{U,stay}$. In words, $\varepsilon_j^{u,*}$ is the migration preference shock value that makes an unemployed worker indifferent between staying in the country or emigrating. Then, for any $\varepsilon_t \geq \varepsilon_{j,t}^{u,*}$ the unemployed worker will emigrate and obtain the value of emigrating W_j^A plus the migration preference shock ε_t.

The value of being unemployed $U_j(s)$ can then be written as follows:

$$U_{j,t} = G\left(\varepsilon_{j,t}^{u,*}\right) V_{j,t}^{U,stay} + \left(1 - G\left(\varepsilon_{j,t}^{u,*}\right)\right)\left(W_j^A + \mathbb{E}\left[\varepsilon_t | \varepsilon_t \geq \varepsilon_{j,t}^{u,*}\right]\right) \tag{2.11}$$

where $G\left(\varepsilon_{j,t}^{u,*}\right) = Prob\left(\varepsilon \leq \varepsilon_{j,t}^{u,*}\right)$ is the probability that the unemployed worker does not emigrate[32].

Employed workers

Recall that workers can be employed in jobs of known or unknown quality. As the unemployed workers, in every period all employed decide whether to emigrate or not. Importantly, the value of emigrating is the same for all workers regardless their employment status (see Equations (2.9) and (2.10)).

Workers employed in a match of known quality

The value for a worker of staying in the country as employed in a match of known quality is the following:

$$V_{j,t}^{*,stay}(x) = \mathbb{I}_{j,t}(x) \left\{ \underbrace{w_{j,t}^*(x) + \beta\left[(1-\lambda) W_{j,t+1}^*(x) + \lambda U_{j,t+1}\right]}_{V_{j,t}^{stay}} \right\} + \left(1 - \mathbb{I}_{j,t}(x)\right) U_{j,t} \tag{2.12}$$

$$\text{where} \quad \mathbb{I}_{j,t}(x) = \begin{cases} 1 & \text{if} \quad \left(V_{j,t}^{stay}(x) \geq U_{j,t}\right) \wedge \left(J_{j,t}(x) \geq V_t^o\right) \\ 0 & \text{otherwise} \end{cases}$$

where $w_{j,t}^*(x)$ denotes the wage paid to a worker of type j in a job with match quality x. The value function (2.12) has two terms. The first term stands for the expected discounted value for the worker if she keeps the job. That is, $\mathbb{I}_{j,t}(x) = 1$, which means that for both the worker and the firm the value of remain matched is higher than their respective outside option (the

[32]Notice that since ε follows an independent and identically-distributed distribution (Fan et al. (2017)) the value functions (2.8)−(2.11) do not depend on ε.

value of unemployment $U_{j,t}$ and the value of a previously created unfilled job V_t^o). If that is the case, today the worker gets the wage $w_{j,t}^*(x)$. Next period, with probability λ the job is destroyed and the asset value will be given by $U_{j,t+1}$. With probability $1-\lambda$ the job survives and the value is $W_{j,t+1}^*(x)$. Last, the second term states that in the case of dissolving the match today ($\mathbb{I}_{j,t}(x) = 0$), the worker obtains the value of employment $U_{j,t}$.

Denote as $\varepsilon_{j,t}^{*,*}(x)$ the migration threshold value such that $W_j^A + \varepsilon_{j,t}^{*,*}(x) = V_{j,t}^{*,stay}(x)$. Then, the value of being employed in a job of known quality can be written as:

$$W_{j,t}^*(x) = G\left(\varepsilon_{j,t}^{*,*}(x)\right) V_{j,t}^{*,stay}(x) + \left(1 - G\left(\varepsilon_{j,t}^{*,*}(x)\right)\right)\left(W_j^A + \mathbb{E}\left[\varepsilon_t | \varepsilon_t \geq \varepsilon_{j,t}^{*,*}(x)\right]\right) \tag{2.13}$$

where $G\left(\varepsilon_{j,t}^{*,*}(x)\right) = Prob\left(\varepsilon \leq \varepsilon_{j,t}^{*,*}(x)\right)$ is the probability that the worker employed in a job of known quality x does not emigrate.

Workers employed in a match of unknown quality

The value for a worker staying in the country as employed in a match of unknown quality is the following:

$$\widetilde{V}_{j,t}^{stay} = \widetilde{w}_{j,t} + \beta\left[\lambda U_{j,t+1} + (1-\lambda)\left(\alpha \int_0^{x^{max}} W_{j,t+1}^*(x')\, dF_j(x') + (1-\alpha)\widetilde{W}_{j,t+1}\right)\right] \tag{2.14}$$

where $\widetilde{w}_{j,t}$ is the wage paid to a worker employed in a job of unknown quality. If the worker chooses to stay, she receives the wage $\widetilde{w}_{j,t}$. Next period, with probability λ the worker is unemployed and gets U_{t+1}. On the contrary, if the job survives, two events may occur: (1) with probability α the match quality is discovered and the worker makes a draw of x; (2) the match quality remains unknown and then the asset value becomes $\widetilde{W}_{j,t+1}$.

Again, these workers must decide whether to emigrate or not. Let us denote by $\widetilde{\varepsilon}_{j,t}^*$ the migration threshold value such that $W_j^A + \widetilde{\varepsilon}_{j,t}^* = \widetilde{V}_{j,t}^{stay}$. Then, the value of being employed in a job of unknown quality can be written as:

$$\widetilde{W}_{j,t} = G\left(\widetilde{\varepsilon}_{j,t}^*\right)\widetilde{V}_{j,t}^{stay} + \left(1 - G\left(\widetilde{\varepsilon}_{j,t}^*\right)\right)\left(W_j^A + \mathbb{E}\left[\varepsilon_t | \varepsilon_t \geq \widetilde{\varepsilon}_{j,t}^*\right]\right) \tag{2.15}$$

where $G\left(\widetilde{\varepsilon}_{j,t}^*\right) = Prob\left(\varepsilon \leq \widetilde{\varepsilon}_{j,t}^*\right)$ is the probability that a worker employed in a job of unknown quality does not emigrate.

2.3.4 Firms' Problem

Matched firms

Firms may be employing workers in matches of known or unknown quality.

Firms employing a worker in a match of known quality

The value function of firm employing a worker in match of known quality can be written as:

$$\begin{aligned} J_{j,t}^{*}(x) =& G\left(\varepsilon_{j,t}^{*,*}(x)\right)\left[\mathbb{I}_{j,t}(x)\left\{z + x - w_{j,t}^{*}(x) + \beta\left(1-\lambda\right)J_{j,t+1}^{*}(x)\right\} + (1-\mathbb{I}_{j,t}(x))V_t^o\right] + \\ & \left(1 - G\left(\varepsilon_{j,t}^{*,*}(x)\right)\right)V_t^o \end{aligned} \tag{2.16}$$

$$\text{where} \quad \mathbb{I}_{j,t}(x) = \begin{cases} 1 & \text{if} \quad \left(V_{j,t}^{stay}(x) \geq U_{j,t}\right) \wedge \left(J_{j,t}(x) \geq V_t^o\right) \\ 0 & \text{otherwise} \end{cases}$$

First of all, the value for the firm depends on the emigration decision. With probability $1 - G(\widetilde{\varepsilon}_{j,t}^{*})$ the worker emigrates, the match is dissolved and the firm obtains the value of a previously created unfilled job V_t^o. Now, if the worker stays, then they make the match preservation decision. If the match is preserved, the value for the firm is composed by two terms. The first term is the present profit, given by the difference between production and the wage paid to the worker. The second term is the expected future discounted profits, which depends on the probability that the job is exogenously destroyed: with probability $1-\lambda$ the job remains productive in which case the value of expected discount profits will be equal to $J_{j,t+1}^{*}(x)$; with the remaining probability λ the job is exogenously destroyed and then the future profits will be zero. Last, if the match is endogenously dissolved, the firm obtains V_t^o.

Firm employing a worker in a match of unknown quality

The value function of a firm employing a worker in a match of unknown quality is the following:

$$\begin{aligned} \widetilde{J}_{j,t} =& G\left(\widetilde{\varepsilon}_{j,t}^{*}\right)\left[z + \bar{x}_j - \widetilde{w}_{j,t} + \beta\left[(1-\lambda)\left(\alpha\int_{x^{min}}^{x^{max}} J_{j,t+1}^{*}(x')dF_j(x') + (1-\alpha)\widetilde{J}_{j,t+1}\right)\right]\right] + \\ & \left(1 - G\left(\widetilde{\varepsilon}_{j,t}^{*}\right)\right)V_t^o \end{aligned} \tag{2.17}$$

Again, the value function depends on the workers' emigration choice. The first term stands to the value obtained by the firm if the worker does not emigrate. If that is the case, at period t the firm obtains the present profit, given by the differences between production and the wage paid to the worker. Next period value is given by the expected future discounted profits, which again depend on the exogenous destruction rate. With probability λ the job is destroyed and firms obtain zero profits. Now, if the job survives, two events may occur: (1) with probability α the match quality is discovered and the worker makes a draw of x, in which case the firm will obtain $J^*_{j,t+1}(x')$; (2) with probability $1-\alpha$ the match quality is not revealed and then the firm's asset value is $\widetilde{J}_{j,t+1}$. Finally, the second term is the value for the firm if the worker emigrates, which is given by the value of a previously created unfilled job V^o_t.

Firms with a previously created unfilled job

The value of a firm with a previously created unfilled job is given by:

$$V^o_t = \max\left\{\underbrace{-\kappa + \beta\left[q(\theta_t)\left(\phi_t\widetilde{J}_{M,t+1} + (1-\phi_t)\widetilde{J}_{N,t+1}\right) + (1-q(\theta_t))V^o_{t+1}\right]}_{V_t}, 0\right\} \tag{2.18}$$

where $\phi_t = \dfrac{u_{M,t}}{u_t}$ is the share of unemployed immigrants among the total number of unemployed.

Every period firms with a previously created unfilled job decide whether to post the job or not. If the job is posted, the value for the firm is composed by two terms. The first term κ is the flow cost incurred by the firm when posting a job. The second term is the expected future discounted value, which depends on the probability of filling the posted job. With probability $q(\theta_t)$ the posted job is filled. Since search is random, then the firm's option value depends on the probability that the job is filled by a native or an immigrant worker, which are ϕ_t and $1-\phi_t$, respectively. Those probabilities are simply the share of each workers type among the total pool of unemployed workers. On the contrary, with probability $1-q(\theta_t)$ the posted job is not filled and the firm continues to obtain V^o_{t+1}. Finally, if the job is not posted, firms get zero in that period.

New firms

With the presence of a fixed cost $\bar{K}$ to create a new job, the free entry condition now takes the form:

$$\begin{aligned} V_t = \bar{K} \quad & \text{if} \quad k_t^n > 0 \\ 0 \leq V_t < \bar{K} \quad & \text{if} \quad (k_t^n = 0 \quad \& \quad k_t^{o,p} > 0) \\ 0 > V_t \quad & \text{if} \quad (k_t^n = 0 \quad \& \quad k_t^{o,p} = 0) \end{aligned} \tag{2.19}$$

Given the timing of the model, a new job created at t can be filled in that period. Equations (2.18) and (2.19) imply that all new jobs created at t will also be posted in that period.

Unlike the standard model with free entry, the existence of a fixed cost implies that an unfilled vacancy has a positive value in equilibrium.

2.3.5 Steady-State Equilibrium

Definition. Given z, a steady-state equilibrium is a list $\{w_j^*(x)$, $\widetilde{w}_j$, u_j, k^o, k^n, $\widetilde{e}_j$, e_j^*, $J_j^*(x)$, $\widetilde{J}_j$, U_j, $W_j^*(x)$, $\widetilde{W}_j$, V, V^o, W_j^A, $\mathbb{I}_j(x)$, $\mathbb{I}_{post}$, $\widetilde{\varepsilon}_j^*$, $\varepsilon_j^{*,*}(x)$ and $\varepsilon_j^{u,*}\}$ such that:

1. Agents optimise. Given $w_j^*(x)$, $\widetilde{w}_j$, u_j, k^o and k^n, the value functions $J_j^*(x)$, $\widetilde{J}_j$, U_j, $W_j^*(x)$, $\widetilde{W}_j$, V, V^o and W_j^A satisfy equations (2.8) - (2.18); the match preservation and job-posting decision rules $\mathbb{I}_j(x)$ and $\mathbb{I}_{post}$ satisfy equations (2.12) and (2.18), respectively; and the migration preference shock thresholds $\varepsilon_j^{u,*}$, $\varepsilon_j^{*,*}$ and $\widetilde{\varepsilon}_j^*$ satisfy equations (2.11), (2.13) and (2.15), respectively.

2. Job-creation condition. Given $w_j^*(x)$, $\widetilde{w}_j$, the ratio $\frac{v}{u}$ must be such that $V = \bar{K}$.

3. Bargaining. The wage functions $w_j^*(x)$, $\widetilde{w}_j$ solve the Nash bargaining problem in (2.3) and (2.4).

4. The distribution of workers and jobs are time-invariant for the laws of motion described in equations (2.22) - (2.25) (in the Appendix A.1).

2.3.6 Equilibrium Transition Path

Definition. Given a sequence of aggregate productivity $\{z\}_{t=t_0 \ldots t_1}$ and a sequence of fixed wages $\left\{\overline{w^*}_j(x), \overline{\widetilde{w}}_j\right\}_{t=t_0 \ldots t_1}$, an equilibrium transition path with rigid wages between t_0 and t_1 is a sequence of distributions $\left\{u_{j,t}, k_t^o, k_t^n, \widetilde{e}_{j,t}, e_{j,t}^*\right\}_{t=t_0 \ldots t_1}$, a sequence of value functions $\left\{J_{j,t}^*(x), \widetilde{J}_{j,t}, U_{j,t}, W_{j,t}^*(x), \widetilde{W}_{j,t}, V_t, V_t^o, W_j^A\right\}_{t=t_0 \ldots t_1}$, a sequence of match preservation decision rules $\{\mathbb{I}_{j,t}(x)\}_{t=t_0...t_1}$, a sequence of job-posting decision rules $\{\mathbb{I}_{post,t}\}_{t=t_0...t_1}$ and a sequence of migration preference shock thresholds $\{\widetilde{\varepsilon}^*_{j,t}, \varepsilon^{*,*}_{j,t}(x), \varepsilon^{u,*}_{j,t}\}_{t=t_0...t_1}$ such that:

1. Agents optimise. Given the sequence of $\left\{\overline{w^*}_j(x), \overline{\widetilde{w}}_j, u_{j,t}, k^o_t, k^n_t\right\}_{t=t_0...t_1}$, the sequence of value functions $\left\{J^*_{j,t}(x), \widetilde{J}_{j,t}, U_{j,t}, W^*_{j,t}(x), \widetilde{W}_{j,t}, V_t, V^o_t, W^A_j\right\}_{t=t_0...t_1}$ satisfy equations (2.8) - (2.18) in every period t; the sequence of match preservation and job-posting decision rules $\{\mathbb{I}_{j,t}(x)\}_{t=t_0...t_1}$ and $\{\mathbb{I}_{post,t}\}_{t=t_0...t_1}$ satisfy equations (2.12) and (2.18) in every period t, respectively; and the sequence of migration preference shock thresholds $\{\varepsilon^{u,*}_{j,t}, \varepsilon^{*,*}_{j,t}(x), \widetilde{\varepsilon}^*_{j,t}\}_{t=t_0...t_1}$ satisfy equations (2.11), (2.13) and (2.15) in every period t, respectively.

2. Job-creation condition. Given the sequence of $\left\{\overline{w^*}_j(x), \overline{\widetilde{w}}_j, u_{j,t}, k^o_t, k^n_t\right\}_{t=t_0...t_1}$, the ratio $\frac{v_t}{u_t}$ in every period t must be such that $V_t = \bar{K}$ if new jobs are created ($k^n_t > 0$); $0 \leq V_t < \bar{K}$ if no new jobs are created but firms are posting their previously created unfilled jobs ($k^n_t = 0$ and $k^{o,p}_t > 0$); $V_t < 0$ if neither new jobs are created nor previously created unfilled jobs are posted ($k^n_t = 0$ and $k^{o,p}_t = 0$). That is, Equation (2.19) holds in every period t.

3. Law of motion. The distributions evolve according to the law of motions described in equations (2.22) - (2.25) (in the Appendix A.1).

2.4 Simulating the Great Recession

The focus of the model is on simulating the performance of the labour market during the Great Recession that took place in $2008Q2$[33]. Formally I will consider an economy in a pre-crisis state (in $2008Q2$, characterized by a given level of aggregate productivity $z = z^H$) and introduce a permanent and unexpected shock (MIT shock) in the form of a drop in the aggregate productivity[34] (such that $z = z^L < z^H$ for $t \geq 2008Q2$). The transition towards the new steady state at 2016 (post-recession) is then computed, which is reached after T periods. The simulated transition path from $2008Q2$ to 2016 is what I call the Great

[33]The second quarter of 2008 is chosen as the start of the Great Recession as it was the first quarter with a negative quarterly growth rate of real GDP in Spain.

[34]I abstract from the underlying causes of the negative shock that triggered the onset of the Great Recession. In the model, the drop of the aggregate productivity z could be interpreted as the reduced form of the main global and idiosyncratic-to-Spain causes that set off the crisis: the burst of the real state bubble, global financial turbulences, the pre-crisis low real productivity growth, high level of private debt... See Fernández-Villaverde et al. (2010), Ortega and Peñalosa (2012) or Garcia-Santana et al. (2016) for more details on the roots of Spanish Great Recession.

Recession[35].

The standard approach would be to first solve the economy in 2008Q2 as a steady-state, then introduce a negative MIT shock to aggregate productivity, and finally compute the transition path towards the final steady-state at 2016. The issue is that as Figure 2.1 shows, the Spanish economy right before the crisis was characterized by the combination of low unemployment rates, high foreign inflows and low foreign outflows, i.e. the share of immigrant workers among the labour force was growing. That scenario is hardly stationary, which prevent us to assume that the pre-crisis economy (2008Q2) was in is a steady-state equilibrium[36]. To overcome this problem I start the model before, in the year 2000. I then take the following steps, as depicted in Figure 2.4:

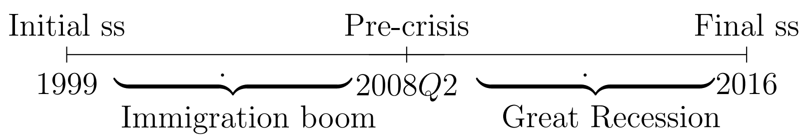


Figure 2.4: Roadmap

- I first solve the model for an initial steady-state at the beginning of 1999, with $z = z^H$. This economy aims to resemble the Spanish economy of the years before the Great Recession. For that purpose, the model is calibrated to match data moments for Spain in the period 2005Q1-2008Q2[37]. Importantly, I use the immigrants' share in 1999 as a target[38], which ensures that the condition on stationarity in the immigrants' share is reasonable.

- The economy is then unexpectedly shocked by the immigration boom[39]: an equilibrium transition path from 2000 to 2008Q2 is solved by introducing the actual inflows of

[35] As explained in Section 2.5, the models' period is a month, implying that the transition lasts $T = 102$ periods. Computational results shows that this time span is long enough for the economy to reach the new steady-state.

[36] In particular, assuming that the pre-crisis economy is on a steady-state would impose the unrealistic equilibrium condition on the stationarity of the distribution of immigrants, which by definition only holds when foreign inflows equal foreign outflows. Notice that this is not an issue in 2016 (final steady-state)

[37] Ideally I would like to use data moments for the period 2000-2008. However, the SLFS-Flows (used to compute employment flows) only started to provide information on respondents' nationality from 2005. Nevertheless, as Figure 2.1 shows, unemployment rates from 2000 to 2005 did not vary much, so I do not expect big differences in the employment transition rates during that period.

[38] I choose 1999 as the target for the immigrants' share because the condition on the stationarity of workers' distributions holds in the data. In that year foreign inflows were already higher than foreign outflows. However, the difference was not large enough to generate an increase of the immigrants' share, as natives' active population also increased during that year. See Moraga and Molina (2018) for a detailed description on gross flows of migration in and out of Spain.

[39] See Dolado et al. (2018) for a similar transition implementation.

foreign-born workers $\{m_{M,t}\}_{t=2000...2008Q2}$ that are observed in the data for that period[40]. This transition is called the immigration boom. Agents expect the immigration boom to last forever (i.e firms and workers do not expect that the transition will stop and aggregate productivity will drop in 2008Q2).

- I solve the model for the final steady-state in 2016. Two exogenous changes are introduced with respect to the initial steady-state. First, I introduce an unexpected negative MIT shock to aggregate productivity ($z = z^L < z^H$). Second, the parameter governing the immigrants' inflows m_M is also modified, since it is now set to the observed foreign inflows for the period 2014-2016. Remember that here I impose the wage rigidity described in Section 2.3.1. Section 2.8.1 explores the results of the model when relaxing this assumption.

- Finally, the equilibrium transition path from 2008Q2 to 2016 is computed (Great Recession). Appendix B.2 provides the detailed computation algorithm. As in the previous transition path, foreign-born worker inflows $\{m_{M,t}\}_{t=2008Q2...2016}$ are set to the actual data on inflows in that period.

2.5 Calibration

The model is calibrated to the Spanish economy and the reference period is 2005Q1-2008Q2. First, I need to assume some functional forms and discretization for the distribution of match quality draws and the migration preference shock. Next, I explain the calibration strategy, which is undertaken in two steps: firstly, some of the parameters are set exogenously by taking either empirical counterparts or values commonly used in the literature. Secondly, I jointly calibrate the rest of the parameters to match relevant moments of the Spanish data.

2.5.1 Functional forms and discretization

Functional forms

I assume that the distribution of match quality draws $F_j(x)$ is log-normal with parameters (μ_j, σ_j). Although there is no obvious empirical counterpart to match this distribution, I follow Mortensen and Nagypal (2007) in assuming log-normality. The motivation for this choice is the evidence that wages are log-normally distributed[41]. Subsection 2.5.3 provides

[40] Specifically, $\{m_{M,t}\}_{t=2000...2008Q2}$ is the average inflow of foreign-born workers that arrived to Spain from 2000 to 2008Q2.

[41] Instead of assuming that wages follow a log-normal with parameters $(0, 1)$ as in Mortensen and Nagypal (2007), I calibrate the parameters of the distribution $F_j(x)$.

details of the identification of each of the parameters. With respect to the distribution of the migration preference shock, $G(\varepsilon)$ is assumed to be a normal distribution[42] with zero mean[43] and standard deviation σ_ε.

Discretization

In order to solve the model I discretize the match quality draws and the distribution of migration preference shocks. I use 100 equidistant nodes to approximate the log-normal distribution of the match quality productivity $F_j(x)$ and 200 equidistant nodes for the grid of migration preference shocks.

Foreign inflows

As discussed in Subsection 2.3.1, foreign inflows m_M are taken as exogenous. They are set to the average foreign inflows in 1999 at the initial steady-state. For the final steady-state I set m_M to the average foreign inflow in the post-crisis period (2014-2016)[44]. Regarding transitions, for the immigration boom transition (2000-2008Q2), I fix $\{m_{M,t}\}_{t=2000...2008Q2}$ to the average foreign inflows from 2000 to 2008. Similarly, in the Great Recession transition (2000-2008Q2), $\{m_{M,t}\}_{t=2008Q2...2016}$ are set to the average foreign inflow from 2009 to 2014.

2.5.2 Pre-specified Parameters

The pre-specified parameters of the model are summarized in the top panel of Table 2.3. I normalize the mean wage of the native workers to be 1 in equilibrium. Aggregate productivity z is set to 0.31. The model's period is a month[45] and therefore the discount factor β is set to 0.9967 to reflect an annualized real interest rate of 4.1%. As in most of the literature, the elasticity of the matching function δ is set to 0.5. The worker's bargaining power γ is set to 0.8[46]. This value is higher than usual in the literature and is motivated by the

[42]Extreme Value Type-1 distributions are more usual in the migration literature as they simplify the analysis when the migration choice involves choosing destination among several alternatives. Since here the migration choice is simply stay or leave the country, assuming normality does not involve technical complications

[43]From equations (2.9) and (2.10) we can see that the mean of the migration preference shock distribution and the flow payment associated with working abroad w_j^A play the same role in the model. Therefore, by assuming that the migration preference shock distribution has zero mean we drop one redundant parameter that otherwise would had to be estimated.

[44]Again, I use this period because the fraction of immigrants in the labour force remained roughly constant, which is a steady-state equilibrium condition.

[45]For the sake of comparison with the data, I time-aggregate some of the model generated moments to a quarterly frequency.

[46]In a model with endogenous separations, Mortensen and Nagypal (2007) also choose a higher than standard worker bargaining power equal to 0.71, arguing that the role of this parameter differs with respect

well-documented high rigidities that characterize the Spanish labour market[47]. As Bils et al. (2011), I give a predominant role to the endogenous match separation channel over exogenous separations by setting the exogenously monthly separation probability equal to 0.0017 (or 0.005 quarterly). Last, using the estimates in Hall and Milgrom (2008), I fix the flow payment of unemployment b_j to account for 70% of the mean wage of each group, implying $b_N = 0.7$ and $b_M = 0.47$.

Table 2.3: Calibration Results

Description	**Parameter**	**Value**	**Target/Source**	**Data**	**Model**
Calibrated externally					
Discount factor	β	0.9967	From literature		
Matching function parameter	δ	0.5	From literature		
Workers' bargaining power	γ	0.8	From literature		
Job destruction	λ	0.0016	Bils et al. (2011)		
Native unemp. benefit	b_N	0.700	Hall and Milgrom (2008)		
Immigrant unemp. benefit	b_M	0.471	Hall and Milgrom (2008)		
Calibrated internally					
Matching efficiency	ξ	0.138	Native JFR	0.310	0.304
Probability to discover quality	α	0.272	Immigrant SR	0.055	0.056
Flow cost of posting a job	κ	0.058	Worker hiring cost	0.420	0.395
Fixed cost of creating a job	$\bar{K}$	15.362	Vacancy rate	0.080	0.080
Immigrant wage abroad	w_M^A	0.302	Immigrants LF share	0.021	0.021
Native mean match quality	μ_N	0.292	Native mean wage	1.000	1.000
Imm. mean match quality	μ_M	0.076	Imm. mean wage	0.700	0.670
Native match quality s.t.d.	σ_N	0.456	Native SR	0.027	0.027
Imm. match quality s.t.d.	σ_M	0.325	Wage s.t.d. N/M ratio	1.618	1.570
Migration shock s.t.d.	σ_ε	239.653	Migration prob. ratio	1.467	1.260

to the standard version of the model with exogenous separations.

[47]This can be interpreted as a reduced form way of accounting for the evidence that Spanish labour institutions are less conducive to low unemployment than those of similar developed countries. In particular, as argued by Bentolila and Jimeno (2006), in Spain, the combination of high incidence of industry-level (collective) bargaining and high union power drive wages up and move them away from workers' productivity. See Bentolila and Jimeno (2006) and Bentolila et al. (2012a) for more details on the institutional settings of the Spanish labour market.

2.5.3 Calibrated Parameters

The remaining 10 parameters are jointly calibrated in order to match relevant features of the data. I search for the combination of parameters that minimizes the following loss function:

$$\mathbb{L} = \sum_{c=1}^{C} \left| log\left(m_c^M\left(\Theta\right)\right) - log\left(m_c^D\right) \right| \tag{2.20}$$

where m^D is a C-by-1 vector containing the data moments used as calibration targets and $m^M(\Theta)$ is the C-by-1 vector containing the counterpart model moments, which is function of the whole set of parameters to be calibrated Θ. I choose $C = 10$, so the model is exactly identified. The bottom part of Table 2.3 specifies the list of the parameters that are jointly estimated and the data moment that identifies each of them.

The labour market statistics (job-finding rates and job-separation rates) are obtained from the Spanish Labour Force Survey-Flows 2005Q1-2008Q2. For wages I use data from the Spanish Wage Structure Survey of 2006[48]. See Appendix D.1 for a detailed description of the data. The vacancy rate is computed for the period 2000-2008[49]. I use administrative data on Social Security registers ("Muestra Continua de Vidas Laborales") to approximate the return migration probabilities of employed and unemployed immigrants. Last, as mentioned before, the share of immigrants in the labour force is calculated using the Labour Force Survey of 1999.

Given the nonlinearity of the model, in principle the value of all the parameters affects the whole set of moments used as targets. Nevertheless, it is possible to specify which moment is informative of each particular parameter. The mean of the match quality distribution μ_j mainly affects the mean wage of each group. The standard deviation of the natives' match quality distribution σ_N is set to replicate the native job-separation rate. In turn, the standard deviation of the immigrants' match quality distribution σ_M is calibrated to match the natives-immigrants ratio of the standard deviation of wages. The smaller the variance of immigrants' match quality distribution (σ_M), the more concentrated their draws will be and hence the lower the dispersion of their equilibrium wages. The learning parameter α is pinned down to match the immigrants' job-separation rate. The intuition for this goes as follows: in steady-state all the endogenous job-separations (the ones that are not driven

[48] We use this year as representative for the pre-crisis period.

[49] Due to the existence of difference data sources for different spans of time, the analysis of the vacancy data is not straightforward. I follow Boscá Mares et al. (2017) to construct an homogeneous time series of the stock of vacancies through the period 2000-2018 linking three sources: the "Unfilled Job Vacancies" series (OECD), the "Job Vacancy Statistics" (Eurostat) and the "Quarterly Labour Cost Survey" (Eurostat). Appendix D.2 provides the details on the computation.

by the immigrants' return migration) occur when the match quality x is learnt and it turns out that the match surplus for that x is negative[50]. That means that the faster the learning process α, the more bad-quality matches (i.e. matches with an x that is below the threshold x^* that makes the firm indifferent between remaining matched with the worker or dissolving the match) will be revealed, and hence the more separations will occur in equilibrium.

Regarding vacancy costs, the fixed cost $\bar{K}$ is chosen to match the observed vacancy rate. The rationale for this is that the higher the fixed cost $\bar{K}$, the more costly is for a firm to create a job (and therefore, the higher is the opportunity cost of closing it) and the higher will be the pool of previously created unfilled jobs[51]. Next, following Elsby and Michaels (2013), the flow cost κ is chosen so that per-worker hiring costs κ/q equal to 14 percent of quarterly worker compensation[52]. The matching efficiency parameter ξ equals 0.13 in order to match natives' job-finding rate (Bils et al. (2011)).

With respect to the parameters governing the migration decision, the immigrants' wage abroad w_M^A is calibrated to match the proportion of immigrants in the labour force. Finally, the standard deviation of the migration preference shock σ_ε replicates the unemployed-employed return migration probability ratio. The higher the value of σ_ε, the higher the probability that an immigrant employed in a high match quality job will emigrate, and hence the lower the unemployed-employed return migration probability ratio.

2.5.4 Calibration Results

The model matches almost all the targets precisely. In fact, it only falls short in generating the empirical unemployed-employed return migration ratio. This occurs because the variance of the migration preference shock distribution σ_ϵ is too large. In fact, the model struggles to match both this moment and immigrants job-separation rate. This drawback of the calibration is not very problematic for several reasons. On the one hand, as we will see in Section 2.6, with this calibration the model matches the drop in the immigrants' share during the Great Recession. On the other hand, as explained in Section 2.7, both unemployed and employed return migration have a positive impact on the evolution of natives' unemployment

[50]This is a consequence of considering that the match quality is constant over the duration of the match. In Mortensen and Pissarides (1994), endogenous separations arise because the match quality changes stochastically.

[51]Alternatively, we may think that the higher is $\bar{K}$, the further we are from the standard search and matching model with free-entry, where the pool of posted jobs are simply the newly created ones.

[52]This moment target has been widely used in the search and matching literature. I use the estimates from Silva and Toledo (2009). Notice that their definition of worker hiring costs does not include any fixed cost. Therefore, the existence of a fixed cost in my model does not prevent me from using it as a target. As the model's period is a month, and the monthly mean wage is normalized to one, this moment leads to the value 0.42 in Table 2.3.

rate during the Great Recession. Therefore, the main results of the paper would not be significantly affected by a change in σ_ϵ. The model is able to replicate the full extent of the wage gap observed in the data by making the mean of the match quality draws' distribution μ_j lower for immigrants than for natives. Additionally, a certain degree in the dispersion of the distribution is needed in order to match the job-separation rate differences between the two types of workers. In particular, the lower volatility of the immigrants' match quality draws contributes to match both the job-separation rate differential and the observed native-immigrant wage dispersion ratio.

The calibration results imply that the creation cost $\bar{K}$ is 30 times the job-filling cost in steady state. This value, although higher than in Riegler (2019), generates a similar ratio of aggregate creation costs to output of 2%. The estimated value of the probability of learning the match quality α is 0.27, implying that learning is fast: after 3 months, more than 60% of all matches have learnt their actual productivity. This estimate is slightly higher than in Pries and Rogerson (2005) but in line with other papers on the literature, for instance Menzio et al. (2016).

2.6 Model Performance

In this section I first discuss the quantitative properties of the model economy at: (1) the initial steady state; (2) the pre-crisis state; and (3) the final steady state. Then, I will turn to characterize the transitional dynamics from the pre-crisis state to the final steady state, i.e. the model's performance in simulating the Great Recession.

2.6.1 Initial (2000) and Final (2016) Steady State

Table 2.4 summarizes the main quantitative features of the initial and final steady states. There are two differences between the two states. First of all, foreign inflows are different, as explained in subsection 2.5.1. Second, aggregate productivity z is lower at the final steady state. The drop in z is chosen so that the model generates a realistic change in the job-finding rate and output per capita from 2008 to 2016[53], which is achieved with a 1.96% drop.

Regarding labour market outcomes, as expected the model generates an increase in the steady-state unemployment rate, mainly driven by the drop in the steady-state job-finding rate. In turn, this is explained by the fall in the market tightness: the lower aggregate productivity depresses job creation. Moreover, the model generates an increase in the unemployment rate differential between natives and immigrants, due to a higher increment of

[53]Output per capita drops 5.85% in the model and 5.74% in the data

the steady-state job-separation rate for the latter group.

Table 2.4: Initial, Pre-crisis and Final State Results

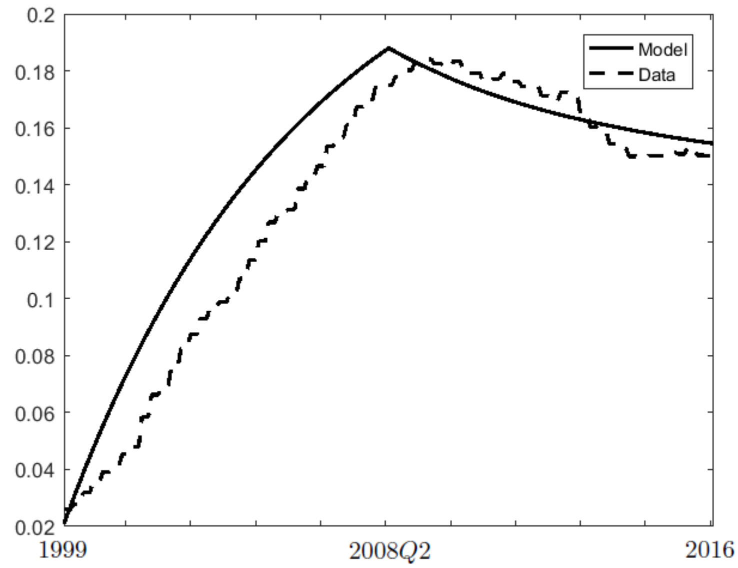
Data Moment	**Initial ss** 2000	**Pre-crisis** 2008Q2	**Final ss** 2016
Aggregate Productivity z	0.313	0.313	0.307
Unemployment Rate			
Natives	0.089	0.098	0.174
Immigrants	0.171	0.169	0.230
Separation Rate			
Natives	0.027	0.029	0.031
Immigrants	0.056	0.066	0.067
Job-finding Rate	0.303	0.271	0.177
Market Tightness	0.865	0.713	0.314
Output pc	1.035	0.941	0.886
Mean Wage			
Natives	1.000	1.000	1.018
Immigrants	0.670	0.650	0.682
Foreign Inflows	0.00028	0.0034	0.0020
Foreign Outflows	0.00028	0.0026	0.0020
Immigrant LF Share	0.021	0.188	0.143

2.6.2 Pre-crisis State

Table 2.4 also shows the quantitative predictions of the model in the pre-crisis state. That is the static picture of the state of the economy in the last period of the "immigration boom" transition (i.e. once all the actual foreign inflows from 2000 to 2008Q2 have entered the model labour market). The most obvious feature of the simulation is the increase in share of immigrants in the labour force. Figure 2.5 plots the evolution of this share in the model, from the initial to the final steady state, through the two simulated transitions. As we observe, from 2000 to 2008Q2, the immigrants' share raised from 2.1% to 18.8%.

Interestingly, through the transition path the unemployment rate of both groups increases. The mechanism behind this result is the following: as more immigrants enter the labour market, the higher is the share of less productive workers among the job searchers (since $\mu_M < \mu_N$, see Table 2.3). As a consequence, firms' expected profit of filling a job decreases (see Equation (2.18)) and therefore job creation is reduced. This implies a lower market tightness with respect to the initial steady-state (from 0.86 to 0.71) and a hence a lower job-finding rate. The increase in natives' unemployment rate during the immigration

Figure 2.5: Low-skilled immigrant labour-force share: Model economy vs data.



boom (2000−2008Q2) is not observed in the data. This occurs because in the model economy the only event that takes place from 2000 to 2008Q2 is the increase in immigration.[54].

2.6.3 The Great Recession

Figure 2.6 plots the time series of the labour market transitions during the Great Recession in the model (top panel) and in the data (bottom panel). The model is successful at generating a smooth decrease in the job-finding rate (left panel). As argued in Fujita and Ramey (2007), this is the result of introducing a fixed cost of creating a job: the smooth drop in the market tightness cannot be replicated in the standard model with free entry, where posted jobs (vacancies) are a jump variable. Figure 2.7 displays the evolution of the job-finding rate in the baseline model and in the standard model without fixed cost of creating jobs[55]. As we can see, in the standard model the job-finding rate converges immediately to its final steady-state value. Last, given the assumption of random search, the model is not able to endogenously account for the higher drop in the immigrants' job-finding rate that is observed

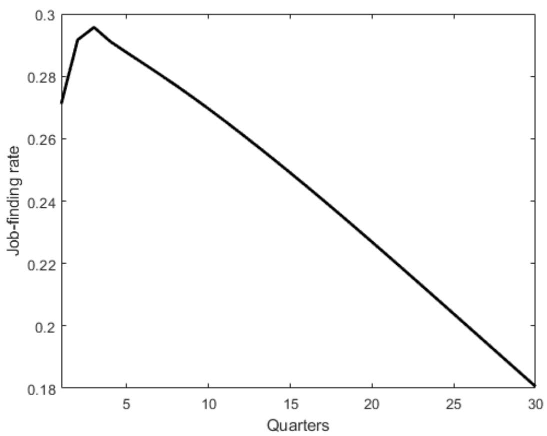
[54] I keep the modelling of that period as simple as possible as the analysis of the expansionary period is out of the scope of the paper. I am only interested in matching the increase in the immigrants' share. In fact, many other factors affecting the labour market behaviour occurred in Spain over that period: euro introduction, decreased in interest rates or large capital inflows. The model fit could be improved by adding a positive shock to aggregate productivity.

[55] For solving the model without fixed cost of creating a job ($\bar{K} = 0$), I keep unchanged all parameters but the flow cost of posting a vacancy κ, which is set to 0.15. That value is chosen so that the model matches the job-finding rate at the initial steady-state.

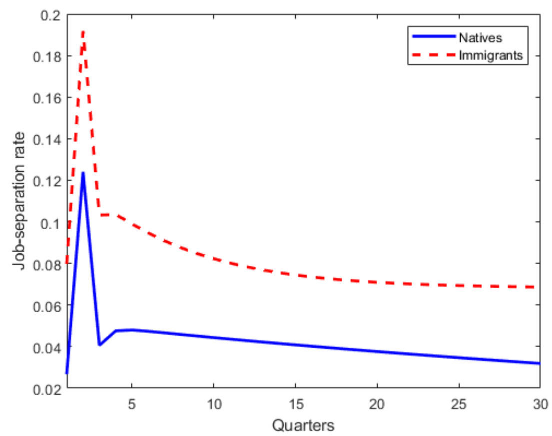
in the data.

Figure 2.6: Model performance in the Great Recession: Labour market flows

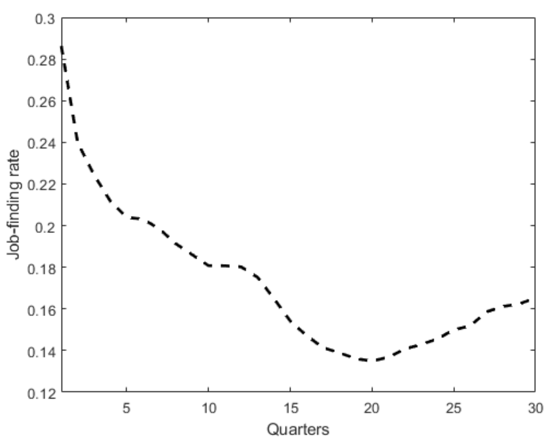
Native Job-finding Rate: Model



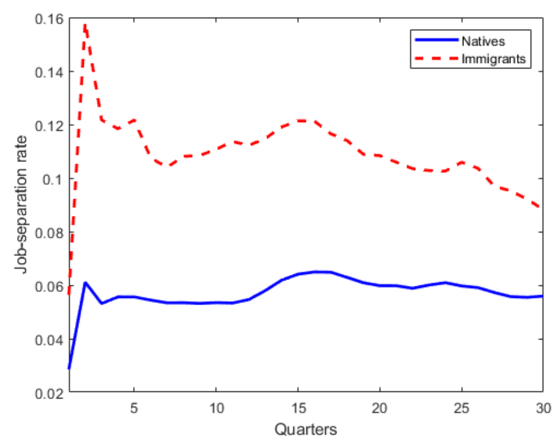
Job-separation Rates by nationality: Model



Native Job-finding Rate: Data



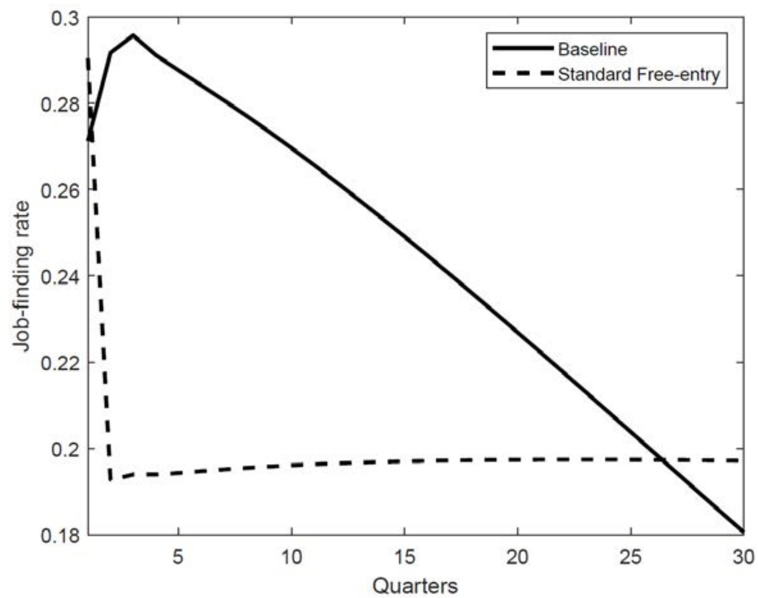
Job-separation Rates by nationality: Data



Source: Owns calculations based on the Spanish LFS-Flows for the period 2008Q3-20116Q1. Job-finding and job-separation rates are filtered by a 4-quarters moving average.

Regarding job-separation rates (right panel of Figure 2.6), the model can account for the spike on employment destruction for both type of workers. Furthermore, it is consistent with the empirical fact that immigrants are more sensitivity to the cycle. In the top right panel we can observe that the increase in the job-separation rate is higher for immigrants (11 percentage points) than for natives (8.6 percentage points). The reason for this result is that match quality draws are more homogenous for immigrants than for natives (i.e. $\sigma_M < \sigma_N$, see Section 2.3 and the Panel A of Figure 2.15, in Appendix E). This implies that

Figure 2.7: Native Job-finding Rate: Baseline model vs Standard free-entry model



in equilibrium, immigrant workers are more concentrated among matches that are employed with a match quality x close to the match quality threshold for firing (Panel B of Figure 2.15, in Appendix E). Hence, when the crisis hits (i.e when the aggregate productivity z drops), a higher proportion of matches becomes unproductive and hence a higher share of workers endogenously get separated. Last, notice that the model overshoots the rise of job-separation rates on impact. This occurs because the drop in aggregate productivity z is a one-time shock. Consequently, the model compresses all the employment adjustment in a single period[56].

Finally, as Figure 2.5 shows, the model endogenously generate a drop in the immigrant labour force share that is very close to the observed in the data. Since the foreign inflows are fixed to the actual figures (see Subsection 2.5.1), the model succeed at matching this empirical fact by endogenously generating foreign outflows (return migration flows) that are very similar those observed in the data.

[56]I keep the modelling of the negative shock as simple as possible for computational reasons. Nevertheless, the model fit could be improved by adding some frictions in the firing decision or by imposing a smooth drop in z.

2.7 The Effects of Immigration in the Great Recession

I now use the model to assess the impact of immigration in the Great Recession. I do so by solving the Great Recession (i.e. the transition path from the pre-crisis state ($2008Q2$) to the final steady-state (2016)) of a counterfactual economy without foreign inflows during the expansion. I will refer to this counterfactual as the "no immigration" economy.

Precisely, the "no immigration" counterfactual is an economy transiting from the initial steady state at 2000 to the pre-crisis state at $2008Q2$ without immigrants entering to the labour market (i.e. foreign inflows are set to zero: $\{\bar{m}_{M,t}\}_{t=2000...2008Q2} = 0$[57]). Once the pre-crisis state of the "no immigration" economy is found, I hit the economy with the same drop in the aggregate productivity z as in the baseline model and solve for the Great Recession.

I compare the labour market outcomes of the "no immigration" counterfactual with those of the baseline economy. The counterfactual exercise aims to quantify "by how much the native unemployment rate would have increased during the Great Recession in the absence of the pre-crisis immigration boom".

2.7.1 Model Mechanisms

The model outlined in the previous section features three different channels through which a higher immigrant share affects the native job-finding rate and therefore their labour market outcomes during the recession. Before showing the results of the counterfactual exercise, I will explain the three channels. This in turn will help us to better understand the quantitative results.

Job-creation Effect

In a framework with random search and two types of workers as the one described here, firms' incentives to create jobs depend on the share of each worker type among the job searchers (see Equation (2.18)). Think of a firm that is deciding whether or not to create a new job position. Because of the assumption of random search, the probability that the posted job will be filled by an immigrant or a native worker is given by the share of each worker type among the unemployed[58]. Consequently, a change in the composition of the

[57] Notice that the initial steady state (2000) is common for the baseline and the "no immigration" economy. On the other hand, in the "no immigration" economy, despite inflows are set to zero, there are immigrant outflows: this is the reason of the slight drop from 2000 to 2008Q2 in the immigrant share of the "no immigration" economy (Figure 2.16 in Appendix E).

[58] Notice that since I abstract from on-the-job search, unemployed workers are the only job searchers in the labour market.

pool of unemployed workers (e.g. due to an increase of the foreign inflows) affects firms' job creation decisions. That is why I call this channel the job-creation effect.

Now, the sign of this effect depends on whether firms prefer to be matched with an immigrant or a native worker, i.e. whether the firm's expected value of a match with a immigrant ($\widetilde{J}_M$) is lower or larger than the value obtained with a native ($\widetilde{J}_N$). These values, in turn, are determined by the value of the parameters driving workers' heterogeneity. Remember that in the model immigrants and natives differ in three dimensions. On the one hand, immigrants may leave the country while employed. Hence, *ceteris paribus* firms prefer to employ a native worker. On the other hand, immigrants' unemployment flow payment b_M is lower and therefore *ceteris paribus* firms can extract a higher surplus from them than from natives. Last, natives and immigrants draw their match quality from different distributions. Consequently, the sign of the job-creation effect is ambiguous.

The calibration results of Subsection 2.5.3 deliver $\widetilde{J}_N > \widetilde{J}_M$, so the job-creation effect is negative: the higher the share of immigrants among the unemployed ($\uparrow \phi$), the lower the firms' expected surplus from a match. This has two implications. On the one hand, the final state (at t_F) with more immigrants will feature a lower number of new jobs in equilibrium. On the other hand, during the recession, as there are more immigrants in the labour market, firms will delay the period at which the job creation is reactivated. This in turn implies a lower job-finding rate through the transition, putting upward pressure on the native unemployment rate.

Return Migration Effect

First, remember that in the presence of a fixed cost of creating a job position, one employed worker emigrating implies one additional job becoming available to be posted again and hence filled by an unemployed worker. In order to understand the return migration effect, let us imagine an economy without immigrants. If this economy is hit by the crisis, there will be no emigration[59]. Consider the opposite case of an economy with many immigrants. If now this economy experiences a recession, some immigrants that are employed will decide to leave the country. Consequently, *ceteris paribus*, in this economy there will be an increase in the pool of created but vacant positions ($\uparrow v^o$, (2) and (3) in Equation 2.25) and hence, the job-finding rate will go up.

So far I only discussed the return-migration effect of employed immigrants. What about the effect of unemployed immigrants emigrating? Remember that the calibration results imply that the job-creation effect of immigration is negative. Therefore, as unemployed

[59]Recall that the framework abstracts from native emigration.

immigrants emigrate, the share of immigrants among the total pool of unemployed (ϕ) decreases, driving up the expected benefit from creating a job. In other words, return migration of unemployed immigrants moderates the negative effects of the job-creation channel: the more unemployed immigrants leave the country, the higher the "improvement" of the pool of unemployed workers. This, in turn, will enhance (or speed up) job creation ($\uparrow v_n$) and hence increase natives' job-finding probability.

Match-destruction Effect

As pointed out in Subsection 2.3.1, following Pries and Rogerson (2005) I assume that after an endogenous separation, the job position is not destroyed but enters the pool of previously created unfilled jobs k^o (see (4) in Equation (2.25)). This, together with the fact that match destruction is higher for immigrants than for natives (see Figure 2.6) implies that the higher the share of immigrants, the higher the proportion of workers who will lose their job after the crisis hits. Therefore, the larger will be the increase (on impact) of k^o and hence the increase the natives' job finding rate. This match-destruction effect is unambiguously positive on impact. However, its sign is unclear in the long-run: as a larger number of immigrants joins the pool of unemployed, there will also be a worsening on firms' job-creation incentives (job-creation effect), which in turn will delay the creation of new jobs.

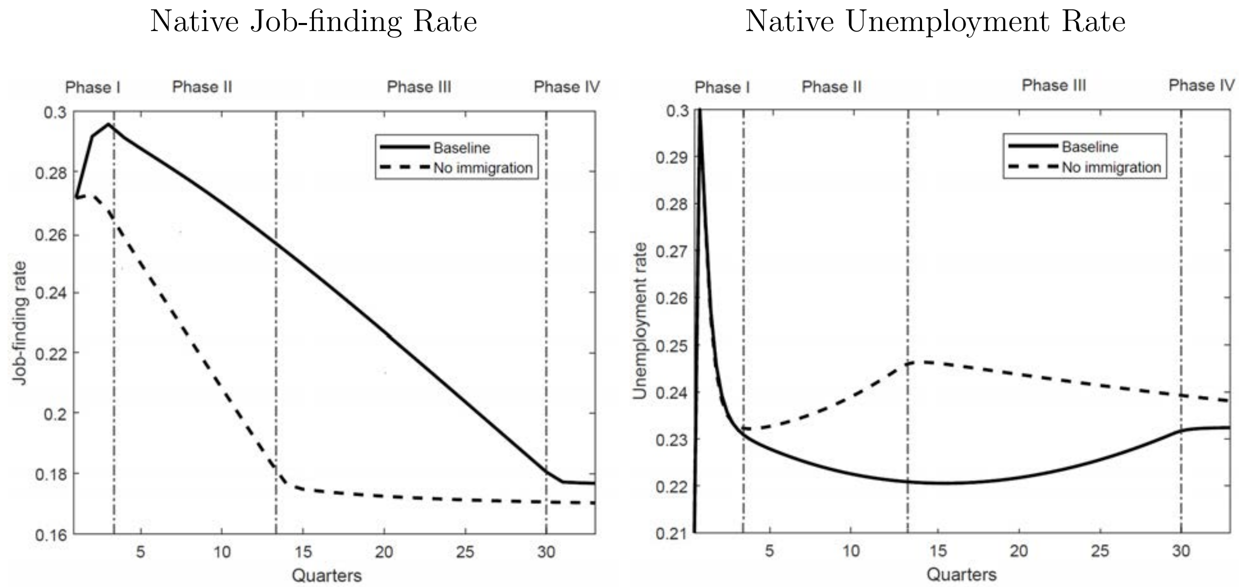
2.7.2 Results

This section displays the results of the counterfactual experiment explained in Section 2.7. In the first subsection I study the effects on natives' labour market outcomes. The second subsection evaluates the effects on natives' welfare, taking into account that differences may arise by employment status. Last, in subsection 2.7.3 I run a decomposition analysis in order to disentangle the relative importance of each of the channels discussed in 2.7.1.

Native Labour Market Performance and Vacancy Dynamics

Figures 2.8 and 2.9 illustrate the transition path of the main labour market indicators in the baseline economy (solid line) and in the counterfactual economy without foreign inflows during the expansion (dashed line). These two economies differ in the immigrants' share (Figure 2.16 in Appendix E). Additionally, since their starting point of the transition is different (by definition, their pre-crisis state is not the same) for the sake of comparison all the figures are normalized by setting their starting point to the pre-crisis values of the baseline economy.

Figure 2.8: The effect of immigration: Native labour market performance



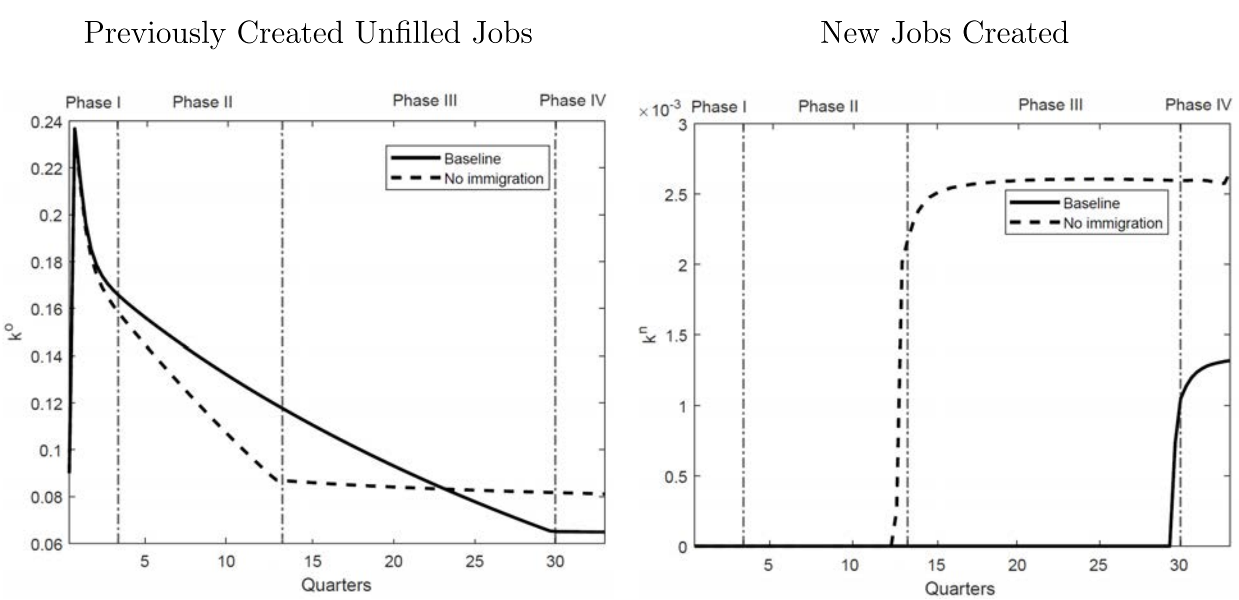
The right panel of Figure 2.8 plots the evolution of the natives' unemployment rate. First of all, notice that the natives' match destruction is the same in both economies, which implies that the increase in natives' unemployment rate is identical on impact. This occurs because the model delivers an almost identical increase in the match quality threshold for firing in the baseline and counterfactual economies. Yet, their unemployment rates diverge shortly along the transition. Precisely, the drop in natives' unemployment rate is faster in the baseline than in the counterfactual economy without immigration. In other words, the model suggests that the native unemployment rate would have been higher without immigration. This result implies that the joint action of the return migration and the (on impact) match-destruction effects of immigration dominates the (negative) job-creation and long-run match-destruction effects. Quantitatively, the model predicts that three years after the negative shock to aggregate productivity the native unemployment rate would have been three percentage points higher (around 260,000 workers[60]) in the case of no immigration.

In order to understand why the unemployment rate is higher in the counterfactual, it is key to compare the evolution of the job-finding rate in the two economies. As the left panel of Figure 2.8 shows, the decline of the job-finding rate is more moderate in the baseline than in the counterfactual economy. This result explains the faster drop of the natives'

[60]To obtain this number I use the following formula: $(e^b_N - e^c_N)e^{data}_N$, where e^b_N, e^c_N are the total number of employed natives in the baseline and the counterfactual economy, respectively, and e^{data}_N is the total number of employed natives in 2007Q4.

unemployment rate of the baseline economy (right panel). Furthermore, by analysing the evolution of the job-finding rate it is possible to distinguish each of the channels through which the presence of immigrants affects natives' labour market performance. Let us first focus on the "match-destruction effect". In the baseline economy the share of immigrants among the employed is higher. Therefore, in this economy the proportion of matches that are endogenously destroyed on impact is larger[61]. This in turn implies a larger increase (relative to the "no immigration" economy) in the stock of previously created unfilled jobs (left panel of Figure 2.9) and hence a higher jump in the native job-finding rate right after the shock. Secondly, notice that the job-finding rates of the two economies diverge during the transition. This is due to the "return migration effect": as the economy transits to the new steady-state, in the baseline economy some employed immigrants leave the country. As explained in Subsection 2.7.1, the employed immigrants' return migration enhances the job availability and hence drives the job-finding rate up. Finally, the transition path of the new jobs (right panel of Figure 2.9) illustrates the "job-creation effect". The higher immigrants' share in the baseline economy has two negative effects regarding job creation. On the one hand, it takes more time for firms to start creating (and hence posting) new job after the crisis hit. On the other hand, they create fewer new jobs at the final steady-state equilibrium.

Figure 2.9: The effect of immigration: Vacancy dynamics



[61] Remember that in the model the increase of the job-separation rate is higher for immigrants than for natives. Therefore, the higher the share immigrants among the employed workers, the higher the proportion of jobs that are endogenously destroyed after the negative shock hits the economy.

For a better understanding of the divergent transition paths of the natives' unemployment rate between the two scenarios, I split the Great Recession in four phases. In the first phase, $Q \in [1-3]$), the unemployment rate drops very quickly in the two economies. This occurs (even though there is no job creation, see right panel of Figure 2.9) because the job-finding rate remains high due to the increase in the stock of previously created unfilled jobs (left panel of Figure 2.9) after the increase in the endogenous separations took place following the shock. Interestingly, in this first phase we can identify the effect of immigration through the match-destruction channel. In the baseline economy, with more immigrants, there are more endogenous separations on impact. And that explains the higher jump in the pool of jobs and therefore the larger increase in the job-finding rate right after the crisis in the baseline model. Yet the evolution of unemployment rate during this phase is very similar in the two scenarios, suggesting that the magnitude of the match-destruction effect is weak. Subsection 2.7.3 will confirm this result.

In the second phase, $Q \in (3, 13]$, both economies still lack job creation. Therefore, again all the match formation is given by the availability of jobs that were already created (i.e. previously created unfilled jobs). This pool is decreasing in both scenarios, but less so in the baseline economy (left panel of Figure 2.9). As explained above, this is due to the return migration effect: since in the "no immigration" economy there are almost no employed immigrants leaving the country, there are no jobs that open up. This explains the increase of natives' unemployment rate in the counterfactual economy at this phase. On the contrary, in the baseline the return migration of employed immigrants buffers the fall in the job-finding rate (left panel of Figure 2.8) and it enhances the drop of the natives' unemployment rate (right panel of Figure 2.8).

In a third phase $Q \in (13, 30]$, the native unemployment rates of the two economies converge. Here the job-creation effect becomes relevant. As the right panel of Figure 2.9 shows, at $Q = 13$ the job creation is reactivated in the "no immigration" economy, whereas in the baseline firms are not yet creating new jobs. Consequently, the job-finding rate stops dropping in the counterfactual and the unemployment rate decreases, in contrast to the baseline economy. As stated before, job creation recovers faster in the counterfactual because the pool of unemployed is "better" than in the baseline economy (i.e. the job-creation effect of immigration is negative). Of course, in the absence of unemployed workers' return migration, firms' job creation would be delayed even longer in the baseline economy.

Last, after $Q = 30$, firms start creating new jobs again in the baseline economy as well. As a consequence, natives' unemployment falls in the two economies.

Who wins & who loses?

Welfare effects by employment status

The previous section shows that a higher immigrants' share in the labour force enhances the natives' employment recovery after a negative aggregate shock. This suggests that unemployed workers are the main winners from immigration since they benefit from the increase in the job-finding rate. In order to quantify the impact of immigration by workers' employment status, I compare the relative change in the value function from the pre-crisis state to the recession (two years after the shock) in both the baseline and the counterfactual economy without foreign inflows[62].

Table 2.5 displays the results for native workers. Here I discuss the welfare effects of immigration on natives, although the results for immigrant workers can be found in Table 2.9 of Appendix E . First, notice that the negative aggregate shock involves welfare drops for all native workers regardless their employment status. The first column displays the change in welfare for native unemployed workers. The model suggests that the welfare drop would have been 0.41 pp higher in the case of no immigration[63] (natives' unemployed welfare falls by 3.50% in the baseline and by 3.90% in the counterfactual). From the second column we can see that in the baseline economy the welfare drop is also lower for the native workers employed in a job of unknown quality. In this case, their welfare drop is 0.28 pp higher in the "no immigration" economy than in the baseline. The model also delivers welfare effects of immigration for native workers employed in a job with a match quality x that get fired in both economies[64]. The last column shows that the welfare effect of immigration is negligible for workers employed with the highest match quality. This finding is reasonable. The channels by which immigrants cushion the impact of the recession go through the job-finding rate. And the probability that a worker employed with a high match quality becomes unemployed is very small (λ). Therefore, the value function is essentially unaffected by a change in the immigrants' share.

[62] Value functions are the most appropriate measure of welfare in the model. By risk neutrality, they equal the expected discounted wages. We can interpret the change in the value that workers attain in equilibrium as the consumption equivalent change in the present discounted value of flow utility after the drop in aggregate productivity.

[63] Notice that because of the way I computed the last row of the Table 2.5 (see Notes), a positive difference means that the welfare drop is lower in the baseline than in the counterfactual economy.

[64] From the calibration results I find that the model delivers the same natives' firing cut-off change after the shock is realized. That is, the productivity threshold x^* that makes firms indifferent between dissolving the match or not is the same in the baseline and in the no immigration economy, in both the pre-crisis state and the recession.

Table 2.5: Natives welfare change (pp) in the baseline and the "no immigration" economy

	(1) $\mathbb{W}_{\mathbb{N}}{}^{U}$	(2) $\widetilde{\mathbb{W}}_{N}$	(3) $\mathbb{W}^{*}_{N}(x^{*})$	(4) $\mathbb{W}^{*}_{N}(x^{max})$
Baseline	-3.50	-3.24	-4.51	-0.32
No immigration	-3.90	-3.52	-4.83	-0.32
Difference	0.41	0.28	0.32	0.00

Note: Welfare change for: (1) unemployed workers; (2) workers employed in matches of unknown match quality; (3) workers employed in matches endogenously destroyed in both the baseline and counterfactual economy; (4) workers employed in matches with the highest quality. The welfare change is computed two years after the negative aggregate shock. The row with the difference is the result of subtracting the welfare drop obtained in the counterfactual to the one obtained in the baseline model.

Inequality

The model allows us to study the impact on inequality of a higher presence of immigrants during a recession. I compute the growth of the Gini index (using the value functions) from the pre-crisis state to the recession (again two years after the shock) in both the baseline and the "no immigration" economy. The results suggest that the increase in inequality would have been higher without immigrants before the crisis. Precisely, the model delivers a 11.20% rise in the Gini index in the baseline economy, whereas the increase in the counterfactual is more pronounced (12.30%).

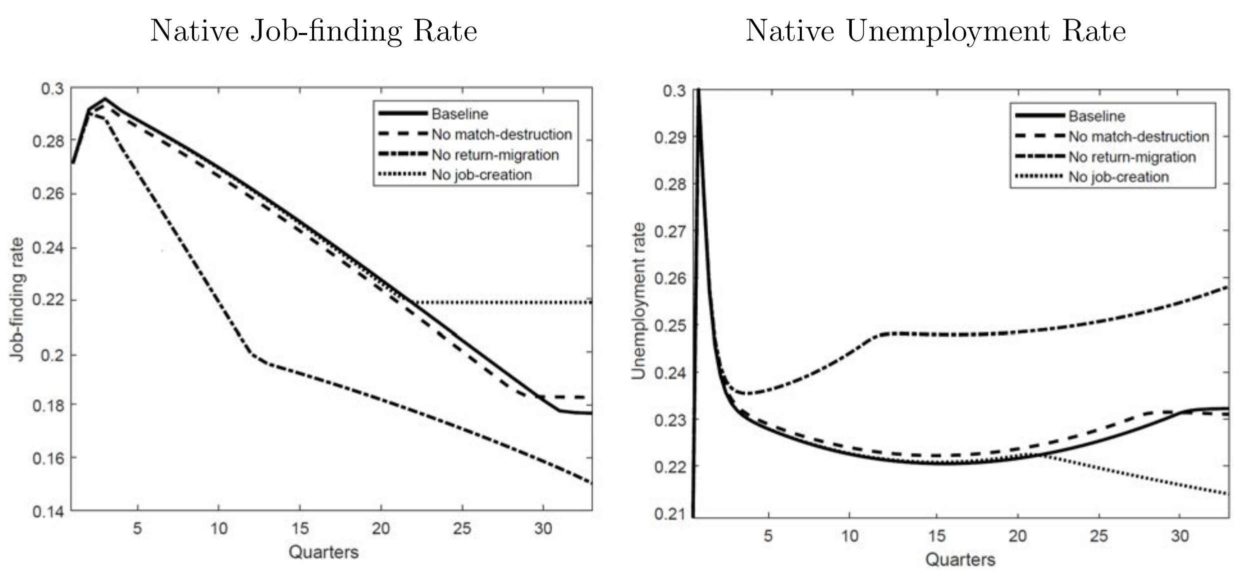
2.7.3 Decomposition Analysis

The contribution of each mechanism

In this section I quantitatively assess the importance of each of model's channels (job-creation, return-migration and match-destruction) in delivering the effect of immigration in the Great Recession. To this aim, I carry out a decomposition experiment by shutting down each of these channels. I then compare the transition path of the main labour market outcomes in each of the three restricted model versions compared to the baseline (full) model. The exercise will shed light on the relative importance of each channel. The details on the implementation of the decomposition analysis can be found in the Appendix C.

Figure 2.10 depicts the time series of the natives' job-finding and unemployment rates in each of the restricted model versions as well as in the baseline. Let us first focus on the model without job-creation. By altering the firms' beliefs regarding the share of immigrants among the unemployed, job creation is reinforced. That is, firms resume their job creation sooner than in the baseline model (right panel of Figure 2.18). Specifically, in this restricted model the creation of new jobs picks up 5 years after the shock ($t = 65$). As left panel of Figure 2.10 shows, only from that period the job-finding rate diverges from the baseline and hence natives' unemployment rate recovers faster[65]. As Table 2.6 shows, in the long-run (8 years after the shock), natives' unemployment rate is 1.8 percentage points lower in the model without the job-creation channel than in the baseline model. As differences with respect to the baseline model only show up around 5 years after the shock, from Table 2.6 we can see that the job-creation channel has no impact on natives' unemployment rate in the short-run.

Figure 2.10: Decomposition Analysis: Native labour market performance



Moving to the model's predictions without match-destruction, we can see the trade-off that this mechanism embeds. In the short-run, shutting down the match-destruction effect has a (very small) negative impact on the natives' unemployment rate (e.g two years after the shock, natives' unemployment rate is 0.12 percentage points higher than in the baseline, see first row of Table 2.6). Again, the reason is that, right after the crisis hits, the rise in k^o is lower than in the baseline (left panel of Figure 2.18). Yet, in the long-run, the match-destruction effect is negative: 8 years after the Great Recession, the native unemployment

[65] Notice that by exogenously imposing a lower proportion of immigrants among the pool of unemployed (ϕ), the final steady-state is also altered. Therefore not only does the unemployment rate fall faster in this version model, but it is also lower in steady state.

Table 2.6: Natives' unemployment rate difference (pp) between each restricted model and baseline

Years after the shock	1	2	3	6	8
No match-destruction	0.10	0.12	0.10	0.23	-0.10
No return-migration	0.62	1.62	2.66	2.57	2.47
No job-creation	0.00	0.00	0.00	-0.39	-1.75

Note Difference in natives' unemployment rate in each of the restricted model's versions with respect to the baseline model. A positive number means that natives' unemployment rate is higher in the restricted model than in the baseline.

rate without "match-destruction" is 0.10 percentage point lower than in the baseline. This is because as no immigrants join the pool of unemployed, the job-creation effect is alleviated. Therefore firms restart job creation sooner (right panel of Figure 2.10). Still, quantitatively the match-destruction effect is almost negligible (both job-finding and unemployment rates are very similar to those in the baseline model, see Figure 2.10 and first row of Table 2.6).

Finally, the decomposition analysis suggests that immigrants return migration is the key channel explaining the smoother drop in the native job-finding rate during the Great Recession. As the left panel of Figure 2.10 shows, in the economy without return migration, the drop in the job-finding rate is much steeper. Three years after the shock, natives' unemployment rate is 2.66 percentage points higher when return-migration is not allowed (second row of Table 2.6). The impact of return-migration remains large in the long run: 8 years after the shock, natives' unemployment is 2.47 percentage points higher than in the baseline economy.

Overall, we conclude that immigrants' return-migration is quantitatively the most important channel both in the short-run and in the long-run. In the short-run (1 to 6 years after the shock), the average impact of return-migration on natives unemployment rate is 10 times as large as the sum of the others two channels. Regarding the long-run (8 years after the shock), the positive impact of return-migration overcomes the negative effect of the other two channels. As Table 2.6 shows, its impact is 1.34 times as large as the sum of the (negative) impact of the others two channels.

The Return Migration Effect

The previous subsection showed that the return migration is quantitatively the most important channel explaining why the natives' unemployment rate recovers faster in the baseline than in the "no immigration" economy. Remember that the overall effect of the immigrants' return migration is explained by the interaction of two forces: the return migration of the unemployed immigrants and that of the employed immigrants. Understanding which one is the main driver of the overall effect has important implications for policy. For instance, if a government aims to promote return-migration, the optimal policy should focus on designing economic incentives for the return-migration of the group whose impact is the largest, as we could expect that employed and unemployed workers respond differently to economic incentives[66]. In order to disentangle the relative importance of each of the two components, I solve the Great Recession in two restricted versions of the model. In the first one I shut down the employed return migration by only allowing the unemployed immigrants to leave the country. In a second restricted model, unemployed return migration is shut down.

Table 2.7: Natives' unemployment rate difference (pp) between each restricted model and baseline

Years after the shock	1	2	3	6	8
No eM return	0.12	0.47	0.89	1.76	1.16
No uM return	0.12	0.31	0.50	1.11	1.24

Note: Difference in natives' unemployment rate in each of the restricted model's versions with respect to the baseline model. A positive number means that natives' unemployment rate is higher in the restricted model than in the baseline.

As expected, restricting return migration of any of the two groups (employed or unemployed) raises the native unemployment rate (See Figure 2.19 in the Appendix E). Interestingly, the relative importance of each of them depends on the time horizon that we consider. Table 2.7 displays the difference in the native unemployment rate from the restricted to the baseline model, for several years after the negative shock. In the short run (1 to 6 years after the shock), shutting down the employed return migration has a higher impact. However, in the long run (8 years after the shock), the main driver is the emigration of the unemployed immigrants. The finding is economically intuitive: in the short run the economy transits in a scenario of no job creation (first and second phases described in Subsection 2.7.2). There, all the new matches are from jobs that become available after employed immigrants emigrate. Therefore, if the return migration of employed workers is not allowed, the job-finding rate would fall deeper than in the baseline economy (left panel of Figure 2.19) and the native unemployment rate would be higher. Precisely, Table 2.7 shows that six years after the shock, natives' unemployment rate would be almost 2 pp higher if employed immigrant did

[66]A policy on this spirit was implemented by the Spanish government in 2008, with limited impact. See Amuedo-Dorantes and Pozo (2018)for details on the policy's design and effectiveness.

not emigrate.

Last, in the long run the model suggests that the return migration of unemployed workers has a higher impact on the native unemployment rate. The rationale for this goes as follows. In the long run, the "job-creation" effect becomes more important, since it takes long (around 5 years in the baseline) for firms to start creating jobs again. Therefore, it is only after some years that the composition of the unemployed pool becomes relevant. Now, if no unemployed immigrant leaves the country, job-searcher's composition does not improve during the transition. Hence, firms restart job creation later than in the baseline economy, putting upward pressure on the natives' unemployment rate. The last row of Table 2.7 measures this effect. 8 years after the shock, natives' unemployment rate would be 1.24 pp higher if unemployed immigrants would not emigrate.

2.8 Robustness Checks

2.8.1 Relaxing Wage Rigidity

Motivated by the extensive evidence on downward wage rigidity in Spain during the Great Recession, in the model I assumed that wages do not adjust after the drop in the aggregate productivity z. Two questions arise: (1) is this assumption crucial for the model performance?; (2) are the counterfactual predictions sensitive to allowing a certain degree of wage flexibility? To answer this questions, I modify the model by introducing an exogenous parameter α_w governing how much of the gap between the rigid wage and the fully flexible (Nash-bargained) wage is closed at every period of the Great Recession[67]. In particular, during the Great Recession, wages at period t are given by the following equation:

$$w_{j,t} = \overline{w}_j - t(\overline{w}_j - w_j^{NB})\alpha_w \tag{2.21}$$

where $\overline{w}_j$ denotes the rigid wage (i.e. equilibrium wage Nash-bargained at the initial steady-state) and w_j^{NB} denotes the fully flexible wage (i.e equilibrium wage of the final steady-state under Nash-bargaining).

Model Performance

Wage rigidity matters for the model's performance. Think of a firm right after the drop in aggregate productivity. If in the next period the firm was able to lower the worker's wage,

[67]That is, this parameter specifies the number of periods that it takes for wages to reach their Nash-bargained values of the final steady-state.

the expected future value of staying matched with the worker would increase. Therefore, it may be better for the firm not to dissolve the match today. However, if the firm knows that it will not be possible to lower wages in subsequent periods, its expected future surplus will be lower and more jobs will be endogenously destroyed.

I solve for the Great Recession for different values of α_w keeping the rest of the parameters constant. The faster the wage adjustment (higher α_w), the lower the increase in the job-separation rate (see Panel A and B of Figure 2.20 in the Appendix E), since some matches will survive as firms know that the wage will be lower soon. In fact, for α_w big enough, all matches survive and therefore the model is not able to deliver the increase in the unemployment rate that is observed in the data. Model's prediction regarding the higher increase in the job-separation rate for immigrants than for natives is robust to some degree of wage adjustment. As expected, a faster wage adjustment also accelerates the creation of new jobs (Panel C of Figure 2.20 in the Appendix E). Yet, for certain values of α_w, the model is successful at delivering a smooth drop in the job-finding rate which is consistent with the data.

The Effects of Immigration in the Great Recession

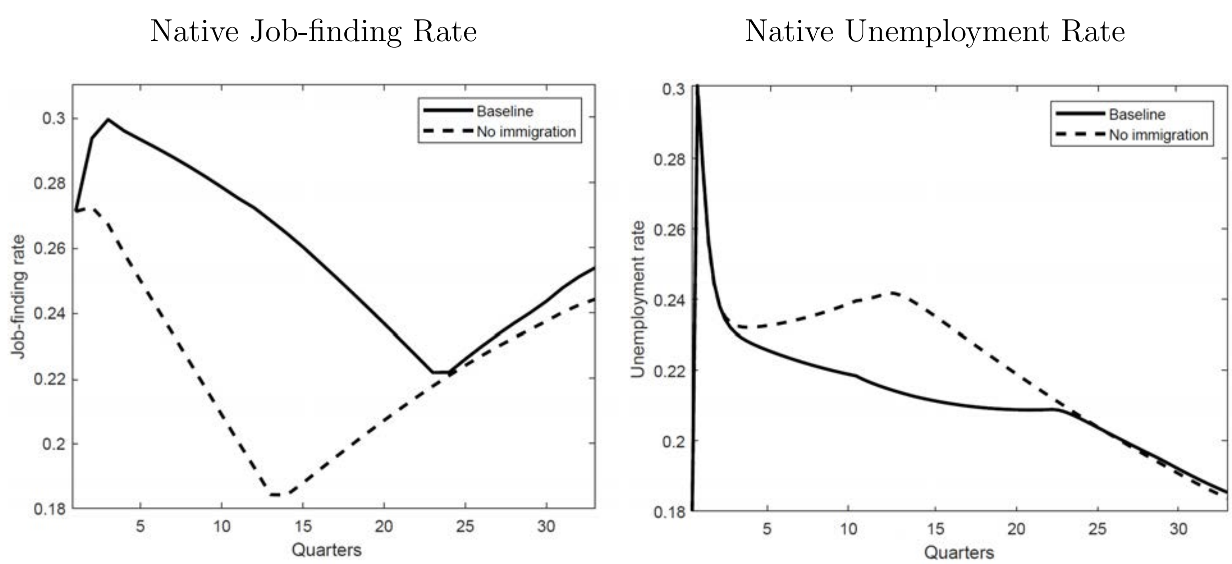
The previous results confirm that the model performs well when a certain degree of wage flexibility is introduced. Here, I perform the same counterfactual of Section 2.7 but setting $\alpha_w = 0.01$[68], and keeping the rest of the parameters constant. This value of α_w implies that it takes four years to close half of the gap between rigid and fully flexible wages. The goal is to check whether the model's predictions of on the impact of immigration in the Great Recession are robust to relaxing the wage rigidity assumption.

Figure 2.11 shows the effect of immigration on the natives' job-finding and unemployment rates under this new version of the model when $\alpha_w = 0.01$. As we can observe, the qualitative prediction of the counterfactual is unaffected: natives' unemployment rate would have been higher without immigration (right panel). Again, the reason is the smoother drop in the natives' job-finding rate in the baseline economy (left panel).

Quantitatively results are also similar. Table 2.8 sheds light on the magnitude of the differences. It displays the average difference in natives' unemployment rate between the baseline and the "no immigration" economy, for the two versions of the model (wage rigidity vs wage flexibility). As we can see, at beginning of the recession (1 to 4 years after the shock), results are very similar. However, over time the model with full wage rigidity predicts a larger impact of immigration. Interestingly, the experiment suggests that with certain degree of

[68] I choose this value because for $\alpha_w = 0.01$ the model is consistent with the empirical evidence of Section 2.2 (see Figure 2.20 in the Appendix E).

Figure 2.11: The effect of immigration with wage flexibility ($\alpha_w = 0.01$): Native labour market performance



wage flexibility, immigration has no effect in the long-run (6 to 8 years after the shock), whereas in the model with full wage rigidity the impact of immigration is long-lasting (last column of Table 2.8).

Table 2.8: Natives' unemployment rate difference (pp) between the "no immigration" economy and baseline

Years after the shock	1-4	4-6	6-8
Wage-rigidity Model	1.84	2.17	1.09
Wage-flexible Model	1.80	1.01	0.00

Notes: Difference in natives' unemployment rate in the "no immigration" economy with respect to the baseline economy, for the model with wage rigidity and wage flexibility. A positive number means that natives' unemployment rate is higher in the economy without immigration.

2.8.2 Shutting Down Mean Match Quality Heterogeneity

In the baseline calibration the wage gap (wage premium) between immigrants and natives arise due to the heterogeneity in the mean of the match quality draws' distribution between the two worker types. Consequently, the baseline calibration delivered a higher mean match quality draw for natives than for immigrants, i.e. $\mu_N > \mu_M$. Yet the literature has explored alternative calibration strategies in order to pin down the immigrants' wage premium. In particular, Battisti et al. (2017) or Albert (2019) assume no productivity differences between immigrants and natives. Instead, they incorporate heterogeneity in the workers' bargaining power to explain differences in observed wages. In this Section I check whether the predictions of the counterfactual are robust to this alternative calibration strategy.

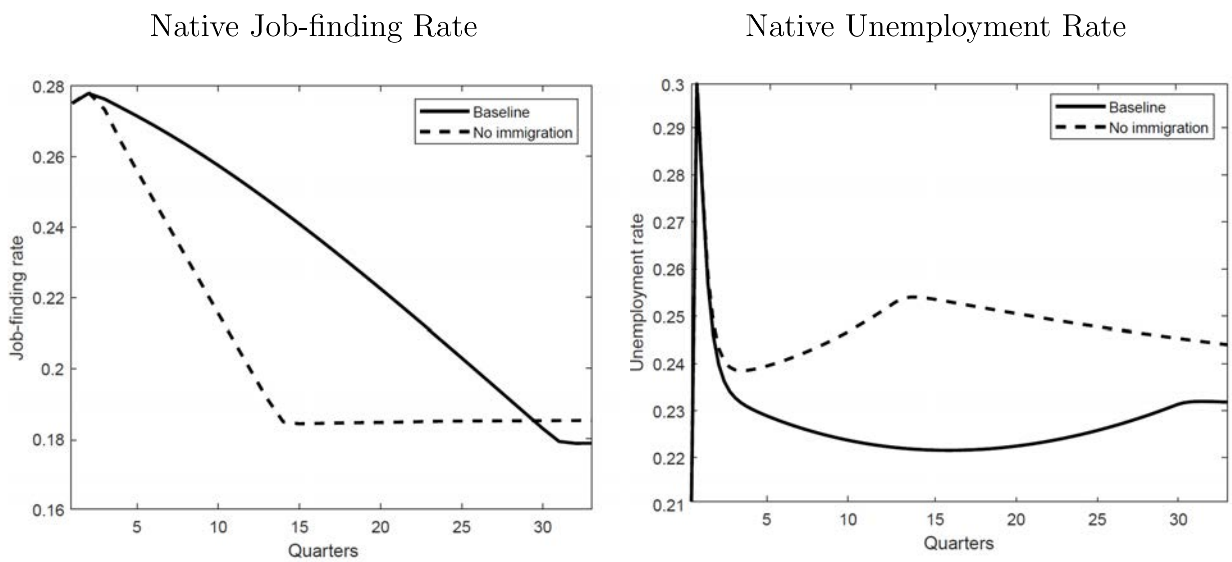
To be more precise, I modify the model as follows. First, I switch off the mean match quality differences by setting $\mu_M = \mu_N = \mu$. Second, I introduce heterogeneity in the worker's bargaining power so that $\gamma_N \neq \gamma_M$. I recalibrate the model following the same strategy described in Section 2.5. The only difference is that now γ_M pins down the immigrants' mean wage[69]. Table 2.10 in the Appendix E displays the calibration results. As expected, the bargaining power is lower for immigrants than for natives since γ_M is estimated to match the fact that immigrants have lower wages. The intuition for this result is simple: the lower γ_M, the higher the share of the match surplus that firms are able to extract, and hence the lower the immigrants' wage compare to natives'. As we can see from Table 2.10, the model's fit at the initial steady state is virtually unchanged. Moreover, as Figure 2.21 in the Appendix E shows, the model's performance in the Great Recession is very similar to that of the baseline model. We can conclude that the alternative calibration strategy is successful at matching both the initial pre-crisis state of the Spanish economy and the Great Recession.

Last, I repeat the counterfactual experiment and the decomposition analysis of Section 2.7 with the new calibration. Two main results stand out. First, the calibration delivers $\widetilde{J}_N < \widetilde{J}_M$, implying that now the job-creation effect of immigration is positive. To see why this is happening, think of a firm that is deciding to create a job. The firm now knows the following: (1) immigrant and native workers draw their match quality from a distribution with the same mean. Therefore, they are expected to draw a very similar match quality x; (2) immigrants have a lower bargaining power than natives. Hence, the firm will be able to extract a higher share of the surplus from them. Altogether, (1) and (2) imply that the firm's expected surplus from a match is higher if filled by an immigrant worker. Consequently, the more immigrants among the job-searchers, the higher the firms' incentives to create jobs.

Second, the results of the main counterfactual are very similar. Figure 2.12 compares the evolution of the natives' job-finding and unemployment rates in the baseline and in the "no immigration" economy. As we can see, the natives' unemployment rate in the counterfactual is higher than in the baseline economy. Remember that under this calibration the

[69] The natives' mean wage is still identified by the value of the mean match quality μ which is equal to μ_N of the baseline calibration.

Figure 2.12: The effect of immigration without mean match quality heterogeneity: Native labour market performance



job-creation effect of immigration is positive. The fact that the results of the counterfactual experiment are very similar with respect to the baseline calibration confirms that the "job-creation" effect is not quantitatively very relevant. The positive sign of the "job-creation" effect effect shows up very clearly in Figure 2.22 in the Appendix E. Notice that when the "return-migration" channel is switched off, the long-run natives' unemployment rate is lower than in the baseline. The rationale for the result goes as follows: since the "job-creation" effect of immigration is positive, the fact that unemployed immigrants leave the country affects negatively the firms' job-creation incentives. That is, the more unemployed immigrants return migrate, the longer firms will delay the creation of new jobs. Therefore, natives' unemployment rate would be lower if return migration was not allowed.

2.9 Conclusions

This paper studies the impact of foreign-born workers on the labour market during a recession. First, using Spanish data I provide evidence that the impact of the Great Recession on employment transitions was different for immigrant and native workers. Second, I document that foreign outflows were very responsive to the crisis as many immigrants left the country. Them I build a random search model of the labour market with vacancy persistence, endogenous return migration and downward wage rigidity that captures these empirical findings.

I find that three years after the Great Recession, Spanish natives' unemployment rate would have been 2.6 percentage points higher in the absence of the pre-crisis immigration boom. A key result of the quantitative analysis is that the job-creation effect of immigration is negative. Yet, the counterfactual exercise predicts that return-migration and match-separation effects are positive and dominate the job-creation effect, implying overall welfare gains for native workers. In fact, the decomposition analysis reveals that the return-migration channel is quantitatively the most relevant channel.

The findings of this paper have important policy implications. Stricter immigration enforcement is predicted to be detrimental as it would remove one important channel through which labour markets adjust during a recession. The adverse effects of this policy on natives would be especially large if either negative aggregate shocks are frequent, or the labour market is particularly rigid. Moreover, given the positive impact of return migration, a policy subsidising immigrants for a voluntary return (lump-sum bonuses, higher unemployment benefits than what they are entitled to obtain) will help the labour market adjustment during a recession and hence will enhance the employment recovery.

This paper abstracts away from many channels that could be potentially important for the results presented, and are relevant research questions on their own. First, I focus on a national-broad perspective, restricting my attention to international labour mobility. However, data shows that foreign-born workers are also more prone to move across regions than natives. In a framework with vacancy persistence as the one developed here, the impact of immigration is asymmetric in recessions and economic expansions. In other words, with vacancy persistence, immigrants leaving the labour market in a context of no job-creation (recession) has a positive effect on natives' job-finding rate. However, immigrants entering in a local market where jobs are created in a normal fashion (expansion) would have a very small impact on the job-finding rate (effect only goes through search externalities). Consequently, in this setup I expect that the positive effect of immigration in the region that is more negatively affected by the crisis (from where immigrants move) would be higher than in the baseline model with only a national labour market. Finally, I expect that the impact of immigration in regions barely affected by the crisis (to where immigrants move) would be very small.

Second, I abstract from selection of returned immigrants. As immigrants that decide to leave the country may be very different with respect to stayers, the composition of the remaining immigrants will be affected. Taking into account this variation in the composition of the pool of immigrants could deliver important implications regarding the impact of immigration on firms' job-creation incentives.

Last, this paper ignores potential fiscal implications of migrants. In theory, the net impact of immigration on the government budget is not obvious. On the one hand, immigrants are younger than natives and therefore can alleviate the pension burden. This channel could be particularly relevant for some European countries where the ageing of the population is becoming a first-order issue. On the other hand, the empirical evidence presented here suggests that immigrants are also more likely than natives to lose jobs in a recession. Therefore a higher immigrants' share could increase the government expenses on unemployment benefits. Incorporating this trade-off in a life-cycle framework is a promising avenue for future research.

2.10 Appendix

Appendix A. Flow Equations

Employed workers

Workers employed in a match of unknown quality

The mass of workers employed in a match of unknown quality evolves as follows:

$$\widetilde{e}_{j,t+1} = \left[1 - \left(\underbrace{(1 - G(\widetilde{\varepsilon}^*_{j,t}))}_{(1)} + G(\widetilde{\varepsilon}^*_{j,t}) \left(\underbrace{\lambda}_{(2)} + \underbrace{(1-\lambda)\alpha}_{(3)}\right)\right)\right] \widetilde{e}_{j,t} + p(\theta_t) G\left(\varepsilon^{u,*}_{j,t}\right) u_{j,t} \quad (2.22)$$

Workers employed in a match of unknown quality can exit the pool of employed workers of unknown quality for three reasons: (1) they emigrate, (2) their job becomes obsolete, (3) they learn their actual match quality. On the other hand, unemployed workers who find a job enter into the pool.

Workers employed in a match of known quality

The mass of workers employed in a match of known quality evolves according to:

$$\begin{aligned} e^*_{j,t+1}(x) = & \left[1 - \left(\underbrace{\left(1 - G\left(\varepsilon^{*,*}_{j,t}\right)\right)}_{(1)} + G\left(\varepsilon^{*,*}_{j,t}\right) \left(\underbrace{\lambda \mathbb{I}_{j,t}(x)}_{(2)} + \underbrace{(1 - \mathbb{I}_{j,t}(x))}_{(3)}\right)\right)\right] e^*_{j,t}(x) + \\ & + G\left(\widetilde{\varepsilon}^*_{j,t}\right)(1-\lambda)\alpha F_j(x) \widetilde{e}_{j,t} \end{aligned} \quad (2.23)$$

Again, three reasons explain the exits from the pool of $e^*_j(x)$. The first two are the same as for $\widetilde{e}_j$, i.e. worker's emigration and job obsolescence. The last term (3) refers now to the endogenous separations. Last, entries to the pool come from the mass of employed who discover that their actual productivity is precisely x.

Unemployed Workers

As for the evolution of unemployed we have:

$$u_{j,t+1} = \left[1 - \left(\underbrace{\left(1 - G\left(\varepsilon^{u,*}_{j,t}\right)\right)}_{(1)} + \underbrace{G\left(\varepsilon^{u,*}_{j,t}\right)p(\theta_t)}_{(2)}\right)\right] u_{j,t} + \underbrace{G(\widetilde{\varepsilon}^{*}_{j,t})\lambda}_{(3)}\,\widetilde{e}_{j,t} +$$
$$\int_0^{x^{max}} G\left(\varepsilon^{*,*}_{j,t}\right)\left(\underbrace{\lambda \mathbb{I}_{j,t}(x)}_{(4)} + \underbrace{(1 - \mathbb{I}_{j,t}(x))}_{(5)}\right) e^{*}_{j,t}(x) + \underbrace{m_{j,t}}_{(6)} \tag{2.24}$$

First of all, the unemployed workers may exit unemployment if: (1) they leave the country or (2) they find a job. Second, workers may become unemployed because job obsolescence (3) and (4) or endogenous separation (5). Last, we assume that foreign inflows enter into the country as unemployed.

Previously Created unfilled jobs

This stock evolves as follows:

$$k^{o}_{t+1} = \left[1 - \underbrace{q(\theta_t)\sum_j G\left(\varepsilon^{u,*}_{j,t}\right)\frac{u_{j,t}}{u_t}}_{(1)}\right]\underbrace{(k^{n}_{t} + \mathbb{I}_{post,t}k^{o}_{t})}_{v_t} + \underbrace{\sum_j \left(1 - G\left(\widetilde{\varepsilon}^{*}_{j,t}\right)\right)\widetilde{e}_{j,t}}_{(2)} + \underbrace{\sum_j \int_0^{x^{max}} \left(1 - G\left(\varepsilon^{*,*}_{j,t}\right)\right) e^{*}_{j,t}(x)}_{(3)}$$
$$+ \underbrace{\sum_j \int_0^{x^{max}} G\left(\varepsilon^{*,*}_{j,t}\right)(1-\lambda)\left(1 - \mathbb{I}_{j,t}(x)\right)}_{(4)} e^{*}_{j,t}(x) + (1 - \mathbb{I}_{post,t})k^{o}_{t} \tag{2.25}$$

The first term (1) is the mass of jobs that exits the stock of previously created unfilled jobs. It is given by the total number of jobs that are filled in that period. The rest of the components are the ins to the stock of previously created unfilled jobs: (2) and (3) refers to the increase in the stock produced by the employed workers' emigration. Last, (4) is the amount of jobs that are endogenously destroyed.

Appendix B. Computational Algorithm

Appendix B.1. Steady-State Equilibrium

The following computation algorithm is used to find the steady-state equilibrium:

(1) Guess an initial distribution of workers and vacancies $\mu^0 = \left\{\widetilde{e}_j^{\,0}, e_j^{*0}, u_j^0, k^{o0}, k^{n0}\right\}$. Given the guess, compute $\theta_D^0 = \frac{k^{o0}+k^{n0}}{u^0}$ and use Equation (2.18) and the entry condition (2.19) to find θ_E^0.

(2) Given θ_D^0, we solve the Nash bargaining and the value functions and policy functions as follows:

   (a) Guess an initial wage function $w_j^0 = \left\{w_j^{*0}, \widetilde{w}_j^0\right\}$.

   (b) Given w_j^0, solve the value functions and policy functions as a linear system of equations.

   (c) Given the value functions and policy functions computed in (3b), solve the Nash bargaining problem in (2.3) and (2.4) and obtain $w_j^1 = \left\{w_j^{*1}, \widetilde{w}_j^1\right\}$.

   (d) If w_j^1 and w_j^0 are close enough, then move on to step (3). Otherwise go back to (2a) with a new guess for the wage function: $w_j^{0'} = \xi_w w_j^1 + (1-\xi_w) w_j^0$.

(3) Use the policy functions obtained in step (2) to compute the time-invariant distribution $\overline{\mu^0}$ by iterating the law of motion of the distributions in Equations (2.22) - (2.25).

(4) Given $\overline{\mu^0}$ and the value functions computed in (2), use Equation (2.18) and the entry condition (2.19) to find θ_E^1.

(5) If θ_E^1 and θ_E^0 are close enough, then move on to step (6). Otherwise go back to (1) with a new guess $\mu^{0'} = \overline{\mu^0}$.

(6) Denote the converged θ_E found in step (5) as $\overline{\theta}_E$. Use $\overline{\mu^0}$ found in step (4) to compute $\overline{\theta}_D = \frac{\overline{k^{o0}}+\overline{k^{n0}}}{\overline{u^0}}$. If $\overline{\theta}_E$ and $\overline{\theta}_D$ are close enough, then we found the steady state. Otherwise go back to (1) with a new guess $k^{o0'} = (1+\xi_{k^o})\mathbb{I}_\theta k^{o0} + (1-\xi_{k^o})(1-\mathbb{I}_\theta)k^{o0}$, where $\mathbb{I}_\theta$ is an indicator function that takes the value 1 if $\overline{\theta}_E > \overline{\theta}_D$ and 0 otherwise.

Appendix B.2. Equilibrium Transition Path

The following computation algorithm is based on Dolado et al. (2018) and it is used to find the transition path between two states.

(1) Set the wage fixed to the initial state value $\{w_{j,t}, \widetilde{w}_{j,t}\}_{t=t_0\ldots t_1} = \left\{\overline{w}_j, \overline{\widetilde{w}}_j\right\}_{t=t_0\ldots t_1}$.

(2) Guess a path for the market tightness $\{\theta_t^0\}_{t=t_0\ldots t_1}$ and for the proportion of unemployed immigrants among the total pool of unemployed $\{\phi_t^0\}_{t=t_0\ldots t_1}$.

(3) Set the value functions at t_1 to their value at the final state.

(4) Given $\{\theta_t^0\}_{t=t_0...t_1}$, solve the value functions and policy functions from t_1 to t_0 by backward iteration.

(5) Set the distribution of workers and vacancies at t_0 to their value in the initial state.

(6) Use the path of value and policy functions obtained in step (4) and the law of motion of the distributions in Equations (2.22) - (2.25) to compute the evolution of the distributions of workers and vacancies from t_0 to t_1. We denote the distributions' transition path as $\{\mu_t\}_{t=t_0...t_1}$.

   (a) Starting at $t = t_0$, use Equation (2.18) and the entry condition (2.19) to obtain $\theta_{E,t}$.

   (b) Use $\theta_{E,t}$, u_t and $v_{o,t}$ to obtain $v_{n,t} = \theta_{E,t} u_t - v_{o,t}$.

   (c) Use the law of motion of the distributions to obtain $\tilde{e}_{j,t+1}, e^*_{j,t+1}, u_{j,t+1}$ and k^o_{t+1}.

   (d) Go back to (a) until $t = t_1$.

(7) Use $\{\mu_t\}_{t=t_0...t_1}$ obtained in step (6) to compute $\{\phi\}_{t=t_0...t_1}$ and $\{\theta_{D,t}\}_{t=t_0...t_1} = \left\{\frac{k^n_t + k^o_t}{u_t}\right\}_{t=t_0...t_1}$.

(8) If both $\left(\{\theta_{D,t}\}_{t=t_0...t_1} \text{ and } \{\theta_t^0\}_{t=t_0...t_1}\right)$ and $\left(\{\phi_t^1\}_{t=t_0...t_1} \text{ and } \{\phi_t^0\}_{t=t_0...t_1}\right)$ are close enough, then we are done. Otherwise go back to (2) with new guesses $\left\{\theta_t^{0'}\right\}_{t=t_0...t_1} = \{\xi_{\theta_t}\theta_{D,t} + (1-\xi_{\theta_t})\theta_t^0\}_{t=t_0...t_1}$ and $\left\{\phi_t^{0'}\right\}_{t=t_0...t_1} = \{\xi_\phi \phi_t^1 + (1-\xi_\phi)\phi_t^0\}_{t=t_0...t_1}$.

Appendix C. Decomposition Analysis Implementation

The decomposition analysis of Subsection 2.7.3 consists in simulating the Great Recession as explained in Section 2.4, but in three restricted versions of the model. In the first one, I restrict the model by shutting down the match-destruction channel. This is implemented by artificially preventing firms from dissolving their matches with immigrants when the negative shock is realized. As the top left panel of Figure 2.17 (in Appendix E) shows, in this restricted version of the model, immigrants' unemployment rate does not rise on impact. Remember that the match-destruction channel implies that the higher the immigrants' share, the larger the proportion of jobs endogenously destroyed on impact. This, in turn implies that more jobs become available right after the negative shock hits, and hence *ceteris paribus* the more the job-finding rate goes up in the first period (See left panel of Figure 2.8). Therefore, by shutting down immigrants' endogenous separations, the job-finding rate does not increase right after the shock hits.

In the second restricted version of the model I shut down the return migration channel. Specifically I drop the immigrant's wage associated with working abroad w_M^A, so that no immigrant worker decides to leave the country during the Great Recession[70]. The right top panel of Figure 2.17 (in Appendix E) shows that whereas in the baseline model the immigrant share falls during the recession due to the return migration, that does not occur in this restricted model. Since immigrant workers do not choose to leave the country in the latter model, the mechanisms triggered by the return-migration effect (See Subsection 2.7.1) do not occur.

In the third exercise I shut down the job-creation effect. The idea is to remove the negative impact that immigration has on firms' job-creation decision. For that I assume that firms do not update their expectations regarding the probability that posted job will be filled by an immigrant worker[71]. Intuitively, that means that firms think that the proportion of immigrants among the pool of unemployed is the same as it was before the immigration boom. The bottom panel C of Figure 2.17 (in Appendix E) illustrates the magnitude of the change in ϕ from the baseline to this restricted version.

Appendix D. Other Data Sources

Appendix D.1. Wage Structure Survey

The Wage Structure Survey is a four-yearly survey of firms in Spain. It is based on a representative sample of workers employed in private Spanish firms, regardless the size of the firm. Regarding sectors, the survey does not cover agriculture and fisheries, domestic service and public administration. I use the 2006 version, which covers 235,272 workers. The Wage Structure Survey provides information about level of remuneration of establishments' employees, workers' demographic and job characteristics (nationality, sex, age, level of education, tenure in the firm, occupation, type of contract, part-time indicator). The information is provided by the management of the establishment.

Appendix D.2. Vacancy Rate

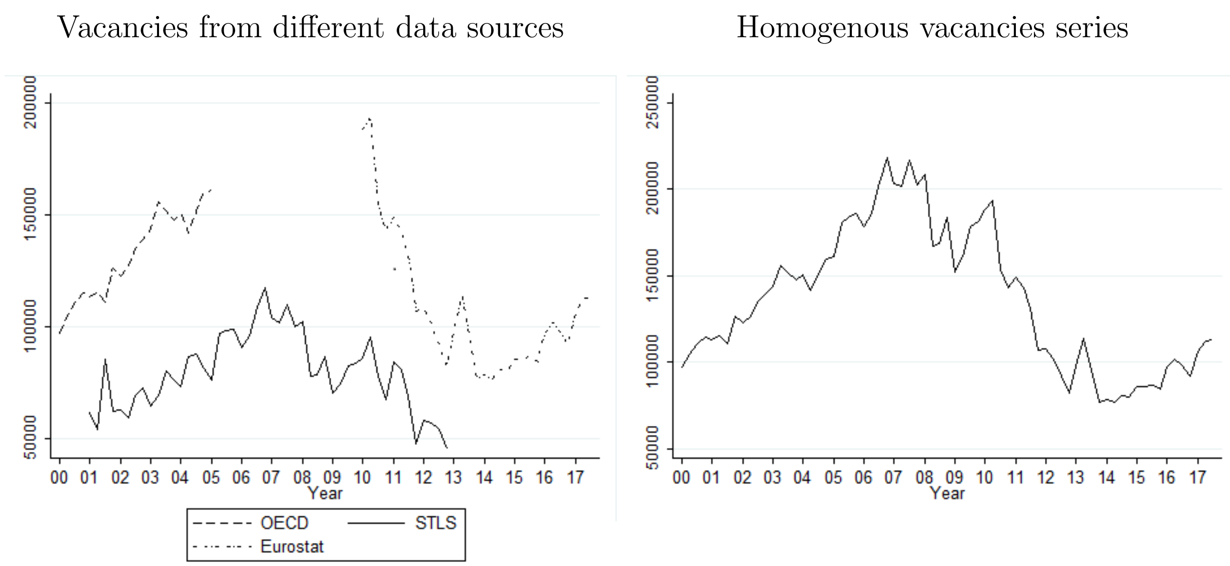
The lack of homogenous series of vacancies for Spain covering long periods make it very hard its study. To compute the vacancy rate used in the calibration, I use the approach developed by Boscá Mares et al. (2017) in order to construct an homogenous time series for the stock of posted vacancies. The approach consists in homogenizing data on posted vacancies from three different data sources: the quarterly Unfilled Job series (published by the OECD but

[70] That is, when I hit the aggregate productivity z in the model, I also exogenously impose a drop in w_M^A. Then the transition is solved.

[71] This is done by fixing the variable ϕ to its value in the initial steady state.

provided by the Spanish Pubic Employment Office (INEM) from 1970 to 2005), the Job Vacancy Statistics series from the Short-term Labour Survey (STLS, Eurostat, from 2001 to 2012), and data on vacancies from the Quarterly Labour Cost Survey (QLCS, Eurostat). This last source provides the most complete information on vacancies (public and private jobs). However, Eurostat only started to offers the series of vacancies in the QLCS in the first quarter of 2010. The left panel of Figure 2.13 displays the three series of vacancies. In order to construct a long time series, the Eurostat data must be homogenize with the other two sources. Two main issues arise. On the one hand, the INEM ceased providing the Unfilled Job series in 2005. On the other hand, the Job Vacancy Statistics series do not include public posted jobs, which complicate the comparison with the other two sources. See Boscá Mares et al. (2017) for details on the linking methodology. The right panel of Figure 2.13 plots the homogenous series of vacancies for Spain after implementing the linking methodology. This is the data that I used in the calibration.

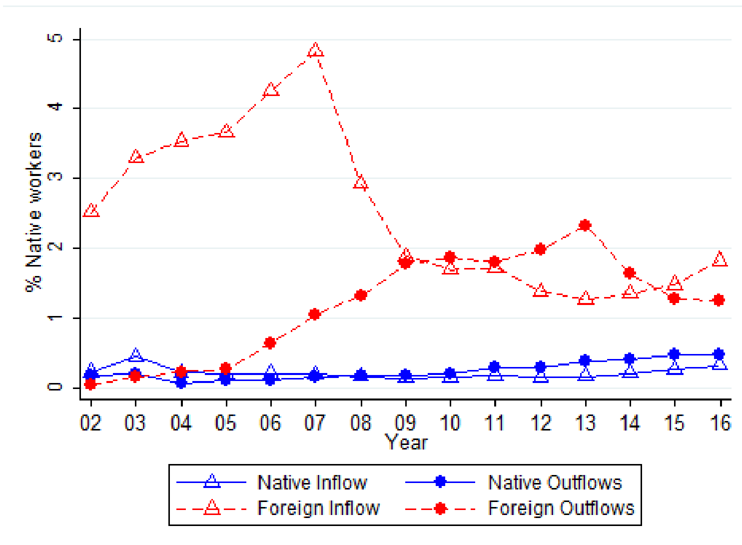
Figure 2.13: Series of vacancies for Spain



Source: Own elaboration from OECD, STLS and Eurostat, based on Boscá Mares et al. (2017) methodology.

Appendix E. Other Figures and Tables

Figure 2.14: Foreign and Native Migration Flows, all workers



Source: Spanish Migration Survey and Labour Force Survey.

Figure 2.15: Low-skilled match quality draws and employment shares in the baseline calibration

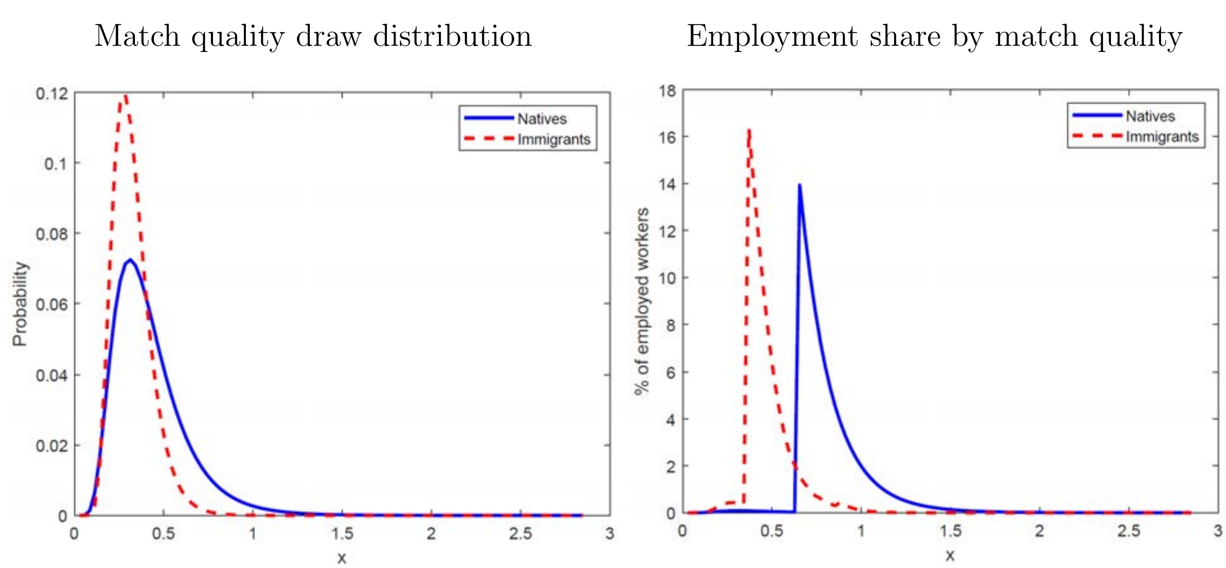


Figure 2.16: Low-skilled immigrant labour force share: Baseline vs No immigration economy.

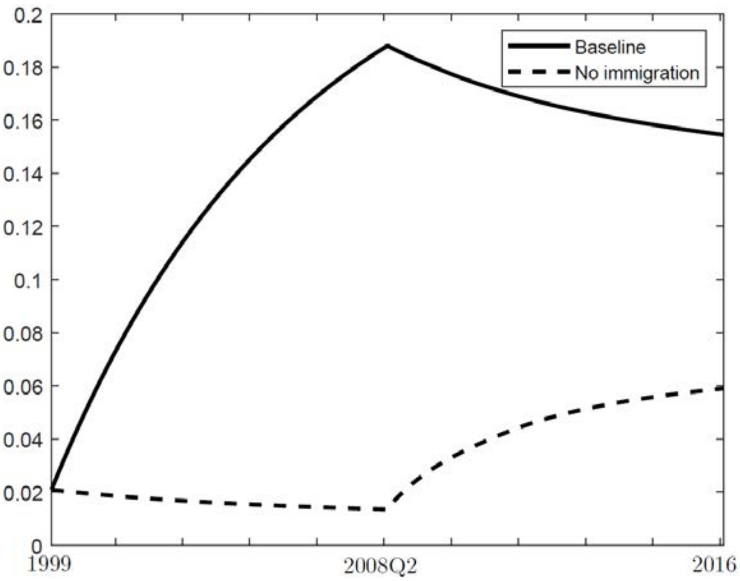


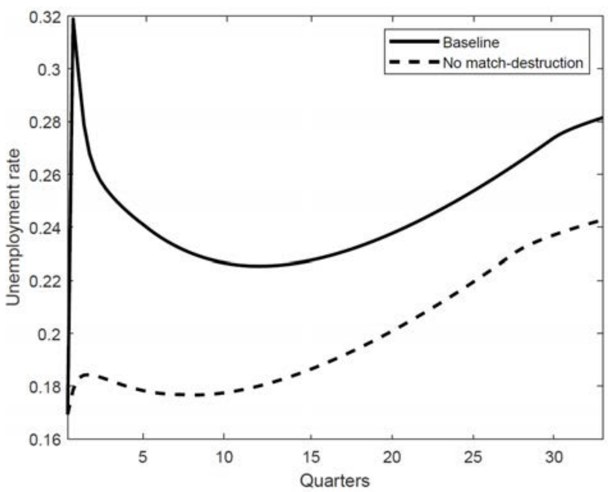
Table 2.9: Immigrants welfare change (pp) in the baseline and the "no immigration" economy

	(1) $\mathbb{W}_{\mathbb{M}}{}^{U}$	(2) $\widetilde{\mathbb{W}}_{M}$	(3) $\mathbb{W}^{*}_{M}(x^{*})$	(4) $\mathbb{W}^{*}_{M}(x^{max})$
Baseline	-0.47	-0.40	-0.55	-0.06
No immigration	-0.71	-0.54	-0.74	-0.06
Difference	0.24	0.15	0.19	0.00

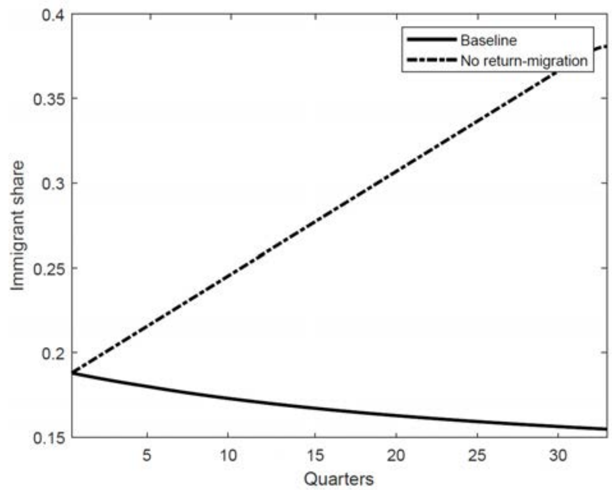
Note: Welfare change for: (1) unemployed workers; (2) workers employed in matches of unknown match quality; (3) workers employed in matches endogenously destroyed in both the baseline and counterfactual economy; (4) workers employed in matches with the highest quality. The welfare change is computed two years after the negative aggregate shock. The row with the difference is the result of subtracting the welfare drop obtained in the counterfactual to the one obtained in the baseline model.

Figure 2.17: Decomposition analysis counterfactuals

No Match-destruction: Immigrant Unemployment Rate



No Return migration: Immigrant Share



No Job-creation: Proportion of immigrants among unemployed ϕ

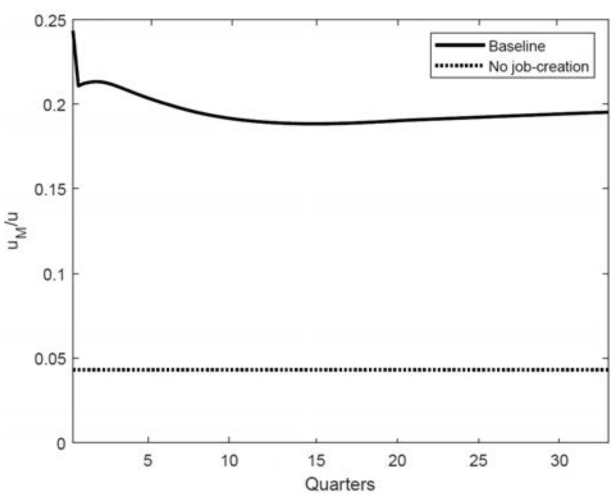


Figure 2.18: Decomposition analysis: Vacancy dynamics

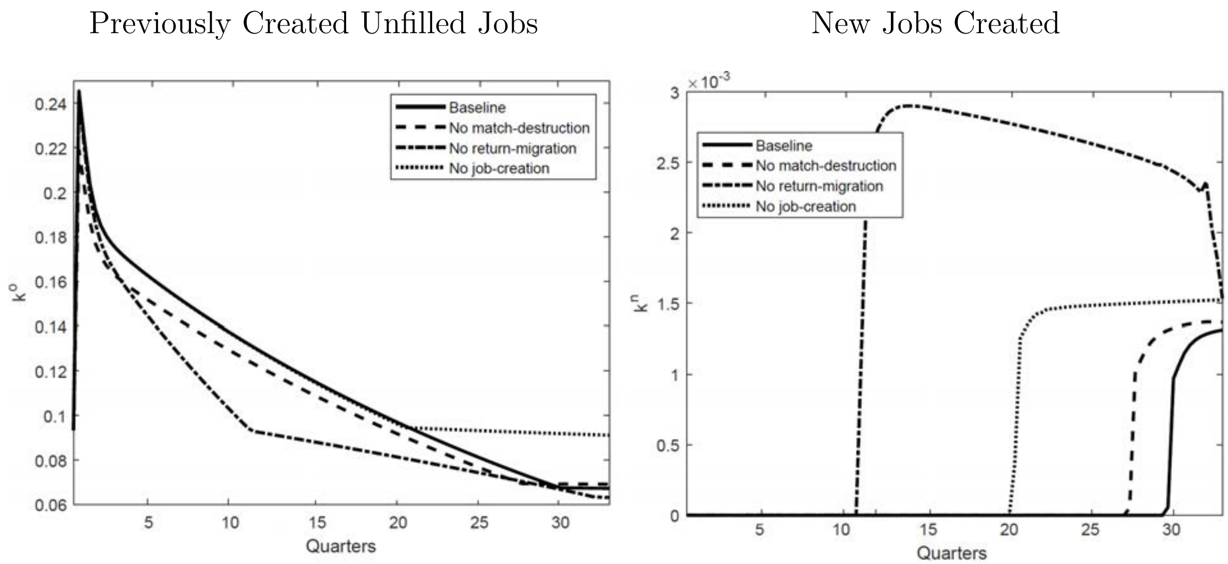


Figure 2.19: The return migration effect: Native labour market performance

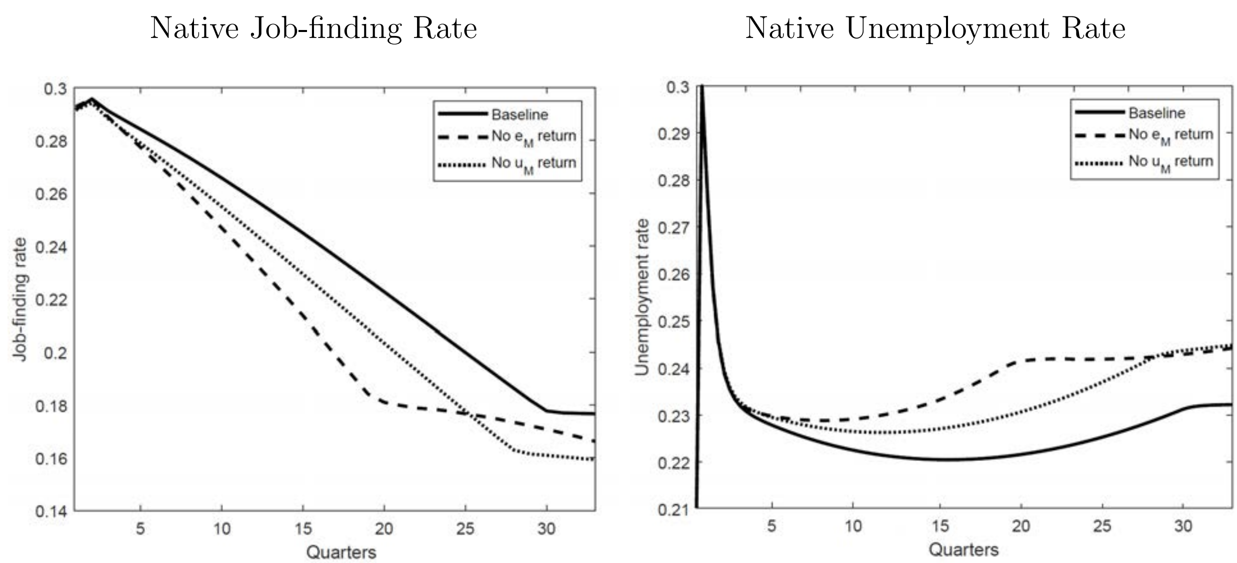
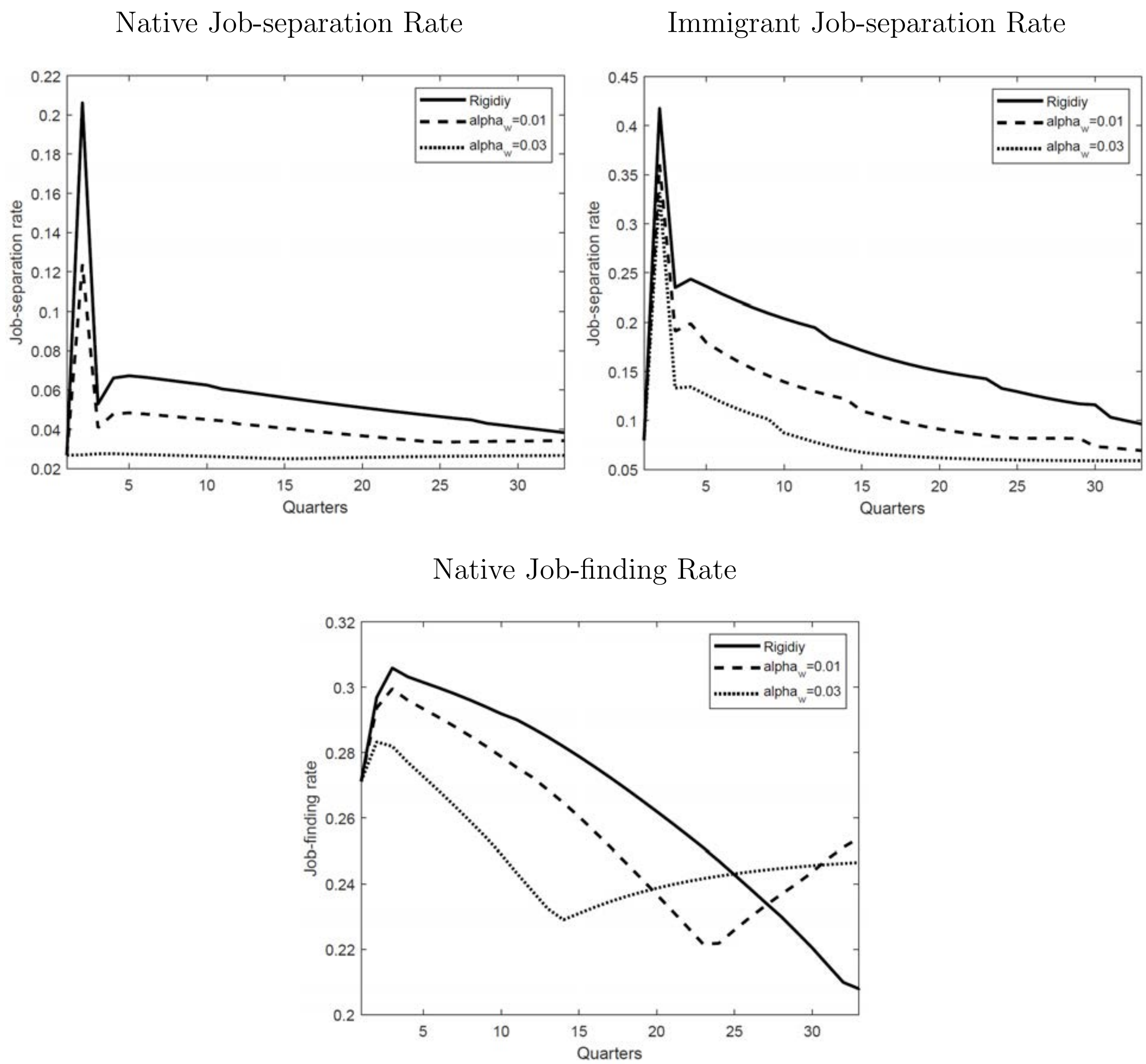


Figure 2.20: Model performance in the Great Recession with wage flexibility



Notes: Evolution of the labour market flows in the model with wage rigidity and in the model with two different values for wage flexibility ($\alpha_w = 0.01$ and $\alpha_w = 0.03$). Drop in aggregate productivity z is the same in all model's versions.

Table 2.10: Calibration Results of the model without mean match quality heterogeneity

Description	Parameter	Value	Target/Source	Data	Model
Calibrated externally					
Discount factor	β	0.9967	From literature		
Matching function parameter	δ	0.5	From literature		
Job destruction	λ	0.0016	Bils et al. (2011)		
Native unemp benefit	b_N	0.700	Hall and Milgrom (2008)		
Immigrant unemp benefit	b_M	0.471	Hall and Milgrom (2008)		
Mean match quality	μ	0.292	Hall and Milgrom (2008)		
Calibrated internally					
Matching efficiency	ξ	0.138	Native JFR	0.310	0.302
Probability discover quality	α	0.272	Immigrant SR	0.055	0.056
Flow cost of a vacancy	κ	0.058	Worker hiring cost	0.420	0.395
Fixed cost of a vacancy	$\bar{K}$	15.362	Vacancy rate	0.080	0.080
Immigrant wage abroad	w_M^A	0.302	Immigrants LF share	0.021	0.021
Native bargaining power	γ_N	0.8	Native mean wage	1.000	1.000
Imm bargaining power	γ_M	0.76	Imm mean wage	0.700	0.720
Native match quality std	σ_N	0.456	Native SR	0.027	0.029
Imm match quality std	σ_M	0.325	Wage std N/M ratio	1.618	1.570
Migration shock std	σ_ε	239.653	Migration prob ratio	1.467	1.260

Figure 2.21: Model performance in the Great Recession without mean match quality heterogeneity

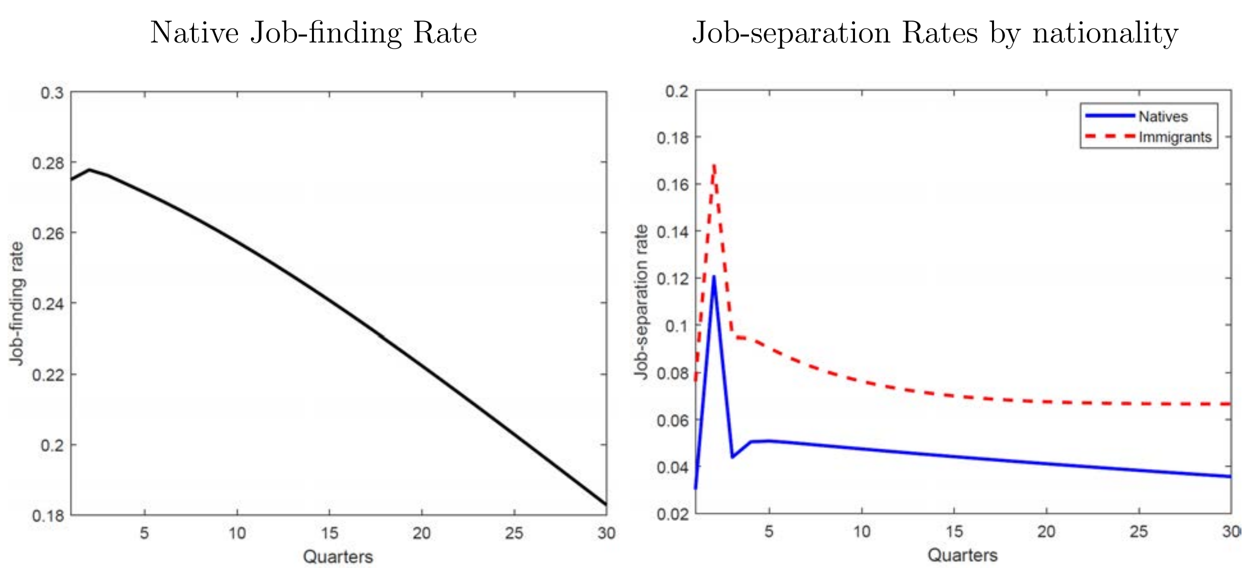
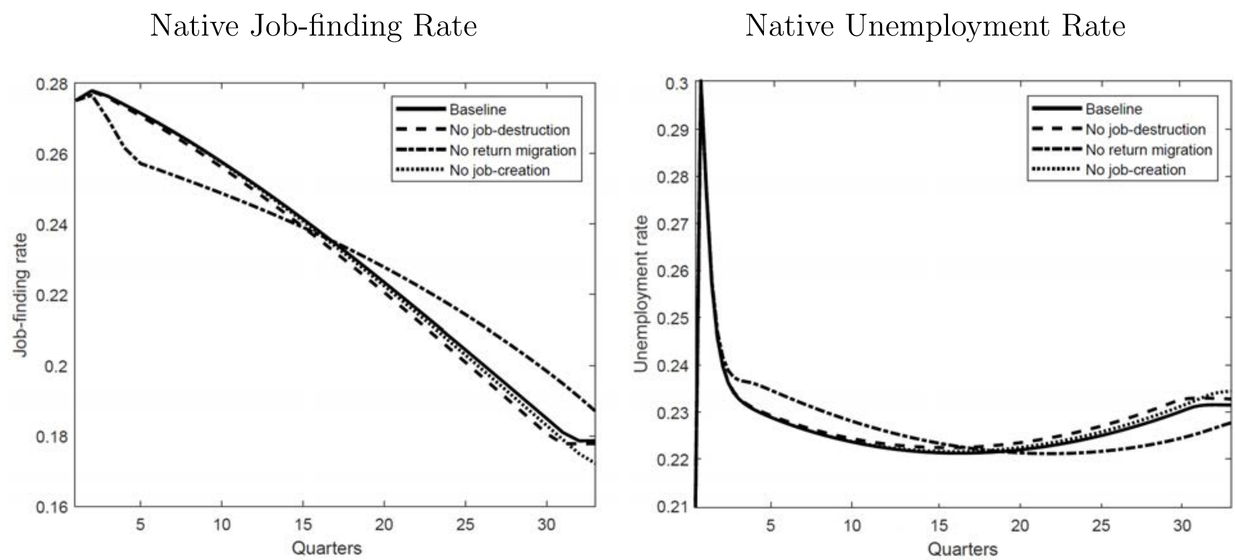


Figure 2.22: Decomposition Analysis of the model without mean match quality heterogeneity: Native labour market performance



Chapter 3

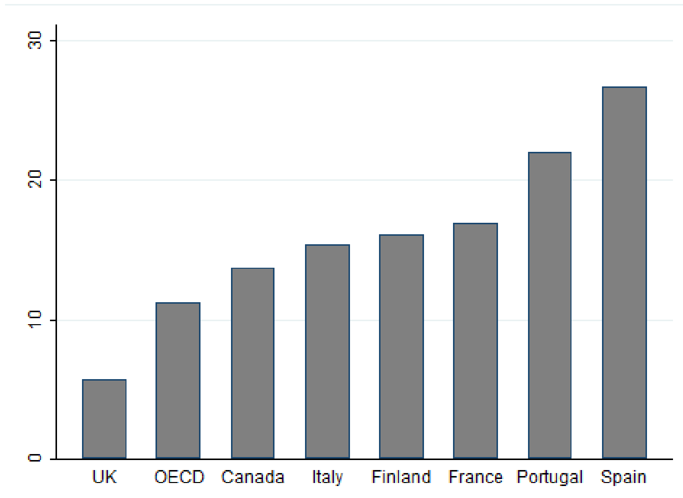
Lifetime Job Instability over the Life-Cycle

3.1 Introduction

Fixed-term (temporary) jobs are defined as having a pre-determined termination date and they entail much lower dismissal costs than regular permanent jobs. Consequently, workers employed in temporary jobs are less protected and have a higher risk of turnover (Bentolila et al. (2008)). Importantly, they account for a big share of salaried employment in many developed countries. Figure 3.1 shows that, in 2017, the average share of temporary employment in OECD countries was more than 10%. However, this number hides large differences across countries. While in the UK temporary employment only accounts for 5% of total employment, in Italy, France or Spain they make up for 15%, 17% and 27%, respectively. Whereas this type of jobs are predominant among young workers (Tealdi (2019)), the temporary rate remains high even among workers above 30 years old. Therefore, the incidence of temporary jobs seems not to be restricted to workers just starting their labour market career.

This paper examines the incidence of temporary employment among *mid-career workers* (defined as workers aged 30 to 35 years old) and quantifies the degree of persistence of temporary jobs. The first contribution of the paper is to quantify the incidence of temporary jobs for mid-career workers. For that, we use Spanish Social Security data and categorize workers by the time spent as temporary, permanent or unemployed in mid-career (mid-career status). We find that around 25% of workers spend more than 50% of their mid-career on-the-job time in temporary jobs. We also show that the incidence of temporary employment at mid-career is not restricted to low-educated workers, as this share is around 20% among

Figure 3.1: Share of temporary employment (2017)



Source: OECD Employment Outlook, 2017. Share of temporary employment among employed workers aged 15 or older. Definitions on temporary employment may vary depending on national circumstances. See OECD Employment Outlook, 2017 for more details.

college graduates. The second contribution of the paper is to examine the long-term effects of accumulating temporary employment at early stages in workers' careers, on both wages and employment outcomes. We find that being employed most of the young-time as temporary is associated with lower wages in permanent jobs at mid-career (around 9%) and with higher job-separation rates in those jobs. Our estimates on lifetime wages suggest that over ages 20 to 40, the wage losses from being employed most of young-time as temporary (compared to being employed as permanent) amount to almost 50,000 euros (the lifetime wage is 15% lower). The third contribution is to quantify the persistence in the time spent as temporary over a worker's career. We find that the time employed as temporary when a worker is young is a powerful predictor of time employed as temporary during mid-career (*lifetime job instability*). For comparable workers, one percentage point increase in the share of time spent as temporary when young is associated with a 0.4 percentage points increase in the share of time spent as temporary at mid-career.

To understand the sources of lifetime job instability, we study workers' young-age labour market performance by their mid-career status. In particular, we examine the age patterns of the job-finding and job-separation rates (both as temporary and permanent) over the life-cycle across mid-career groups. The main finding is that, while both groups start their career with similar job-finding and job-separation rates in permanent jobs, differences emerge early in their career. We also find that mid-career permanent workers had higher wages at permanent jobs right from the beginning, with the wage gap increasing over time. We find small differences in their performance at temporary jobs at young-age.

Ultimately, the goal is understanding the underlying mechanisms that explain the observed persistence in temporary employment (*lifetime job instability*). The literature had pointed out two alternative hypotheses that could be used to explain why some workers end up employed most of their mid-career time in temporary jobs. The first one is the *adverse selection* theory (Carrillo-Tudela and Kaas (2015), Michaud (2018), or Morchio (2018)). According to this theory, mid-career temporary workers are negatively selected, i.e. their unobserved ability is lower than that of mid-career permanent workers. Consequently, over their young-age they spend more time in temporary jobs and unemployment, and that explains their time as temporary also later on[1]. The *human capital* hypothesis (Ljungqvist and Sargent (1998)) assumes that mid-career temporary workers are initially as productive as mid-career permanent workers. However, as they spend more time in temporary jobs at young-age, they accumulate human capital of lower 'quality'. Consequently, they become less suitable over time for firms that look for a permanent worker, increasing their odds of workings as temporary later on. By looking at workers' young-age performance by mid-career categories we can use the data to discipline a model aiming to disentangle which of the two hypotheses is more accurate. Overall, our findings suggest that the adverse selection theory on its own could not fully account for the young-age labour market performance patterns, in particular, the finding that job-separation rates differences by mid-career status categories are only observed as workers age. We think that a combination of workers' unobserved heterogeneity and a simple human capital accumulation mechanism would help to rationalize the life-cycle empirical patterns.

The rest of the paper is organized as follows. In section 2 we describe the data that we use and define the categories of workers that we use through the paper. Section 3 presents descriptive statistics of our sample during mid-career. In section 4 we analyze the life-cycle persistence of job status and investigate how the different mid-career categories of workers perform in the job market when young. Section 5 presents the long term effects of job instability. Section 6 concludes.

Literature Review and Contribution

Our paper relates to the literature studying the effects of temporary contracts. Many of these papers have focused on examining the impact of these contracts on the probability of

[1]These papers propose the combination of unobserved heterogeneity and learning as a candidate explanation for the scars of unemployment or the life-cycle patterns on job-finding rates.

finding a permanent job in order to test the stepping-stone hypothesis (Booth et al. (2002), Güell and Petrongolo (2007), D'Addio and Rosholm (2005), García-Pérez and Muñoz-Bullón (2011)). While most of the literature finds that temporary jobs do help to land to permanent jobs (Güell and Petrongolo (2007), Nagypál (2007)), others highlight that there is a danger of linking too many temporary contracts, causing a decrease in job stability (Blanchard and Landier (2002)). We add to this literature by looking at both the persistence and long-term effects of temporary jobs.

Closely related to our work is the study of García-Pérez et al. (2018), who also uses administrative data from the Spanish Social Security to assess the long-term impact of fixed-term contracts. They exploit the change of the Spanish regulation on temporary contracts of 1984 using a cohort regression discontinuity design. They find that the higher availability of temporary jobs reduced workers' accumulated employment by 7% and accumulated earnings by 22%. Nevertheless, some relevant traits differentiate our approach from theirs. First, they restrict their analysis to workers with less than high school. However, we show that the incidence of temporary employment is also very relevant among college graduates, especially in older ages. Second, we document the sources of long-term job instability by examining the life-cycle patterns of job-finding and job-separation rates by the time spent in temporary employment. Third, while they discuss some of the potential mechanisms explaining their long-term findings, our approach is a first step to build a structural model which aims to rationalize the long-term impact and persistence of temporary employment.

Finally, this paper is related to the empirical literature that investigates the sources of lifetime income inequality, lifetime unemployment and heterogeneity in job-finding and job-separation rates by workers with different mid-career career paths (Huggett et al. (2011) or Kahn and Lange (2014)). Our approach is related to that of Morchio (2018). Using U.S. data, he documents that mid-career unemployment is concentrated among few workers and it is persistent over the life-cycle. Although we share the empirical approach, the scope of our paper is very different, as we focus on the sources of persistence in job instability.

3.2 The data

We use Spanish administrative data from the Continuous Sample of Working Histories (*Muestra Continua de Vidas Laborales*, MCVL hereinafter) on earnings and working histories of workers. The MCVL consists of a 4% representative random sample of all workers affiliated (working as employed or self-employed, receiving a public pension or being registered as unemployed) with the social security administration in the year of the publication of the dataset. The data was released in 2004 and after that year it follows the same sample of individuals over time, adding new observations each year to replace absences while keeping the sample representative of the population. Furthermore, the data provide retroactive information on the workers' entire labour market history. That is, as long as an individual registers one day of activity with social security in any year between 2005–2015 (which is the last year that I include in the analysis), her complete working life history can be recovered up to 1981.

Along with the job history, for each individual, a large amount of information is available, including personal and demographic characteristics (age, gender, education, nationality, region of residence), firm information at the establishment level (location, size) and labour market information (industry, occupation, type of contract). The unit of observation in the data is any change in the individual's labour market status or any modification in job characteristics. Importantly, it also provides earnings data, in nominal terms. Wages are deflated using the consumer price index (base year 2011) provided by the Spanish Statistical Office (INE).

We construct a panel with monthly observations for the period 1996 to 2015. We start with the most updated version of the sample, which is the 2015 edition. After processing the social security and census records of individuals contained in the 2015 edition of the MCVL, we turn to the 2014 edition and extract the social security and census records of the individuals contained in this edition but absent from the 2015 edition. We do the same for the subsequent editions (2012 to 2005).

We restrict the sample to the years after 1996, since the information on the type of contract is not available before that year. We perform the construction of the panel by cohort. Notice that for the purpose of the paper we need the labour market information of the worker when he is young (20-30) and during the mid-career (30-35)[2]. Consequently, the oldest cohort considered in the analysis is the cohort of workers born in 1976 (i.e. they are 20 years old in 1996), and the youngest one in the cohort born in 1980 (i.e they are exactly 35 years old in 2015). These restrictions reduce the sample to 127,045 individuals and 22,972,164 monthly observations.

Definitions

We divide workers by employment status categories, depending on the time that they spend in each employment status: unemployment (U), temporary employment (T), permanent employment (P) and self-employment (SE). To do that, for every year we compute the fraction of time that each worker spends in unemployment as:

[2] In Appendix E we perform several robustness analysis showing that workers' labour market performance at ages 30-35 is highly correlated with their performance at age 30-40, 30-45 and 35-50.

$$\%U_{i,t} = \frac{\sum_{d=1}^{D^T_{i,t}} u_{i,d}}{D^T_{i,t}} \tag{3.1}$$

where $u_{i,d,t}$ is a variable that takes value 1 for days that individual i was unemployed at month t and $D^T_{i,t}$ is the number of days that individual i was employed, self-employed or unemployed in month t. Similarly, for every year we compute the fraction of *employed* time that each worker spends in temporary employment, permanent employment and self-employment as:

$$\%E_{i,t} = \frac{\sum_{d=1}^{D^E_{i,t}} e_{i,d}}{D^E_{i,t}} \tag{3.2}$$

where $e_{i,d,t}$ is a variable that takes value 1 for days that individual i was in employment status $e \in \{T, P, SE\}$ at month t and $D^E_{i,t}$ is the number of days that individual i was employed (as temporary, permanent or as self-employed) in month t[3].

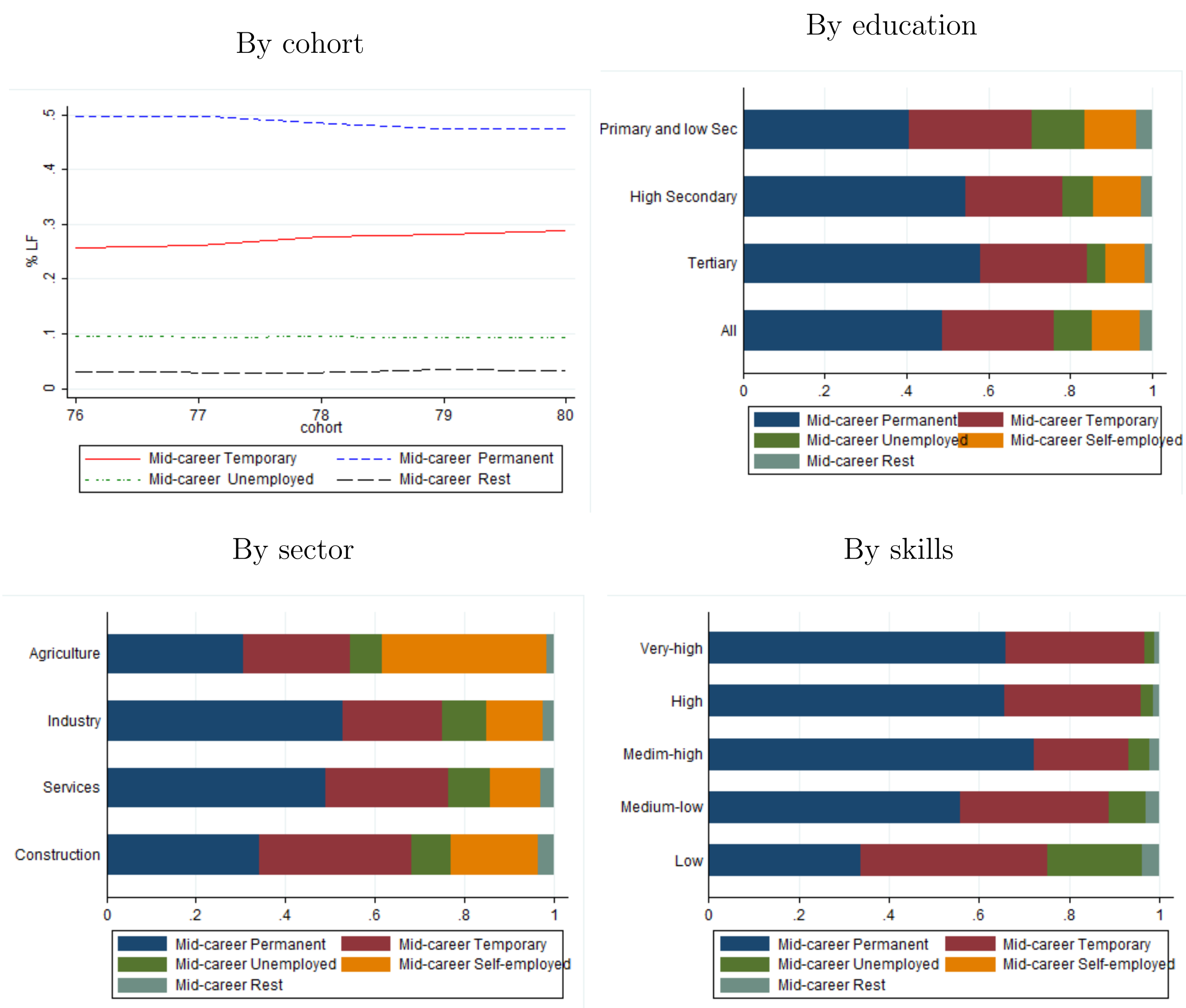
After ranking individuals by the fraction of time spent in unemployment, we define the unemployment category as including workers who are in the top 10% of the unemployment distribution of the sample (Morchio (2018)). The permanent and temporary categories include workers who spent more than 50% of their employed time under a permanent and temporary contract, respectively (Equation (3.2) is higher than 0.5 for $E = P$ and $E = T$, respectively) and they do not enter in the unemployment category. We apply these definitions at young-age (20-30) and mid-career (30-35). An alternative approach is to define the temporary and permanent categories as the fraction of the total time (instead of the employed time) spent in temporary and permanent employment. In Appendix F we show that the results of Section 3.3 and 3.4 are robust to using any of the two alternative definitions of the temporary and permanent categories. However, defining categories as a fraction of total time has some drawbacks: (1) a significant amount of workers would not enter in any of those categories (e.g. those who spent 40% as temporary, 10% as permanent, 20% as self-employed and 30% as unemployed, see Figure 3.10 in Appendix F); (2) the temporary category would deliver a somehow distorted picture of temporary employment, as it would include workers experiencing very few unemployment spells (Figure 3.11 in Appendix F), when one of the main consequences of temporary employment is job-instability: workers repetitively alternate periods of employment and unemployment.

[3]Notice that $D^T_{i,t} = D^E_{i,t} + D^U_{i,t}$, where $E + D^U_{i,t}$ is the number of days that individual i is unemployed in month t.

3.3 The incidence of temporary employment at mid-career

Figure 3.2 summarizes the share and composition of workers by employment status category at mid-career (*mid-career status*). As the top left panel shows, for all cohorts, around 26-29% of workers enter in the temporary employment category (*mid-career temporary workers*). The top right and bottom panel of Figure 3.2 report the education, sector and skill level composition of workers included in each mid-career status. We divide the sample in three educational groups: low secondary education or less (i.e. primary education and lower secondary education), high secondary education, and college education.

Figure 3.2: Share of workers by mid-career status



Source: Own calculations using MCVL.

The share of mid-career temporary workers remains roughly constant around 15% in all education levels (top right panel). One can see that mid-career permanent workers are more predominant among the tertiary-educated. However, this is not because temporary workers are less relevant, but because the share of mid-career unemployed workers is lower. In fact, the share of mid-career temporary workers is higher among college graduates than among workers with low secondary education at most. Overall, the data suggest that the high incidence of temporary employment late in the worker career is not restricted to low-educated workers.

The same conclusions are reached when dividing the sample by skill levels (bottom right panel). Following Roca and Puga (2017), we classify salaried workers into five groups: very-high, high, medium-high, medium-low and low-skilled depending on their occupation (see Table 3.7 in Appendix F for details on the occupations included in each group). Mid-career temporary workers account for a big share of the total workers in the high skilled groups (around 35%, bottom right panel). As expected, mid-career unemployment workers are more predominant among low skill levels, but again this is at the expense of a lower fraction for mid-career permanent workers. In fact, among the lowest skill level, there are more temporary than permanent mid-career workers.

Sectoral differences are less important than expected. Mid-career temporary workers are slightly more predominant in the construction sector (30% vs 28% in average), as this sector is more subject to seasonal activity. However, its weight is very similar in the industry or services sectors (25% and 29%).

Figure 3.26 in Appendix F summarizes the share and composition of workers by employment status categories at young-age (*young-age status*). As expected, since temporary jobs are more predominant among young workers, the share of workers entering in the temporary employment category is slightly higher at young-age (*young-age temporary workers*, around 40-45%) than at mid-career. There are also less young-age permanent workers than at mid-career (30% vs 50% at mid-career), as most of the workers start their career as temporary and it usually takes time to find a permanent job. Overall, the shares remain even more constant than at mid-career within each education group (top right panel of Figure 3.26), and skill levels (bottom right panel). As before, young-age temporary workers account for a bigger share of workers employed at the construction sector (55%), but the weight is very similar in the services (50%) or industry sectors (45%).

3.4 Lifetime job-instability

3.4.1 Persistence of temporary employment

In this section, we document that young and mid-career temporary employment are strongly correlated and we provide suggestive evidence of high persistence in the time employed in temporary jobs. Table 3.1 shows the Markov transition matrix from young-age status to mid-career status. The first row shows the probability that a young-temporary worker ends up as a temporary, permanent, unemployed, or self-employed worker at mid-career (first, second, third and fourth column, respectively). For comparison, the last row of Table 3.1 displays the unconditional probability of being in each category at mid-career. The results are interpreted as follows: a young-age temporary worker is 4 times more likely to be mid-career temporary than a young-age permanent worker (41.9 vs 10.8, respectively: first and second row of column (1)). Young-temporary workers are also twice as likely to be mid-career unemployed than the young permanent workers, although these probabilities are small (8.6 vs 4.5, respectively). Looking at the elements in the diagonal of the Markov transition matrix one can see that temporary status is more persistent than the unemployment status (41.9 vs 32.5, respectively).

Table 3.1: Markov transition matrix young-to-mid career employment status (%)

	Mid-career				
Young-age	(1) Temporary	(2) Permanent	(3) Unemployed	(4) Self-Employed	(5) Rest
Temporary	41.9	40.9	8.6	5.4	3.1
Permanent	10.8	77.7	4.5	5.4	1.6
Unemployed	31.1	22.9	32.5	9.8	3.7
Self-Employed	14.3	13.5	4.3	64.5	3.3
Rest	22.8	40.7	9.2	18.9	8.3
All	27.3	48.6	9.4	11.6	3.1

Source: *Own elaboration using MCVL.*

These results suggest the existence of a certain degree of persistence in the time spent as temporary. However, in Section 3.3 we have documented that mid-career and young-age temporary workers are slightly more concentrated among low-educated workers or they are more predominant in some sectors of activity such as construction or some services, so the high persistence might be due, in part, to composition effects. We compute the Markov transition matrix by education levels and we find the same pattern of temporary persistence within each educational category (see Table 3.8 in Appendix F). Among workers with the lowest education level, young-age temporary workers are 3.5 times more likely to be mid-career temporary than a young-age permanent worker (44.9 vs 12.8, in column (1) and (2) of the top panel of Table 3.8 in Appendix F). Interestingly, this difference increases with education, as it becomes 3.7 and 5 for high secondary (37.5 vs 10.0, middle panel) and college graduates (40.7 vs 8.2, bottom panel), respectively. Results in Table 3.8 suggest that education heterogeneity across workers by mid-career status does seem to explain the overall persistence displayed in Table 3.1.

Last, we perform a battery of regressions which shows that other observables (sector, skills, experience, gender or region of residence) do not substantially explain the amount of persistence in temporary employment. In particular, we estimate the following linear probability model:

$$\text{\% of T at mid-career}_i = \alpha + \beta^T \text{ \% of T at young} + \beta^U \text{ \% of U at young} + \boldsymbol{\delta X}_i + \varepsilon_i \quad (3.3)$$

where % of T at mid-career$_i$ is the time spent by the worker in a temporary job at mid-career; % of T at young$_i$ and % of U at young$_i$ is the time spent by the worker at young-age in a temporary job or unemployed, respectively; $\boldsymbol{X}_{i,t}$ is a vector of control variables that includes dummies for nationality, education at age 30, gender, region of residence, skill and occupation in which the worker spent most of the time when young and when old, and cohort fixed effects. Importantly, we also add the time spent as unemployed when young as a regressor. The coefficient of interest is β^T, which captures the persistence in temporary employment. The results of the estimation of equation (3.3) are displayed in Table 3.2. Our baseline estimation, obtained after regressing Equation (3.3) with all controls, can be found in column (6) of Table 3.2. For comparable workers, one percentage point increase in the share of time spent as temporary when young is associated with a 0.4 percentage points increase in the share of time spent as temporary at mid-career. As we can see, the time spent as temporary when young is a strong predictor of the time in temporary during mid-career and it is not due to observables such as education, sector of activity or gender. The correlation between temporary employment at young and at mid-career is twice as high as the correlation between youth unemployment and mid-career temporary employment (0.4 vs 0.2, respectively, first and second row in Table 3.2).

As we can see in column (3), estimates of β^T are upward biased if we do not control for the sector of activity at mid-career, suggesting that some sectors contribute to the persistence of temporary employment. Column (4) shows that education heterogeneity does not explain much of the persistence of temporary employment, as expected from Table 3.1.

Table 3.2: Estimation results

	(1) No Young T	(2) No sec/edu/skill	(3) No sec	(4) No educ	(5) No skill	(6) Baseline
% Time T when 20-30		0.437***	0.462***	0.406***	0.396***	0.406***
		(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
% Time U when 20-30	0.0668***	0.187***	0.252***	0.201***	0.151***	0.203***
Education and Skills						
Secondary	-0.004**		-0.004		-0.001	-0.001
Tertiary	0.0178***		0.011***		0.020***	0.016***
Medium-low	-0.008		-0.008	-0.012**		-0.010*
Medium-high	-0.035***		-0.060***	-0.043***		-0.038***
High	-0.003		-0.026***	-0.018***		-0.011***
Very-high	-0.034***		-0.038***	-0.043***		-0.035***
Standard controls	YES	YES	YES	YES	YES	YES
Sector at mid-career	YES	NO	NO	YES	YES	YES
Education	YES	NO	YES	NO	YES	YES
Skills at mid-career	YES	NO	YES	YES	NO	YES
Observations	98658	123970	98658	98658	123970	98658
R-squared	0.134	0.160	0.171	0.222	0.214	0.223

Note: Regression of the time spent as temporary at mid-career on the time spent as temporary and as unemployed when young. The model includes dummies for education, experience, marriage status, age, gender, region of residence, sector of activity, type of contract, type of job and year. Standard errors in parentheses. Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. *Source: MCVL.*

3.4.2 What drives persistence? Labour market performance over the life-cycle

In the previous sections, we have shown: (1) around 30% of mid-career workers spend more than 50% of their active time in temporary jobs (2) temporary employment is persistent. In this section we examine the patterns of real wages, the job-finding and job-separation rates (both as temporary and permanent) over the life-cycle across mid-career status groups. Our intention is to show whether individuals that work more as temporary in the mid-career (*mid-career temporary workers*) had different labour market outcomes from the start of their careers (compared to mid-career permanent workers) or whether those outcomes diverged over time. We will put emphasis on distinguishing the labour market performance of workers in the different outcomes (job-finding, job-separations rates and wages) in permanent versus temporary jobs. Overall, the goal of the analysis is to provide empirical evidence that could help us understand the underlying motives of why some workers spend most of their employed time in temporary jobs at mid-career.

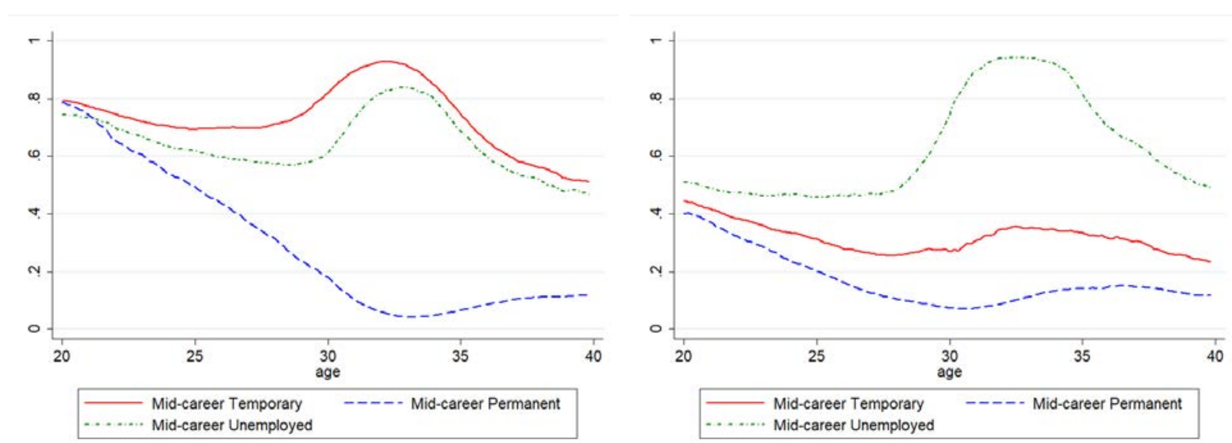
Unemployment and Temporary Rates

The left panel of Figure 3.3 plots the age profile of the temporary rate by mid-career status, while the right panel displays the evolution of the unemployment rate. One can observe that temporary and permanent mid-career workers start with a similar temporary rate, suggesting that both groups of workers predominantly enter into the labour market as temporary. However, the gap in the incidence of temporary employment between the two groups arises relatively fast, as the temporary rate of mid-career permanent workers falls very quickly over their young-age (from 80% at age 20 to less than 20% at age 30) while it remains high for mid-temporary workers during those years (around 80%). Similarly, we can see that mid-career temporary and permanent groups also had a similar unemployment rate at ages 20-22. Again, these differences widen during young-age. At age 25, the unemployment rate for mid-career temporary workers was around 23%, while it was only 10% for mid-career permanent workers.

Finally, mid-career unemployed present an intermediate temporary rate and a significantly higher unemployment rate when young. This suggests that these groups miss out the opportunity of entry temporary jobs, which leads to a higher unemployment hazard later.

Figure 3.3: Temporary and unemployment rate by mid-career status

Temporary Rate　　　　Unemployment Rate



Note: 12 months moving average of unemployment and temporary rate, by mid-career status. Source: Own calculations using MCVL.

Labour Market Flows

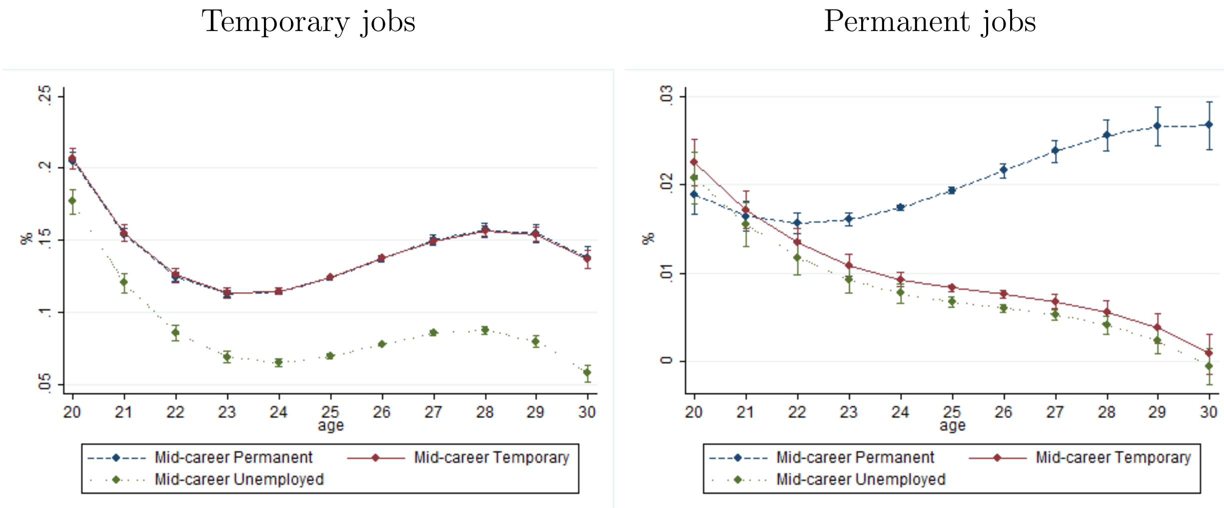
The divergent evolution of the temporary and unemployment rate by mid-career status is the result of differences in the probability that each group of workers transit from unemployment to permanent or temporary jobs (job-finding rate) and from permanent or temporary jobs to unemployment (job-separation rate). We compute the age profile of those four labour market flows for each mid-career status group. Our intention is to show which transitions are most relevant to explain the gap in the temporary and unemployment rate between mid-career temporary and permanent workers. In order to abstract from composition effects, we plot the residuals (evaluated at the average of the other covariates) obtained from estimating a linear regression of each labour market flow (job-finding and job-separation rates, both as permanent and as temporary), on dummies for the mid-career status, age, observables[4] and time and cohort fixed effects. All the unconditional labour market flows can be found in Appendix B.

Job-finding Rates

Mid-career temporary and permanent workers start with a similar job-finding rate as permanent (right panel of Figure 3.4) but differences arise early and widen over age. Ceteris paribus, by age 24 mid-career permanent workers are 3 times more likely to find a permanent job, and by age 28 their job-finding probability is 5 times higher than for mid-career temporary workers. As we can see, the age profile of the job-finding rate as permanent is very similar for mid-career temporary and mid-career unemployed workers. Regarding the job-finding rate as temporary, we find no heterogeneity between mid-career temporary and permanent workers; but mid-career unemployed show a much lower rate. This, together with the evidence of figure 3.3 suggest that the latter group do not benefit as much of the stepping-stone function of early temporary jobs, which harms their careers.

[4]Observables include dummies for education, nationality, region of residence, sector of activity, skill, experience, tenure and coefficient of partial time.

Figure 3.4: Job-finding rate at young-age by mid-career status

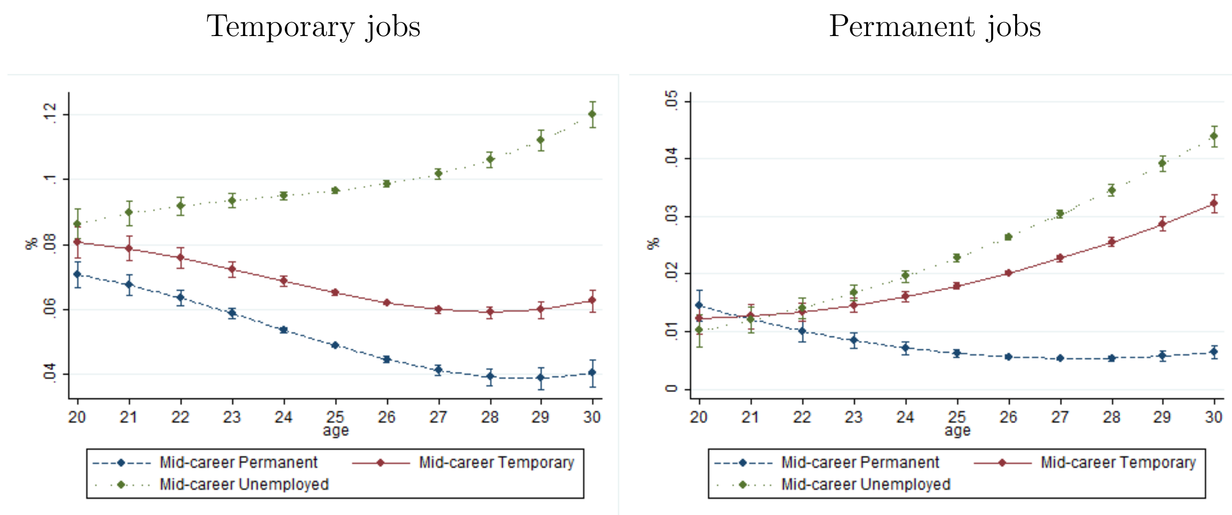


Note: Average monthly job-finding rate as temporary or permanent, by mid-career category. Sample of all workers. Job-finding rates are defined as the probability of transiting from unemployment at month $t-1$ to employment at t. To compute the residuals we run a linear regression on a 2^{nd} degree polynomial in age by mid-career group, controlling for observables and time and cohort fixed effects. Controls include dummies for education, nationality, region of residence, sector of activity, skill, experience, tenure, and coefficient of partial time. Residuals are evaluated at the average of other covariates. Source: MCVL

Job-separation Rates

As for the case of the job-finding rate as permanent (right panel of Figure 3.4), we find that permanent and temporary mid-career workers start with similar job-separation rates as permanent (right panel of Figure 3.5). However, differences emerge early. While among mid-career permanent workers the job-separation rate as permanent decreases with age, for mid-career temporary workers it increases. Consequently, the gap grows quickly over young-age. At age 24 the job-separation rate as permanent is 1.6 higher for mid-career temporary workers than for mid-career permanent workers, being 3 and 8 times higher by ages 26 and 30, respectively. Regarding the evolution of the job-separation rate as temporary (left panel of Figure 3.5), mid-career temporary workers start with a higher job-separation rate as temporary than mid-career permanent workers. But in this case, the gap between the two categories remains roughly constant over age. As for mid-career unemployed, they start with similar separation rates but present higher rates than the other two groups as they age; and in temporary jobs, the monotonicity is opposite from the rest. This adds to the conjecture that mid-career unemployed differ from mid-career temporary workers due to their performance in the temporary job market when young.

Figure 3.5: Job-separation rate at young-age by mid-career status



Note: Average monthly job-separation rate as temporary or permanent, by mid-career category. Sample of all workers. Job-separation rates are defined as the probability of transiting from employment at month $t-1$ to unemployment at t. We only include non-voluntary transitions. To compute the residuals we run a linear regression on a 2^{nd} degree polynomial in age by mid-career group, controlling for observables and time and cohort fixed effects. Controls include dummies for education, nationality, region of residence, sector of activity, skill, experience, tenure, and coefficient of partial time. Residuals are evaluated at the average of other covariates. Source: MCVL

Temporary-Permanent transitions

The last set of relevant labour market flows are the flows within jobs. As expected, we find that workers with permanent status during mid-career are more likely to be promoted from temporary to permanent during their youth (Figure 3.27 in Appendix F). Regarding the permanent-to-temporary transition rate, we see that it is slightly higher for mid-career-temporary workers, although these transitions are very small.

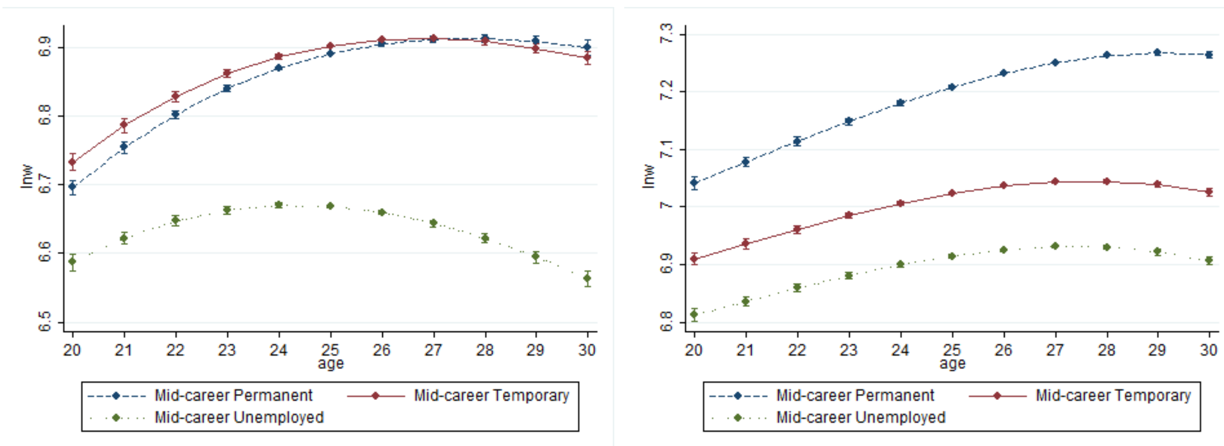
Wages

The evidence presented in the previous section suggests that, at young-age, the labour market outcomes (job-finding and job-separation rates) of mid-career temporary and permanent workers mainly differed in permanent jobs, while both groups always had very similar outcomes in temporary jobs. The analysis of the evolution of real wages confirms this finding.

Figure 3.14 displays the age profile of real wages at temporary (left panel) and permanent (right panel) jobs by workers' mid-career category. As before, to abstract from composition effects, we focus on the residuals from estimating a linear regression of the real

Figure 3.6: Real wages by mid-career status

Temporary jobs | Permanent jobs



Note: Average monthly wage obtained by a worker employed in a temporary or permanent job, by group of mid-career category. Sample of all workers. To compute the residuals we run a linear regression on a 2^{nd} *degree polynomial in age by young-age group, controlling for observables and time and cohort fixed effects. Controls include dummies for education, nationality, region of residence, sector of activity, skill, experience, tenure, and coefficient of partial time. Residuals are evaluated at the average at means of other covariates. Wages are deflated using the consumer price index (base year 2011) provided by the Spanish Statistical Office (INE) Source: MCVL*

wages on dummies for the mid-career status and controls[5] (unconditional real wages are displayed in Figure 3.17 in Appendix B). Mid-career temporary workers start with a slightly higher wage than mid-career permanent workers in temporary jobs, but this small gap is closed at age 25. More substantial differences between the two groups are observed on wages at permanent jobs. As the right panel of Figure 3.14 shows, the wage gap at permanent jobs is big from the beginning. *Ceteris paribus*, at age 20, mid-career permanent workers had wages 15% higher in permanent jobs that mid-career temporary workers. Moreover, it is increasing with age: by ages 25 and 30 their wages were 19% and 25% higher, respectively.

The panel dimension of the MCVL allows us to compute the evolution of the growth of real wages over workers' careers. We distinguish between two cases: job-stayers (workers who continue working with the same firm in two consecutive years) and job-movers (those changing firm in a given month). In the Appendix C we provide details on the calculations of the wage growth of each category and an exhaustive analysis of the results. Briefly, we find that among job-stayers, the wage growth of mid-career permanent workers is higher during young-age than for mid-career temporary workers. This finding is observed both in

[5]See footnote of Figure 3.14 for details on the regression specification.

permanent and temporary jobs (top left and right panel of Figure 3.18 in Appendix C) and also for workers moving from temporary to permanent jobs with the same firm (bottom panel of Figure 3.18). Last, we find small differences between mid-career temporary and permanent workers among job-movers (Figure 3.19 in Appendix C). Altogether, our findings in the wage growth analysis are consistent with the patterns observed on both real wages and labour market flows.

Comparing workers by mid-career status

We can now reflect on the differences in the labour market performance by groups of workers.

First, let us compare the labour market outcomes (at young-age) in permanent jobs between mid-career permanent and temporary workers. We found that (1) the job-finding and (2) job-separation rates are very similar at the beginning, but differences emerge fast; (3) there is a wage gap right from the beginning, which also widen over time. Facts (1) and (3) are consistent with the existence of unobserved worker heterogeneity (with mid-career permanent and temporary workers being high and low-ability workers, respectively) that would be randomly revealed once the worker and the firm meet and start producing. As workers age, the information about their type becomes widely known and that would explain the widening gap in their labour market performance. This mechanism is proposed by Morchio (2018). However, according to this, we should see differences in the job-separation rate from the beginning. For that, we think that a simple human capital accumulation mechanism (where workers only accumulate human capital when employed, and at a higher rate in permanent than in temporary jobs) would be needed. In this setting, as the high-ability workers work more in permanent jobs and they spend less time in temporary jobs and unemployment, they accumulate more human capital, amplifying the initial productivity differences between workers.

With regard to the performance in temporary jobs for mid-career temporary and permanent workers, we find: (1) no differences in the job-finding rates; (2) higher job-separation rates for mid-career temporary workers, but in this case, the gap remains constant over time; (3) very small differences in wages that disappear fast. To reconcile these findings with the mechanisms discussed above, one could think that the productivity heterogeneity between the mid-career permanent and temporary workers (coming from differences in unobserved ability or human capital) does not play a big role to find temporary jobs. However, the fact that mid-career unemployed workers do experience a much lower job-finding rate as temporary suggests that, overall, productivity differences should matter.

Last, compared with mid-career temporary workers, mid-career unemployed: (1) have a lower job-finding rate as temporary from the beginning and the differences increase with age; (2) they start with similar job-separation rates but differences appear over time, especially in temporary jobs; (3) a wage gap is observed from the beginning. Again, unobserved heterogeneity on its own cannot fully account for these patterns, as the job-separation rates gap is only observed as workers age. The human capital mechanism could help to understand the findings. The fact that mid-career unemployed workers are more time unemployed from the beginning (as the job-finding rate as temporary is lower at age 20, see left panel of Figure 3.4) would prevent them from accumulating human capital, neither in permanent (with a higher rate of accumulation) nor in temporary jobs (at a lower rate, but still higher than in unemployment). That, in turn, could explain why over time mid-career unemployed workers find less temporary jobs and experience higher job-separation rates. Under this vision, one could interpret temporary jobs as a *stepping-stone*: workers employed in temporary jobs accumulate less human capital than they would accumulate in permanent jobs, but more than unemployed.

3.5 The scarring effects of job instability

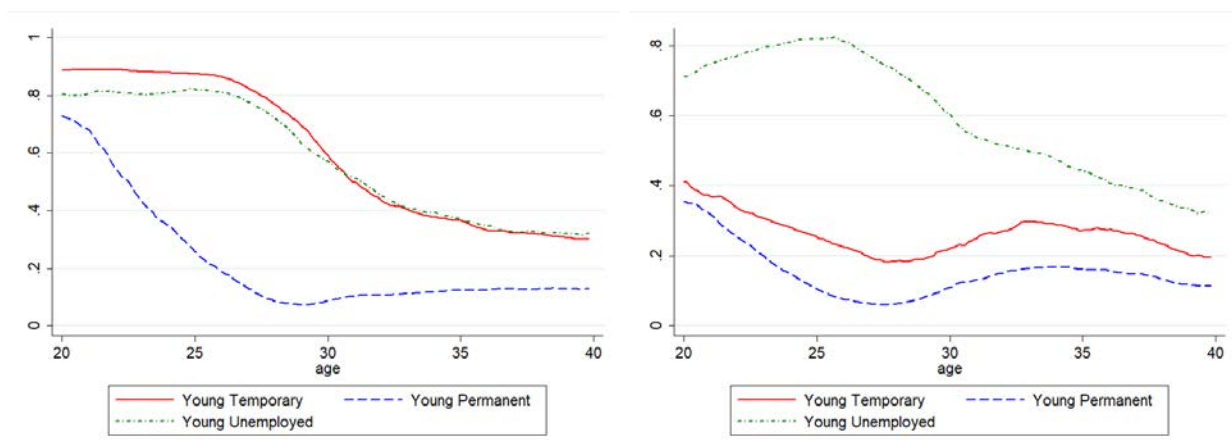
The findings of the previous section suggest that even if we take the view of considering temporary jobs as an intermediate step between unemployment and permanent jobs (stepping-stone hypothesis), they seem to partially affect workers' career prospects. In this section, we estimate the long-term effects of accumulating temporary jobs by examining the differences in workers' mid-career labour market performance by young-age status.

Unemployment and Temporary Rates

The left panel of Figure 3.7 displays the age profile of the temporary rate by young-status. As a consequence of our definitions of young-age status, we see that differences in the temporary rate between young temporary and permanent workers arise very early. Interestingly, the figure shows that the temporary rate of young-temporary and young-unemployment is very similar for all ages. This means that the few employment spells experienced by the top 10% unemployed workers (young-age unemployed) are under a temporary contract. We also see that differences in the temporary rate between young-temporary and young-permanent still exist later in the career. Specifically, at ages 35 to 40, young-age temporary workers have on average a temporary rate of around 30%, whereas for young-permanent workers this rate is around 10%. This figure suggests again the existence of long-lasting persistence in temporary employment.

Figure 3.7: Temporary and unemployment rate by young-age status

Temporary Rate　　　　Unemployment Rate



Note: Temporary rate represents the percentage of employed time spent in temporary jobs. Both graphs are smoothed with a 12 month moving average. Source: Own calculations using MCVL.

The right panel of Figure 3.7 shows that the unemployment rate is higher for young-temporary than for young-permanent workers during the entire workers' career. This is not surprising at young-age, since by definition young-age temporary workers are spending more time in the most unstable jobs (i.e temporary jobs). However, the fact that the unemployment rate is also higher at mid-career is not obvious: it suggests that the effect of employing most of the time as temporary when young has long lasting-effects in terms of unemployment risk. Given the high persistence in temporary employment, the most plausible reason is that young-age temporary workers are also concentrated in temporary jobs also late in their careers (left panel of Figure 3.7).

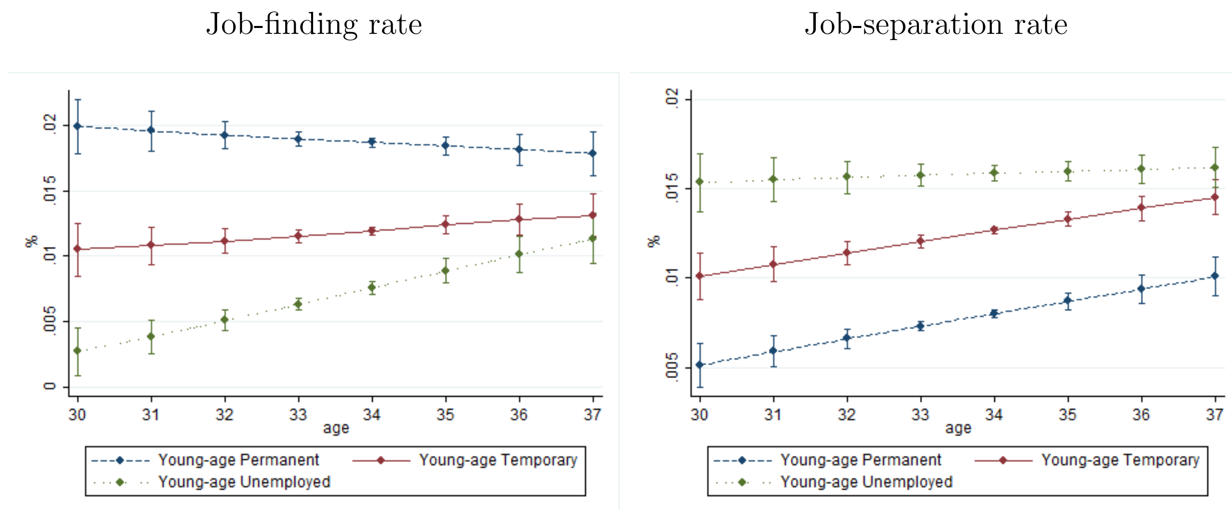
Labour Market Flows

We try to decompose the heterogeneity in the temporary and unemployment rate between young-age categories by looking at the evolution of the different transitions flows. Figure 3.8 displays the age profile of the job-finding (left panel) and job-separation rate (right panel) in permanent jobs, while Figure 3.28 (in Appendix F) shows those rates but in temporary jobs[6]. Consistent with the previous Section, we find higher heterogeneity in the labour market

[6] As before, we calculate both the unconditional age profile of each rate and the residuals obtained after regressing each rate on dummies for the young-age status, age, observables and time and cohort fixed effects. Here we display the residuals evaluated at the average of the covariates, but the unconditional figures can be found in Appendix F.

outcomes in permanent jobs. In particular, we find that, compared to young-age permanent workers, young-age temporary workers have a lower probability of finding permanent jobs also during mid-career (left panel of Figure 3.8). One can observe that the gap between

Figure 3.8: Transition rates in permanent jobs at mid-career by young-age status



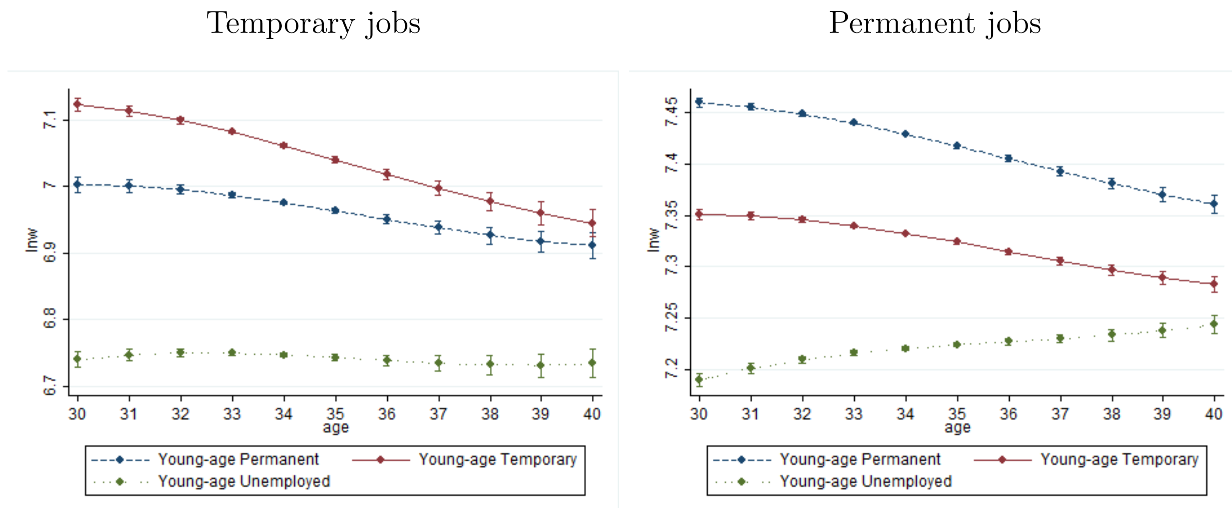
Note: Average monthly job-finding and job-separation rates as permanent, by young-age category. Sample of all workers. Job-finding (separation) rate is defined as the probability of transiting from employment (unemployment) at month $t-1$ to unemployment (employment) at t. To compute the residuals we run a linear regression on a 2^{nd} degree polynomial in age by young-age group, controlling for observables and time and cohort fixed effects. Controls include dummies for education, nationality, region of residence, sector of activity, skill, experience, tenure, and coefficient of partial time. Residuals are evaluated at the average at means of other covariates. Source: MCVL

the two groups does not close even at age 37. We also find significant long-term differences regarding the job-separation rate in permanent jobs (right panel of Figure 3.8), By age 37, after controlling for observables, a young temporary worker is 1.5 times more likely to lose a permanent job than young-age permanent worker, with that number being quite constant from ages 30 to 37. On the other hand, we do not find a persistent effect in the probability of separating from temporary jobs (right panel of Figure 3.28 in Appendix F), but the evidence suggests that accumulating more temporary employment early at the career has long-lasting effects regarding the probability of finding temporary jobs later (left panel of Figure 3.28). This could be because workers spending more time in temporary jobs (and therefore experiencing more unemployment spells) get more efficient at finding temporary jobs, or it could be the result of differences in the degree of patience.

Wages

Last, we study the potential long-term effects on wages of accumulating temporary employment early in the workers' careers. For that, we start by comparing the age profile of real wages by young-age status. The left panel of Figure 3.9 plots the age profile of real wages among workers employed in temporary jobs, while the right panel displays the evolution of wages at permanent jobs. As before, unconditional wage differences by young-age status

Figure 3.9: Real wages by young-age status



Note: Average monthly wage obtained by a worker employed in a temporary or permanent job, by young-age category. Sample of all workers. To compute the residuals we run a linear regression on a 2^{nd} *degree polynomial in age by young-age group, controlling for observables and time and cohort fixed effects. Controls include dummies for education, nationality, region of residence, sector of activity, skill, experience, tenure, and coefficient of partial time. Residuals are evaluated at the average at means of other covariates. Wages are deflated using the consumer price index (base year 2011) provided by the Spanish Statistical Office (INE) Source: MCVL*

could be partially or totally explained by composition effects (young-age temporary workers are slightly over-represented in the construction sector or among low-skilled groups (see Figure 3.26). Therefore, as in previous sections we clean out composition effects by estimating the residuals (evaluated at the average at means of the other covariates) obtained from estimating a linear regression of the real wages on dummies for the young-age status, age, observables and time and cohort fixed effects (unconditional wages are displayed in Figure 3.24 in Appendix D). We find large wage differences at permanent jobs by young-age status, even late in workers' careers (right panel of Figure 3.9). In particular, our estimates suggest that at ages 35-40, young-temporary workers have on average 9% lower wages than young-permanent workers. This is strong evidence on the long-lasting effect of working as temporary when young. The left panel of Figure 3.9 shows that real wages obtained in temporary jobs at mid-career are higher for young-age temporary workers.

The yearly wage gap is large and, importantly, it accumulates over time. We ask what these differences represent once the yearly gap is sum up over the worker's career. To answer this question, we estimate lifetime wages as follows: for each young-age status group, we sum up their average monthly wages over 20 years (ages 20 to 40). Table 3.3 displays the results. In the top panel, we consider both part-time and full-time workers,

Table 3.3: Lifetime wage (ages 20-40) by young-age employment status

	Young-age status				
	Temporary	Permanent	Unemployed	Self-Employed	Rest
All jobs	328027.5	377001.5	269993.8	302392.0	313756.4
Permanent jobs	351256.2	394905.5	318058.9	336038.3	351380.7
Temporary jobs	302672.4	289510.9	234019.5	268664.5	254848.6
Only full time					
All jobs	356656.6	413740.3	321581.0	340401.3	341517.0
Permanent jobs	381333.3	428451.1	363345.7	368565.1	375506.7
Temporary jobs	331466.6	332937.4	287612.1	315117.5	288474.6

Wages are deflated using the consumer price index (base year 2011) provided by the Spanish Statistical Office (INE). Source: *Own elaboration using MCVL.*

while in the bottom panel we restrict to full-time workers. The first row of each panel shows the lifetime wage obtained by pooling both permanent and temporary jobs. Our estimates of lifetime wages are 328,027 and 377,001 euros, respectively, for young-age temporary and young-age permanent workers. This means that over 20 years, the young-age temporary workers obtained around 50,000 euros (2,500 yearly) less than young-age permanent workers (around 15%). This difference is bigger (57,000 euros) when we restrict to full-time workers, as in this case, the lifetime wages are 356,656 and 413,740 euros for young-age temporary and permanent groups, respectively (first row of the bottom panel of Table 3.3). This lifetime wage gap is partially explained by the fact that wages are lower in temporary jobs and we have shown that young-age temporary workers work more as temporary also at mid-career (during their 30's). To account for that, the second row of the top and bottom panels display the estimated lifetime wage obtained by workers that are employed in permanent jobs. We find a similar lifetime wage gap between young-age temporary and permanent workers also when employed in permanent jobs: lifetime wages are 351,256 and 395,905 euros, respectively (the gap is close to 45,000 euros or 2,250 yearly) which is equivalent to say that lifetime wages at permanent jobs are 13% lower for young-age temporary than young-age permanent workers.

Our findings are suggestive evidence of substantial long-term wage losses from accumulating temporary employment at early stages in the workers' career. We also compare our estimates of the lifetimes' wages between young-age temporary and unemployed workers, the second and fourth columns in Table 3.3. Consistent with the results regarding the long-term impact of job instability on the labour market flows, we also find that accumulating unemployment time at young-age has larger negative effects on lifetime wages than accumulating temporary employment. In particular, our estimates of lifetime wages suggest that over 20 years, the young-age unemployed workers received 58,000 and 107,000 euros (20% and 40%) less than young-age temporary and permanent workers, respectively. Interestingly, the lifetime wage gap between young-age temporary and unemployed workers reduces to almost half when restricting to full-time jobs (356,6656 and 321,581 euros, a gap of around 35,000 euros) and it almost disappears when lifetime wages are computed only for workers employed in permanent jobs (381,333 and 363,345 euros). This suggests, first, that a significant part the differences in the lifetime gap are explained by the fact that the young-age unemployed workers work more in part-time jobs than the young-age temporary workers; and second, that accumulating longer unemployment spells when young seems to have a larger long-term impact in the wages received at temporary than at permanent jobs.

3.6 Conclusions

This paper quantifies the incidence of temporary jobs for mid-career workers, its degree of persistence and the long-term effects of accumulating temporary employment at early stages in workers' careers, on both wages and employment outcomes. We find that temporary jobs are commonplace, including college graduates and mid-career workers. We also find that the time employed as temporary when a worker is young is a powerful predictor of time employed as temporary during mid-career (lifetime instability), suggesting a high degree of persistence in the time spent as temporary. When examining the workers' early labour market performance we find that differences between mid-career temporary and mid-career permanent workers at young-age are mainly observed in their performance in permanent jobs. In particular, both groups start their career with similar job-finding and job-separation rates in permanent jobs, but differences emerge early in their career. Last, we show that being employed most of the young-time as temporary has long-lasting effects, as it is associated with lower wages (around 9%) and with higher job-separation rates in permanent jobs at mid-career. The long-term impact of temporary employment on wages is large; our lifetime wages estimates suggest that over ages 20 to 40, the wage losses from being employed most of young-time as temporary (compared to being employed as permanent) amount to almost

50,000 euros (which implies a lifetime wage 15% lower).

The results of this paper show that a significant fraction of mid-career workers spend most of their time employed as temporary. In other words, the incidence of temporary jobs seems not to be restricted to young workers. High incidence of unstable jobs late in workers' careers can have implications regarding the households' saving capacity but also regarding important decisions such as marriage or having children. In turn, delaying (or canceling) these decisions could have negative effects on household investments or population growth. Therefore, policy effort should give priority to reducing temporary employment among mid-career workers.

Our results regarding the persistence and long-term effects of temporary jobs suggest that those jobs could be a stumbling block for workers' careers. Importantly, this is neither restricted to low-skilled, not to low-educated workers. To the extent that temporary employment is mostly involuntary (from the worker point of view), stricter policy on the use of temporary contracts in jobs with a non-temporary nature is predicted to be beneficial for workers, as it would reduce the hazard of working as temporary also later in their career. Of course, here we are ignoring the negative effect that this policy could have on firms' job-creation. Incorporating this potential trade-off in a structural framework is a promising avenue for future research.

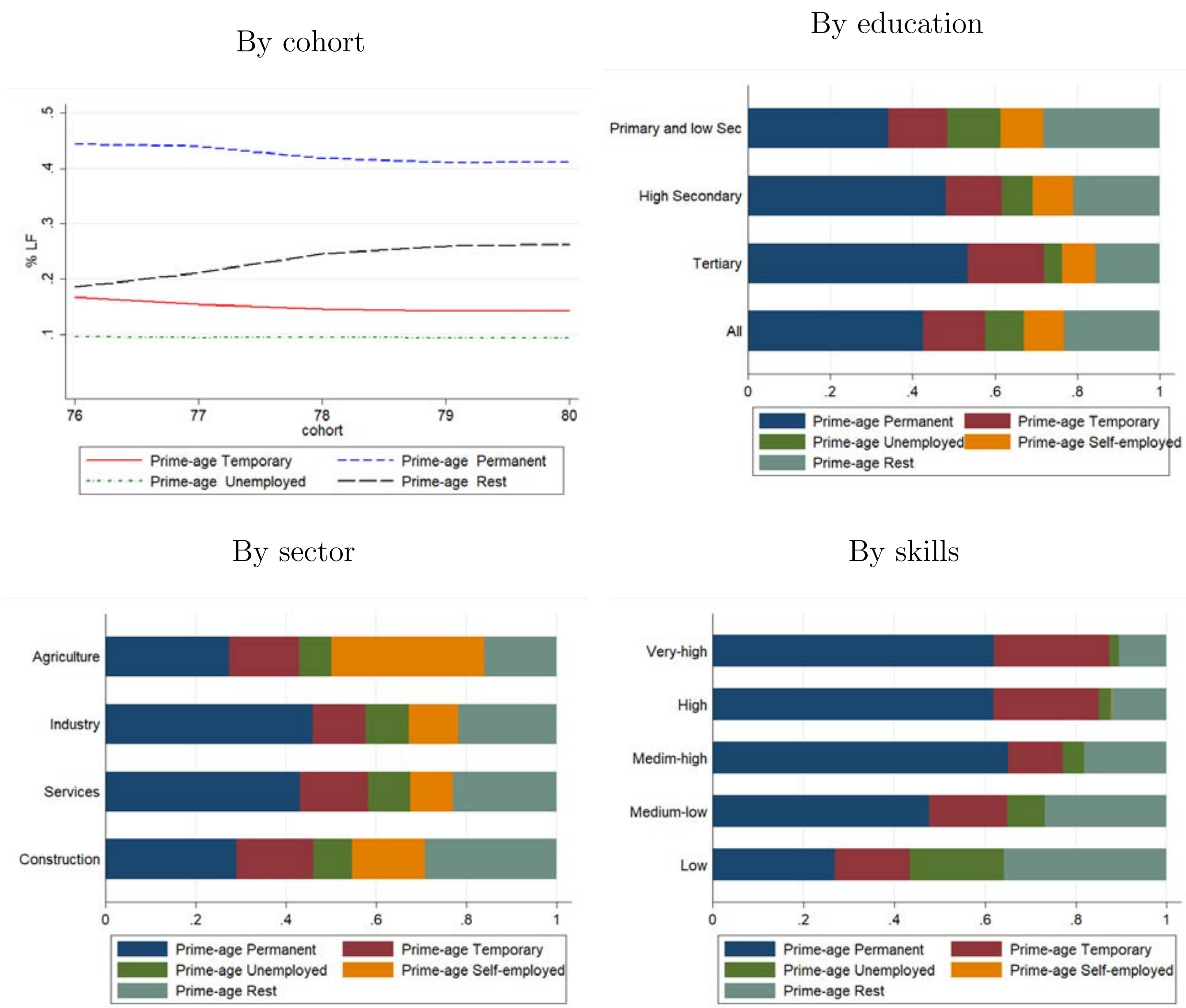
Last, the empirical evidence presented in this paper is planned to be used for understanding the underlying mechanisms that explain the observed persistence in temporary employment (lifetime job instability). The literature had pointed out two alternatives: the *adverse selection* and the *human capital* hypotheses. Overall, our findings suggest that the adverse selection theory on its own could not fully account for the young-age labour market performance patterns, in particular, the finding that job-separation rates differences by mid-career status categories are only observed as workers age. We think that a combination of workers' unobserved heterogeneity and a simple human capital accumulation mechanism would help to rationalize the life-cycle empirical patterns. For future research, we plan to use this empirical evidence to discipline a model aiming to disentangle which of the two hypotheses is more accurate. By that, we could answer the broader question on whether temporary jobs are pernicious for workers as they dampen human capital accumulation, or whether these jobs are only a screening tool used by firms to distinguish "less capable" workers.

3.7 Appendix

Appendix A. Employment categories defined as fraction of total time

The incidence of temporary employment at mid-career

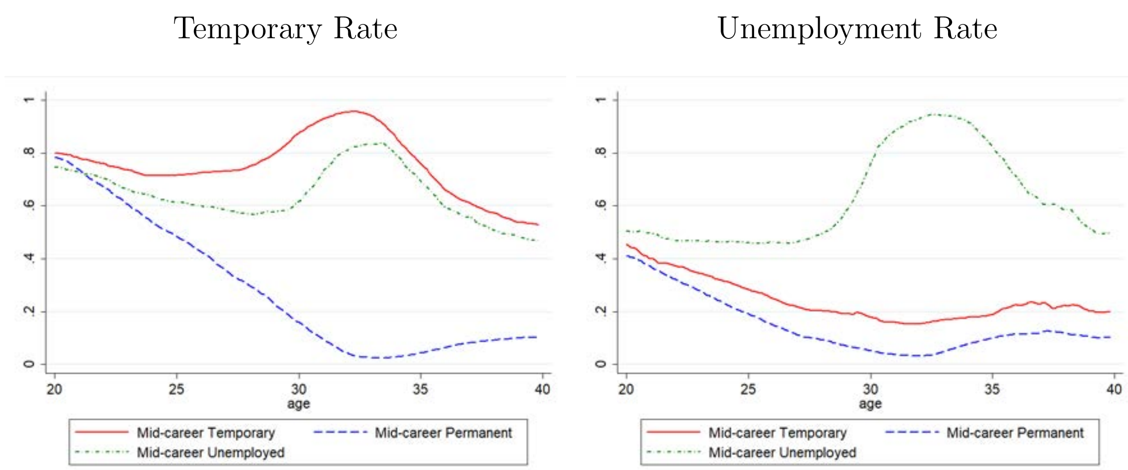
Figure 3.10: Share of workers by mid-career status, defined as fraction of total time



Source: Own calculations using MCVL.

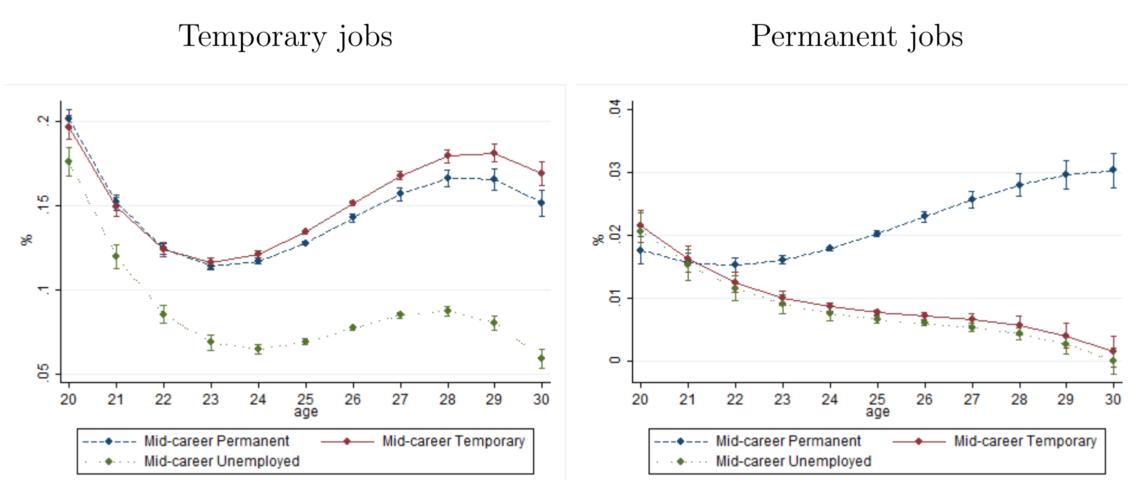
Labour market performance over the life-cycle

Figure 3.11: Temporary and unemployment rate by mid-career status, defined as fraction of total time



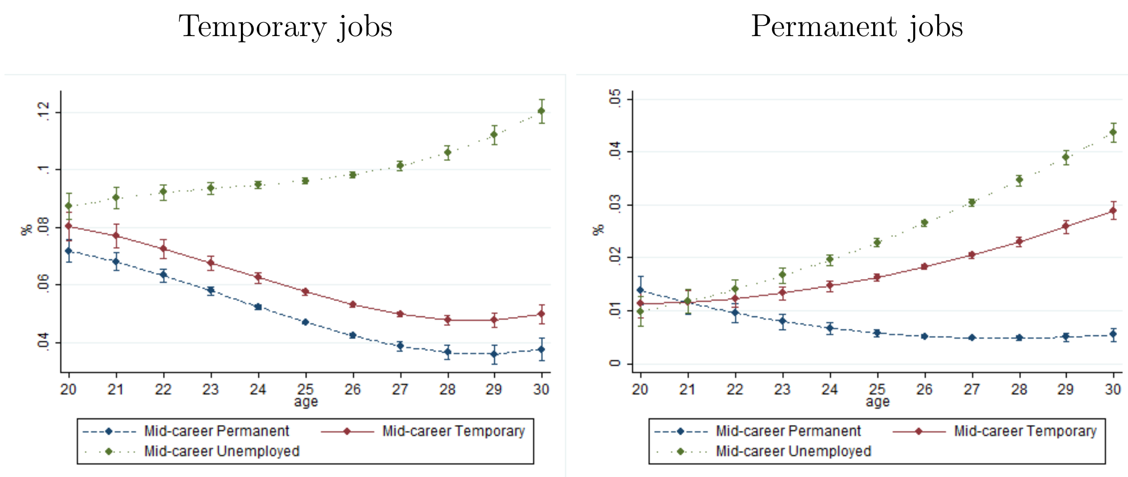
Source: Own calculations using MCVL.

Figure 3.12: Job-finding rate at young-age by mid-career status, defined as fraction of total time



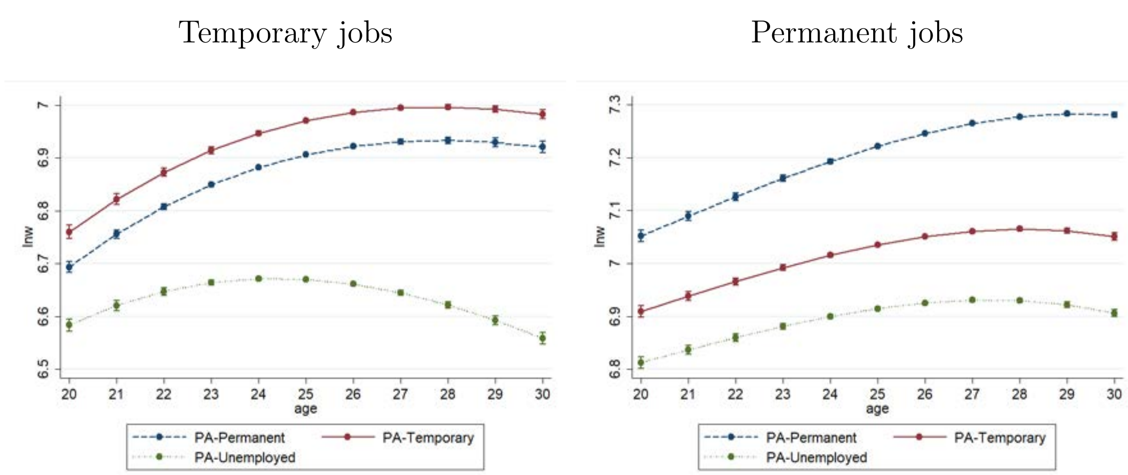
Note: Average monthly job-finding rate as temporary or permanent, by mid-career category. Sample of all workers. Job-finding rates are defined as the probability of transiting from unemployment at month $t-1$ to employment at t. To compute the residuals we run a linear regression on a 2^{nd} degree polynomial in age by mid-career group, controlling for observables and time and cohort fixed effects. Controls include dummies for education, nationality, region of residence, sector of activity, skill, experience, tenure, and coefficient of partial time. Residuals are evaluated at the average of other covariates. Source: MCVL

Figure 3.13: Job-separation rate at young-age by mid-career status, defined as fraction of total time



Note: Average monthly job-separation rate as temporary or permanent, by mid-career category. Sample of all workers. Job-separation rates are defined as the probability of transiting from employment at month $t-1$ to unemployment at t. We only include non-voluntary transitions. To compute the residuals we run a linear regression on a 2^{nd} degree polynomial in age by mid-career group, controlling for observables and time and cohort fixed effects. Controls include dummies for education, nationality, region of residence, sector of activity, skill, experience, tenure, and coefficient of partial time. Residuals are evaluated at the average of other covariates. Source: MCVL

Figure 3.14: Real wages by mid-career status, defined as fraction of total time

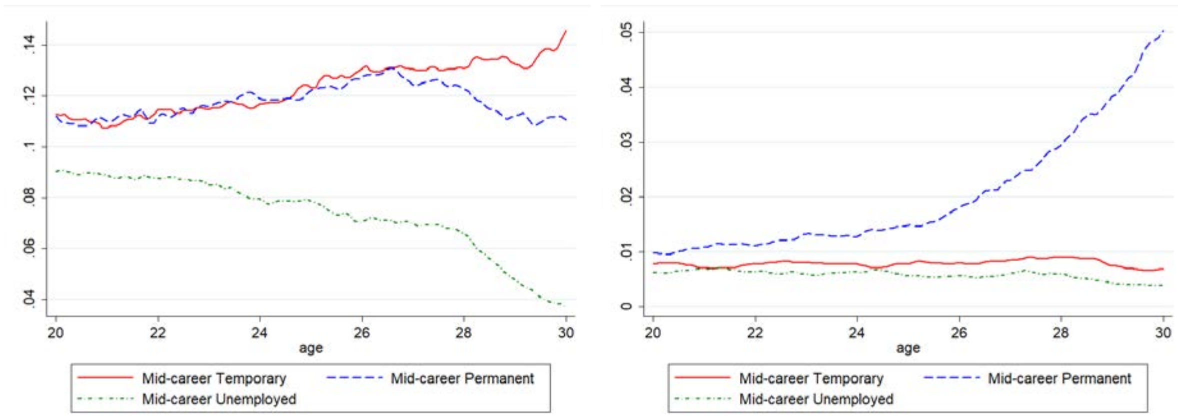


Note: Average monthly wage obtained by a worker employed in a temporary or permanent job, by group of mid-career category. Sample of all workers. To compute the residuals we run a linear regression on a 2^{nd} degree polynomial in age by young-age group, controlling for observables and time and cohort fixed effects. Controls include dummies for education, nationality, region of residence, sector of activity, skill, experience, tenure, and coefficient of partial time. Residuals are evaluated at the average at means of other covariates. Wages are deflated using the consumer price index (base year 2011) provided by the Spanish Statistical Office (INE) Source: MCVL

Appendix B. Unconditional labour market outcomes by mid-career status

Figure 3.15: Job-finding rate by mid-career status, unconditional

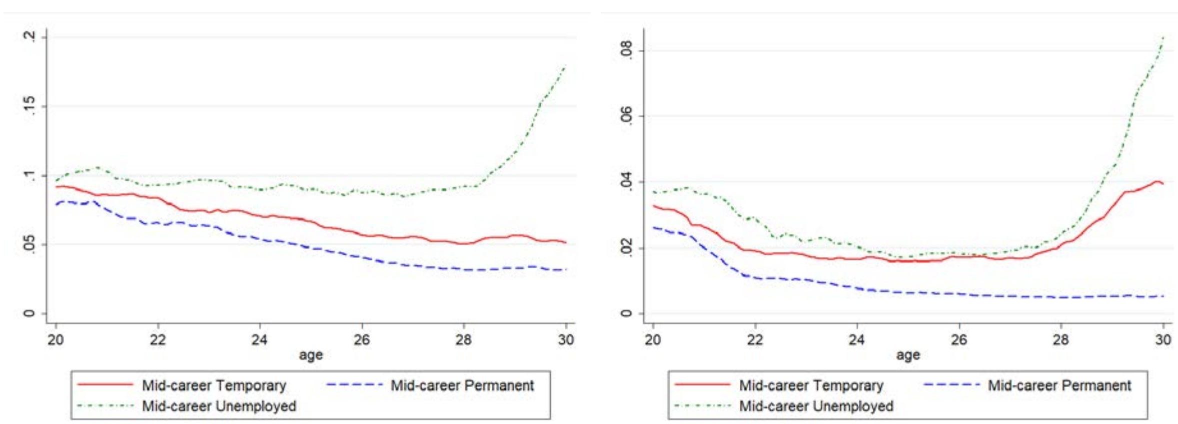
Temporary Jobs　　　　Permanent Jobs



Note: Average monthly job-finding rate as temporary or permanent, by mid-career category. Sample of all workers. Job-finding rates are defined as the probability of transiting from unemployment at month $t-1$ to employment at t. Graphs are smoothed with a 12 month moving average. Source: MCVL

Figure 3.16: Job-separation rate by mid-career status, unconditional

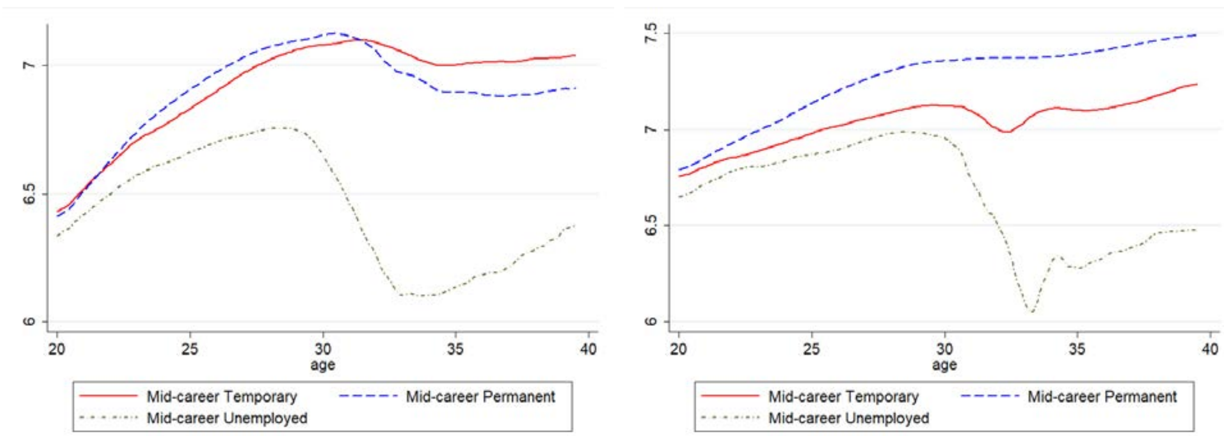
Temporary Jobs　　　　Permanent Jobs



Note: Average monthly job-separation rate as temporary or permanent, by mid-career category. Sample of all workers. Job-separation rates are defined as the probability of transiting from employment at month $t-1$ to unemployment at t. We only include non-voluntary transitions. Graphs are smoothed with a 12 month moving average. Source: MCVL

Figure 3.17: Real wages by mid-career status, unconditional

Temporary jobs   Permanent jobs



Note: Average monthly wages obtained by a worker employed in a temporary or permanent job, by mid-career category. Sample of all workers. Graphs are smoothed with a 12 month moving average. Source: MCVL

Appendix C. Wage growth

The panel dimension of the MCVL allows us to compute the evolution of the growth of real wages over workers' careers. We distinguish between two cases: job-stayers and job-movers. Job-stayers are workers who continue working with the same firm in two consecutive years, while job-movers are workers changing firm from month t to month $t+1$. Among job-stayers, wage growth is computed as the annual change of the average real wage obtained in two consecutive years. Regrading job-stayers, wage growth is simply the change in the real wage obtained at month t (when she was employed in the old firm) and month $t+1$ (wage at the new firm). In our analysis, we also distinguish between wage growth in temporary and permanent jobs and for workers moving from temporary to permanent jobs[7].

We start by focusing on the differences in the wage growth by mid-career status. However, in the Figures 3.20 and 3.21 of the next subsection, we plot the wage growth for our pooled sample to check differences between job-movers and job-changers and between temporary, permanent and temporary-to-permanent jobs (within job-movers and job-stayers).

[7]That is, for job-stayers we compute the wage growth for (1) job-stayers employed in temporary jobs in the two consecutive years; (2) job-stayers employed in permanent jobs in the two consecutive years; (3) job-stayers that were employed as temporary at year t and change to permanent at year $t+1$ in the same firm. Similarly, for job-movers, we calculate the wage growth for: (1) job-movers employed in temporary jobs both in the old and in the new firm; (2) job-movers employed in permanent jobs both in the old and new firm; (3) job-movers employed as temporary at month t and change to a permanent job at month $t+1$ in a new firm.

We find that: (1) as expected, job-movers experience higher wage growth rates than job-stayers (around 5 times higher within permanent jobs, see Figure 3.21 and 3.20; (2) wage growth among workers moving from a temporary to a permanent job is higher both within job-movers and job-stayers (Figure 3.21).

Wage growth by mid-career status

Figure 3.18: Wage growth of job-stayers

Note: Wage growth is computed as the change in the monthly average wage obtained in two consecutive year with the same firm. We distinguish between job-stayers in temporary and permanent jobs and job-stayers that were employed as temporary at year t and change to permanent at year $t+1$ in the same firm. Only full-time workers. Source: MCVL

Figure 3.18 plots the age profile of the wage growth among job-stayers for mid-career temporary and permanent workers[8]. One can see that the wage growth of mid-career permanent workers is higher during young-age in the three job-stayers categories: temporary and permanent jobs (top left and right panel) and also when moving from temporary to permanent jobs (bottom panel). Quantitatively the wage growth gaps are large: for instance, in permanent jobs from ages 20 to 30, on average, wages of mid-career permanent workers grow 5 percentage points more (yearly) than those of the mid-career temporary workers. Differences are similar in the other two job-stayers categories. In Figure 3.19 we repeat the same analysis but for job-movers. In this case, we find small differences between mid-career temporary and permanent workers.

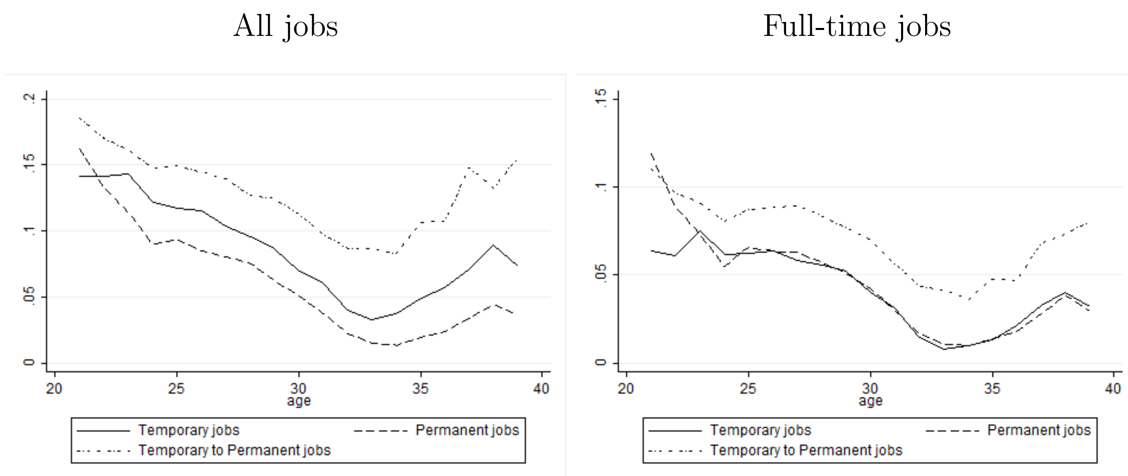
Figure 3.19: Wage growth of job-movers

Note: The wage growth is computed as the change in the monthly wage obtained in month t with the old firm and in month $t+1$ with the new firm. We distinguish between job-movers in temporary and permanent jobs and job-movers that were employed as temporary at year t and change to permanent at year $t+1$ in the new firm. Only full-time workers. Source: MCVL

[8] We restrict our attention to these two groups because the mid-career unemployed wage growth profile is very noisy: those are workers with very few employment spells at mid-career, and therefore there are few wage observations.

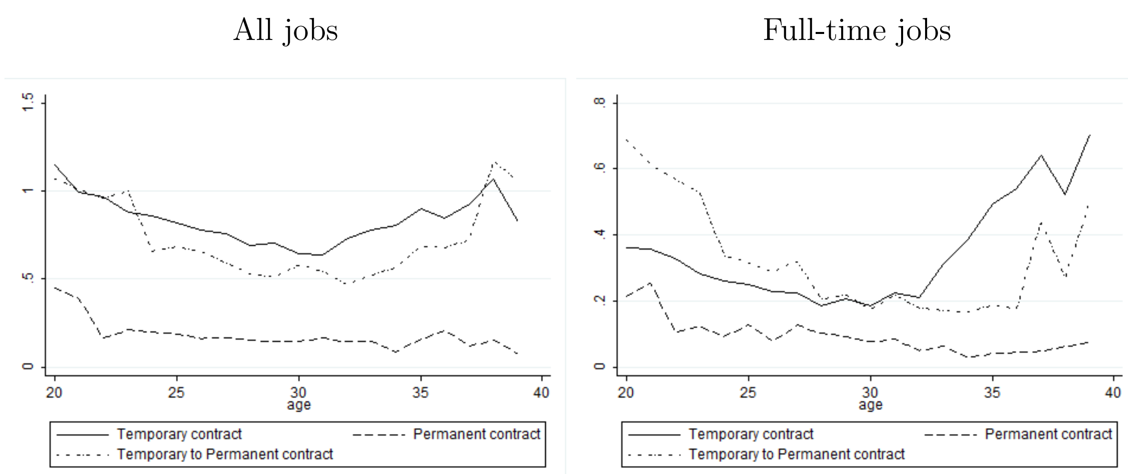
Wage growth, all workers

Figure 3.20: Wage growth of job-stayers



Note: The wage growth is computed as the change in the monthly average wage obtained in two consecutive year with the same firm. We distinguish between job-stayers in temporary and permanent jobs and job-stayers that were employed as temporary at year t and change to permanent at year $t+1$ in the same firm. Source: MCVL

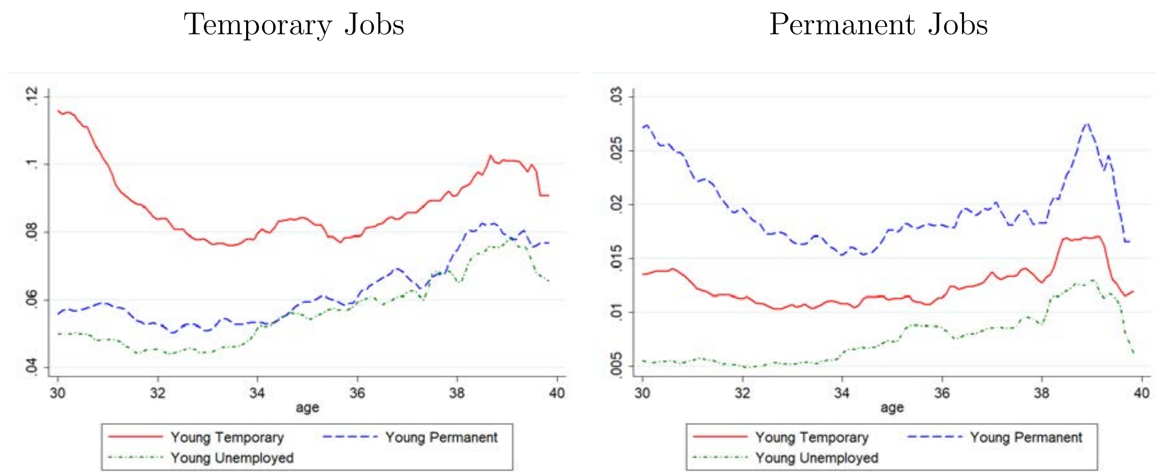
Figure 3.21: Wage growth of job-movers



Note: The wage growth is computed as the change in the monthly wage obtained in month t with the old firm and in month $t+1$ with the new firm. We distinguish between job-movers in temporary and permanent jobs and job-movers that were employed as temporary at year t and change to permanent at year $t+1$ in the new firm. Source: MCVL

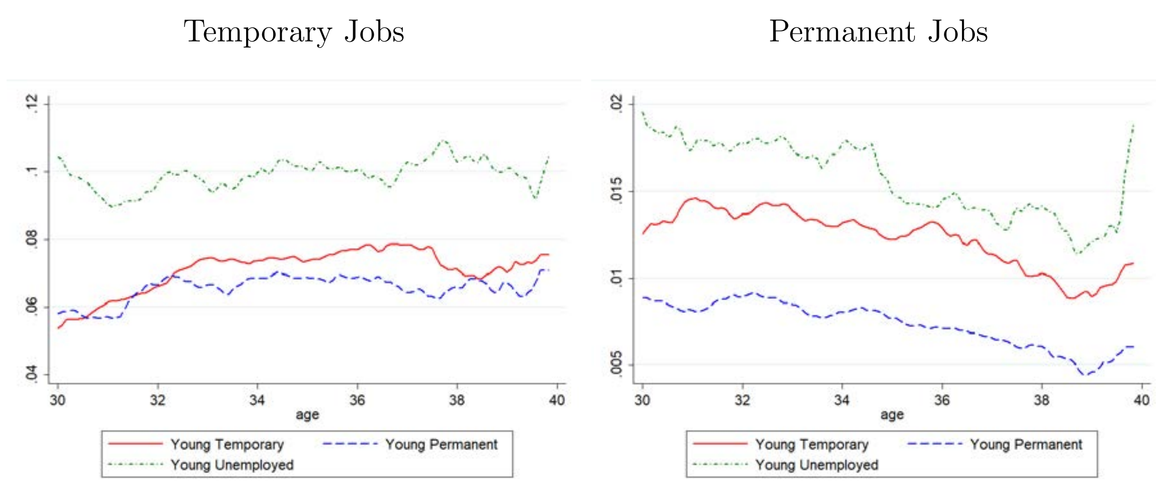
Appendix D. Unconditional labour market outcomes by young-age status

Figure 3.22: Job-finding rate by young-age status



Note: Average monthly job-finding rate as temporary or permanent, by young-age category. Sample of all workers. Job-finding rates are defined as the probability of transiting from unemployment at month $t-1$ to employment at t. Graphs are smoothed with a 12 month moving average. Source: MCVL

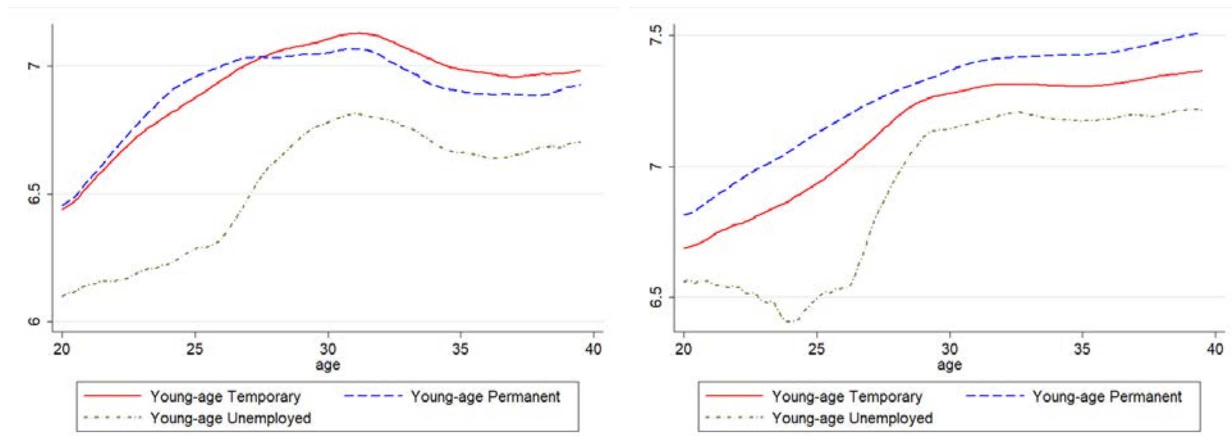
Figure 3.23: Job-separation rate by young-age status, unconditional



Note: Average monthly job-separation rate as temporary or permanent, by young-age category. Sample of all workers. Job-separation rates are defined as the probability of transiting from employment at month $t-1$ to unemployment at t. We only include non-voluntary transitions. Graphs are smoothed with a 12 month moving average. Source: MCVL

Figure 3.24: Real wages by young-age status, unconditional

Temporary jobs | Permanent jobs



Note: Average monthly wages obtained by a worker employed in a temporary or permanent job, by mid-career category. Sample of all workers. Graphs are smoothed with a 12 month moving average. Source: MCVL

Appendix E. Robustness analysis to the mid-career definition

Due to data limitations, our baseline definition of mid-career workers is between 30 to 35 years old. In this appendix, we show that the labour market performance of workers at those 5 years is a very good predictor of the future labour market performance. We start by showing the correlation between workers' performance at ages 30-35 and at ages 30-40. For that, we use data of workers born from 1967 to 1976, as we need cohorts for which we have information at ages 30 to 40, and for which the variable on the type of contract is available (1997-2005). We then apply our definitions of unemployed, temporary and permanent workers at ages 30-35 (baseline mid-career definition) and at ages 30-45. Table 3.4 shows the Markov transition matrix from 30-35 to 30-40 employment status. Looking at the elements of the diagonal of the transition matrix one can see the high degree correlation in all the employment status. In particular, around 70% of the workers included in the temporary status category at ages 30-35 also enter in that category at ages 30-40. As the column (2) of the second row shows, around 20% of those move to the permanent category at ages 30-40, suggesting that some workers find permanent jobs when they are 35 years old or more.As expected, we also find that the correlation is higher for permanent employment status. We compute the Markov transition matrix for each cohort, and we find that for all status categories the correlation is higher for the youngest cohorts (1972 to 1975). We do not report the results, but in Figure 3.25 we plot the share of each employment status category by cohort when the categories

Table 3.4: Markov transition matrix 30-35 to 30-40 employment status (%)

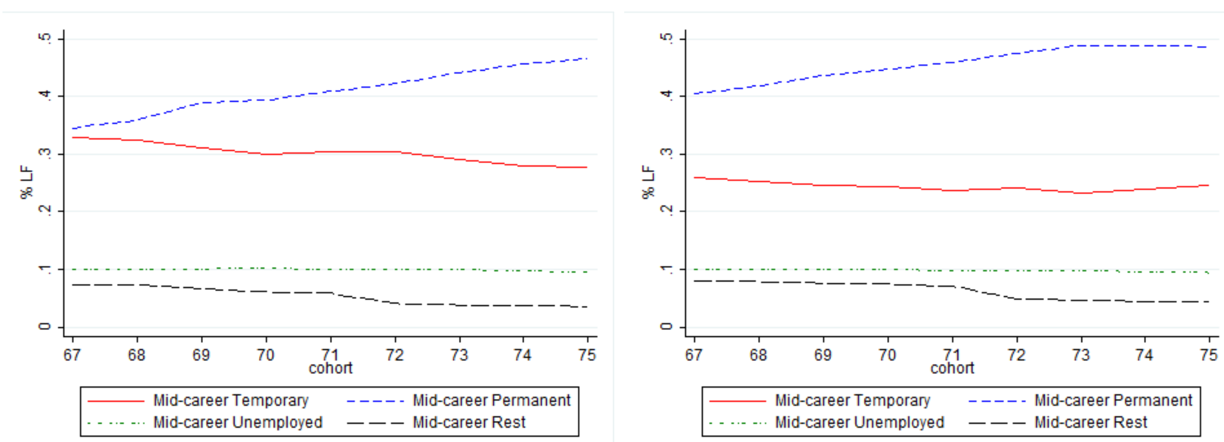
30-35	(1) Temporary	(2) Permanent	**30-40** (3) Unemployed	(4) Self-Employed	(5) Rest
Temporary	68.2	19.7	4.9	2.4	4.9
Permanent	3.2	91.3	1.1	2.1	2.3
Unemployed	10.0	8.4	73.9	5.8	2.0
Self-Employed	5.2	4.1	2.0	83.8	4.9
Rest	14.7	17.4	5.0	8.6	54.3
All	24.3	45.9	9.8	13.9	6.1

Source: *Own elaboration using MCVL.*

are defined at ages 30-35 (left panel of Figure 3.25) and at ages 30-40 (right panel). As we can see, the share of each employment status is more similar between the two age intervals among the youngest cohorts. This finding provides additional support to our claim that the labour market status at ages 30-35 is a very good predictor of the status at ages 30-40. Moreover, those status are likely to be even a better predictor in the cohorts that we use in the analysis (1976 to 1980).

Figure 3.25: Share of workers by mid-career status

Mid-career defined at ages 30-35 | Mid-career defined at ages 30-40



Source: Own calculations using MCVL.

Next, we show that the workers' labour market performance at ages 30-35 is also correlated with their performance at ages 30-45. Notice that the data limitation commented above restrict in this case the analysis to cohorts 1967 to 1970. Table 3.5 shows the Markov transition matrix from 30-35 to 30-45 employment status. We find that more than 50% of workers in the temporary status category at ages 30-35 continue entering in that category at ages 30-45. As before, most of those moving category goes to the permanent status category. Again, we also find a very similar correlation in the temporary and unemployment status category. As expected, the highest correlation is found in the permanent category. Overall, we think that the fact that for all employment categories the correlation is higher than 50% is supportive evidence that the labour market performance at ages 30-35 is a good predictor of the performance at ages 30-45.

Table 3.5: Markov transition matrix 30-35 to 30-45 employment status (%)

30-35	**30-45** (1) Temporary	(2) Permanent	(3) Unemployed	(4) Self-Employed	(5) Rest
Temporary	53.4	30.3	6.7	4.1	5.6
Permanent	3.9	87.3	1.8	4.4	2.7
Unemployed	10.0	16.1	63.0	8.6	2.2
Self-Employed	7.9	9.6	2.8	73.4	6.2
Rest	20.3	27.2	8.5	12.8	31.2
All	20.8	48.9	9.9	15.2	5.2

Source: *Own elaboration using MCVL.*

As a final robustness check, we study if the labour market performance of workers at age 30-35 is a good proxy of the performance at ages 35-50. Table 3.6 displays the transition matrix from the employment status at 35-40 to 35-50 (we construct this matrix for our sample of workers born in cohorts 1962 to 1966). As we can see, the correlation is still higher than 50% for all employment status.

Table 3.6: Markov transition matrix 35-40 to 35-50 employment status (%)

35-40	**35-50** (1) Temporary	(2) Permanent	(3) Unemployed	(4) Self-Employed	(5) Rest
Temporary	53.8	28.9	7.6	4.4	5.3
Permanent	3.1	89.8	1.3	3.8	2.1
Unemployed	10.6	16.5	61.9	9.4	1.6
Self-Employed	4.6	5.9	2.2	82.7	4.7
Rest	16.6	23.9	12.3	10.1	37.1
All	19.2	46.3	9.8	19.7	5.0

Source: *Own elaboration using MCVL.*

Appendix F. Other figures and tables

Figure 3.26: Share of workers by young-age status

Source: Own calculations using MCVL.

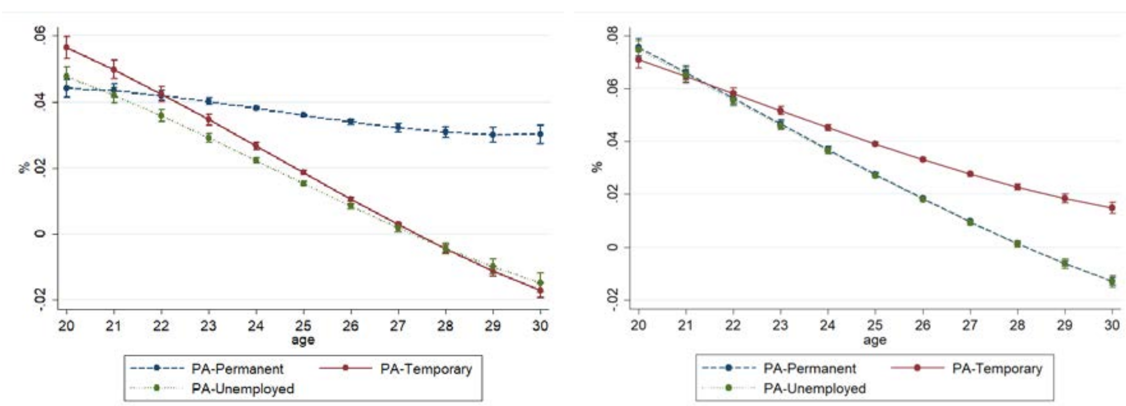
Table 3.7: Occupation Classification

1. Very high skilled
Engineers, college graduates and senior managers
2. High skilled
Technical engineers and graduate assistants
Administrative and technical managers
3. Medium-high skilled
Non-graduate assistants
Administrative officers
Subordinates
4. Medium-high skilled
Administrative assistants
First and second class officers
Third class officers and technicians
5.Low skilled
Labourers

Note: groups are based on the International Standard Classification of Occupations (ISCO-88)

Figure 3.27: Temporary-to-Permanent and Permanent-to-Temporary by mid-career status

Temporary-to-Permanent　　Permanent-to-Temporary



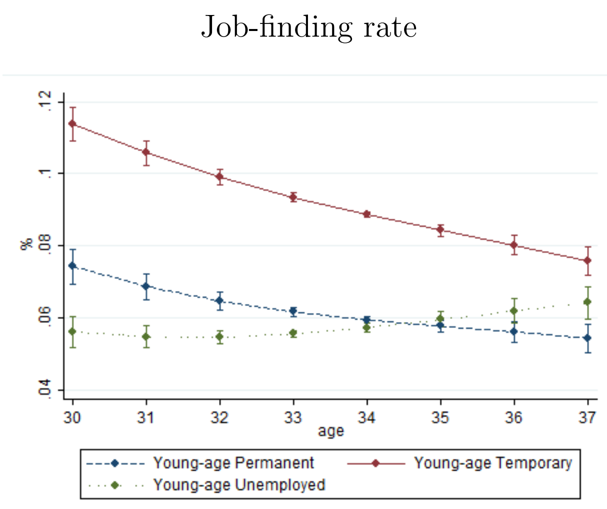
Note: Average monthly temporary-to-permanent and permanent-to-temporary rates by mid-career category. Sample of all workers. Temporary(permanent)-to-permanent(temporary) rate is defined as the probability of transiting from temporary (permanent) employment at month $t-1$ to permanent (temporary) employment at t. To compute the residuals we run a linear regression on a 2^{nd} degree polynomial in age by mid-career group, controlling for observables and time and cohort fixed effects. Controls include dummies for education, nationality, region of residence, sector of activity, skill, experience, tenure, and coefficient of partial time. Residuals are evaluated at the average at means of other covariates. Source: MCVL

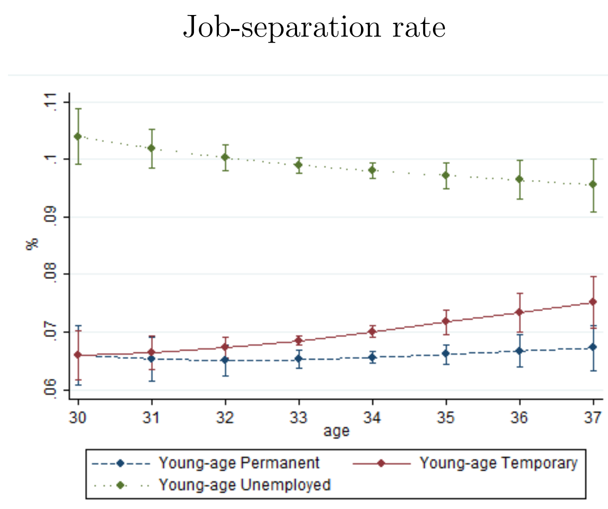
Table 3.8: Markov transition matrix young-to-mid career employment status (%)

	Mid-career				
	Primary and Low Secondary				
Young-age	(1) Temporary	(2) Permanent	(3) Unemployed	(4) Self-Employed	(5) Rest
Temporary	44.9	34.0	11.4	6.0	3.6
Permanent	12.8	72.7	6.1	6.3	2.0
Unemployed	28.2	14.5	45.4	8.2	3.7
Self-Employed	15.2	11.4	5.6	64.1	3.8
Rest	25.3	32.5	12.1	19.0	11.1
All	29.8	40.7	13.0	12.6	3.9
	High Secondary				
Young-age	Temporary	Permanent	Unemployed	Self-Employed	Rest
Temporary	37.5	46.6	7.6	5.1	3.1
Permanent	10.0	79.4	4.3	5.0	1.4
Unemployed	32.6	24.8	26.1	11.9	4.5
Self-Employed	12.6	15.0	3.4	66.4	2.6
Rest	21.2	45.4	7.0	20.8	5.7
All	23.9	54.3	7.5	11.5	2.7
	Tertiary				
Young-age	Temporary	Permanent	Unemployed	Self-Employed	Rest
Temporary	40.7	49.4	3.6	4.4	1.9
Permanent	8.2	84.3	2.1	4.3	1.1
Unemployed	35.2	36.9	14.2	10.8	2.8
Self-Employed	14.6	17.3	2.4	62.9	2.8
Rest	17.4	60.1	3.1	15.9	3.5
All	26.2	58.1	4.2	9.6	1.9

Source: *Own elaboration using MCVL.*

Figure 3.28: Transition rates in temporary jobs at mid-career by young-age status





Note: Average monthly job-finding and job-separation rates as temporary, by young-age category. Sample of all workers. Job-finding (separation) rates are defined as the probability of transiting from unemployment (employment) at month $t-1$ to employment (unemployment) at t. We only include non-voluntary transitions. To compute the residuals we run a linear regression on a 2^{nd} degree polynomial in age by young-age group, controlling for observables and time and cohort fixed effects. Controls include dummies for education, nationality, region of residence, sector of activity, skill, experience, tenure, and coefficient of partial time. Residuals are evaluated at the average at means of other covariates. Source: MCVL

Chapter 4

Labour market flows: Accounting for the public sector

4.1 Introduction

In most European economies, around 20 percent of all workers are employed by the government. Government hire workers to produce goods and services. However, governments face different constraints than private-sector firms and are not driven by profit maximization. Hence, government employment and wage policies are driven by other objectives including: attaining budgetary targets (Poterba and Rueben (1998), Gyourko and Tracy (1989)); implementing macroeconomic stabilization policy (Keynes (1936), Holm-Hadulla et al. (2010), Lamo et al. (2013); redistributing resources (Alesina et al. (2000), Alesina et al. (2001), Wilson (1982)); or satisfying interest groups for electoral gains (Borjas (1984), Matschke (2003), Gelb et al. (1991)). As a consequence, public-sector labour markets might behave differently from their private-sector counterparts.

The objective of this paper is to establish a number of key facts about the French, Spanish, UK and US labour market flows, focussing on the role played by the public sector. We do so by examining data from the French, Spanish and UK Labour Force Surveys and the US Current Population Survey (CPS) over the past 15 years. We chose these four countries because they are large countries with sizeable public sectors, and have been recently facing pressure to reform their public sectors. Furthermore, because they have different labour market institutions, public-sector hiring procedures and wage policies and various weights on different industries, facts that are found to be common across the four countries should be seen as intrinsic characteristics of the public sector. While we do not attempt to explain these facts, we believe that they are an important first step to foster theoretical research on the topic. They can help economists understand the characteristics of the public sector and its policies, as well as provide a guideline of the empirical features that models with a public sector should reproduce and help in the calibration or identification of key parameters. We show that public-sector labour markets do indeed behave differently than the private sector. The size of transition rates into and out of public-sector employment are different and its cyclical pattern as well. Furthermore, the government hires mostly women, college graduates and older workers, which creates asymmetric exposures to public-sector policies for different workers.

In the last decade in European countries, public-sector employment was a key policy variable. Following budgetary constraints, many countries imposed measures such as hiring freezes layoffs of public-sector workers, as well as wage cuts or freezes that affected the retention of these workers (Glassner and Watt (2010)). Given the policy role that public-sector employment played during the last decade, a new wave of research constructs search and matching models of unemployment to study the labour market effects of public-sector employment and wages. Examples include Hörner et al. (2007), Quadrini and Trigari (2007), Afonso and Gomes (2014), Gomes (2015b), Michaillat (2014), Burdett (2012), Bradley et al. (2017), Albrecht et al. (2019), Bermperoglou et al. (2017) and Boeing-Reicher and Caponi (2016). Lying at the heart of these state-of-the-art models are the worker gross flows between private- and public-sector employment and non-employment.

However, the extensive literature that estimates and analyses worker gross flows has systematic ignored the role of the public sector. This literature has focused mainly on disentangling the relative importance of job-finding and job-separation rates in driving the unemployment rate. The most cited papers on the topic - Blanchard et al. (1990), Shimer (2012), Elsby et al. (2009) and Fujita and Ramey (2009) - study the US labour market, proposing different decompositions or examining the role of the time-aggregation bias. Also for the US, Borowczyk-Martins and Lalé (2019) distinguish between full-time and part-time employment, while Elsby et al. (2015a) study the role of the participation margin. Smith (2011) proposes an out-of-steady-state decomposition and analyses the UK labour market. Gomes (2012) further analyses the UK labour market along other dimensions, such as education or labour force attachment, while Fujita (2010) concentrates on on-the-job search and job-to-job transition and Carrillo-Tudela and Kaas (2015) on the extent of worker reallocation across occupations and industries and their cyclicality. In two comparisons of the UK and the US, Razzu and Singleton (2016) study the fluctuations of unemployment among men and women, while Gomes (2015a) examines the role of conditional transition probabilities and how they depend on the frequency of the surveys. Other papers focussing on the UK include Elsby et al. (2011) and Smith et al. (2010).

Several studies examine other European labour markets. Giordano et al. (2011) compare the relative importance of job-finding and job-separation rates across France, the United Kingdom, Spain and the United States. Silva and Vázquez-Grenno (2013) focus on the role of flows in and out of permanent and temporary employment in Spain. Baussola and Mussida (2014) study Italian gross flows, concentrating on unemployment gender gaps. Charlot et al. (2020) split between employment in abstract, routine and manual occupations in France and the US. Other works examining the French labour market include Hairault et al. (2015) and Fontaine (2016). Hertweck and Sigrist (2015) study the German labour market and Daouli et al. (2015) the Greek labour market during the crisis. Despite looking at worker flows from different angles, all the papers in this exhaustive list have ignored the duality between the private and the public sectors.

In Section 4.3, we provide evidence on the size and cyclicality of the flows between public and private employment, unemployment and inactivity. France and the UK have larger public sectors than either Spain or the US. Over the last business cycle, public-sector employment was pro-cyclical in France, countercyclical in the US, and acyclical in Spain and the UK.

In Section 4.4, we quantify how government hiring and separations have contributed to unemployment fluctuations. We show that ignoring these flows in unemployment decompositions can potentially bias the relative importance of job-finding and job-separation rates, although in our sample, this bias turned out to be small. We find a relative split of 80-20 percent of the contribution of private- and public-sector employment to fluctuations in the unemployment rate in UK, 85-15 in France and of 90-10 percent in Spain and the US. We performed a counterfactual analysis and show that since 2008, if governments had kept the same hirings and separations from the previous years, unemployment rate would have been lower, by up to 1 percentage point, in the France and the UK, but it would have been higher in the US and Spain. In our view, this finding reflects the different macroeconomic policies conducted by governments in response to the Great Recession, with a larger focus on austerity policies by some European countries.

We document that jobs are safer in the public sector - aggregate job-separation rates are lower. In Section 4.5, we further investigate this result by using a multinomial logit model to estimate the differences in transition rates from employment to unemployment and inactivity from the two sectors, conditional on observable characteristics. The argument that public-sector jobs are safer is often used in policy discussions surrounding public-sector pay. However, while there are several papers estimating the wage differentials across sectors, there are no estimates of the value of the job-security[1]. We use a simple back-of-the-envelope

[1] Using micro level data, several papers find that, on average, the public sector pays higher wages than

calculation to find the percentage of their wage that private-sector workers would be willing to forgo to have the same job-separation probability as in the public sector. In our preferred scenario, risk-neutral workers would pay 0.5 to 1.6 percent of their wage for the same job security, which can be seen as a lower bound for the insurance value of public-sector employment. Risk-averse workers without any savings mechanism would pay 1.0 to 2.9 percent of their wage, which can be seen as an upper bound. The value of job safety in the public sector is equivalent to between 0.4 to 0.7 percent of total government spending in France and between 0.2 to 0.4 percent in the UK, Spain and the US.

4.2 Preliminary concepts

4.2.1 Labour market dynamics

In order to analyse labour market dynamics, we use some fundamental equations that describe the evolution of the stock of the employed in the private and public sectors (P and G) and the stock of the unemployed U. The pool of the inactive is denoted by I. Adding the four pools gives us the working-age population W, while the sum of employment and unemployment corresponds to the labour force L. The unemployment rate is defined as $u = \frac{U}{L}$ and the participation rate as $p = \frac{L}{W}$.

Changes in private and public employment evolve according to the following equations:

$$\Delta P_{t+1} = \lambda_t^{GP} G_t + \lambda_t^{UP} U_t + \lambda_t^{IP} I_t - (\lambda_t^{PG} + \lambda_t^{PU} + \lambda_t^{PI}) P_t \tag{4.1}$$

$$\Delta G_{t+1} = \lambda_t^{PG} P_t + \lambda_t^{UG} U_t + \lambda_t^{IG} I_t - (\lambda_t^{GP} + \lambda_t^{GU} + \lambda_t^{GI}) G_t \tag{4.2}$$

where λ^{ij} is the transition probability between the pools indicated by the superscript. Similarly, for unemployment and inactivity:

$$\Delta U_{t+1} = \lambda_t^{PU} P_t + \lambda_t^{GU} G_t + \lambda_t^{IU} I_t - (\lambda_t^{UP} + \lambda_t^{UG} + \lambda_t^{UI}) U_t \tag{4.3}$$

$$\Delta I_{t+1} = \lambda_t^{PI} P_t + \lambda_t^{UI} G_t + \lambda_t^{UI} U_t - (\lambda_t^{IP} + \lambda_t^{IG} + \lambda_t^{IU}) I_t \tag{4.4}$$

The transition rate multiplied by the stock is equivalent to the total number of transitions. For each stock, the terms with a positive sign reflect the inflows from the three remaining pools, while the term with a negative sign corresponds to the outflows.

the private sector. Examples include: Katz and Krueger (1991) for the United States; Postel-Vinay and Turon (2007) or Disney and Gosling (1998) for the United Kingdom; and Christofides and Michael (2013), De Castro et al. (2013) and Giordano et al. (2011) for several European countries.

4.2.2 Data

The information about jobs sectors (public/private), individuals' position in the labour market, worker flows and associated transition rates are extracted from each country's representative labour market survey, from which official statistics are drawn: the French *Labour Force Survey* (FLFS), the UK *Labour Force Survey* (UKLFS), Spanish *Labour Force Survey* (SLFS) and the US *Current Population Survey* (CPS).

Since a redesign in 2003, the FLFS is conducted quarterly. The sample of the survey is a rotating panel composed of six waves. In each quarter, one sixth of the sample is renewed: the "oldest" wave leaves the sample, whereas a new wave enters. The survey provides a set of information about individuals' characteristics, such as their education, their labour market status (constructed according to the definitions of the International Labour Organization) and their economic activity. The longitudinal structure of the FLFS allows us to match observations belonging to two consecutive surveys. We compute individuals' transitions and aggregate them to calculate the gross worker flows and transition rates in each quarter. Due to the structure of the database, at best, five sixths of the sample can be matched between two consecutive surveys. Panel attrition and non-response that reduce the size of the longitudinal sample, as well as sample fluctuations, may affect the estimation of labour market states (and so worker flows). In order to solve these statistical problems, Shimer (2012) and Silva and Vázquez-Grenno (2013) drop missing observations and reweight measured transitions by the missing-at-random method. We proceed differently: each longitudinal sample is reweighted by a method similar to the one proposed by Lundström and Särndal (1999). The purpose is to equalize, according to some leading variables (labour market states in the first quarter; age pyramid by gender; household type; and education level), the structure of the longitudinal sample with the known population structure in period t. See Fontaine (2016) for details[2].

The UKLFS is a quarterly survey of households living at private addresses in the United Kingdom. The panel samples around 60,000 households for five successive quarters. The sample is split into five waves. Every quarter, one wave of approximately 12,000 households leaves the survey and a new wave enters. See Gomes (2012) for more details on the survey. Although the quarterly survey effectively starts in 1993, our baseline sample is restricted to the period between 2003:1 and 2018:4 to allow for a more straightforward comparison with the French survey[3]. The Office for National Statistics already provides the census population longitudinal weights, which we use to construct the flows series.

[2]As Lundström and Särndal (1999) demonstrate, this procedure can reduce sample fluctuations and the non-response bias and has been adopted by the French National Institute of Statistics and Economic Studies to correct non-response bias and sample fluctuations in the FLFS.

[3]Furthermore, the current ONS files exclude the April-Sept dataset for 2001 and the Autumn-Winter for 1996. The full sample is available in the dataset that accompanies the paper.

Like its French counterpart, the SLFS is a quarterly representative survey in which the sample is divided into six waves. The SLFS samples about 65,000 households, which is equivalent to around 180,000 individuals. See Silva and Toledo (2009) for more details on the survey. Although the quarterly survey starts in 1999, for the main results we restrict our sample to the period between 2005:1 and 2018:4. The reason is that, before 2005, the Spanish Statistical Office implemented a significant methodological change regarding both the questionnaire and the data collection. As a consequence, it is not possible to link the time series of labour market transitions with the two different methodologies. As no longitudinal weights are provided, we follow the same procedure as the French survey to recalculate them.

For comparison with the rest of the literature, we provide evidence for the US, based on the CPS. The CPS surveys households for four consecutive months, omits them for eight months and then interviews them again for another four months. See Shimer (2012) for a description of the survey. In contrast to the European surveys, the CPS allows the researcher to compute the transition probabilities in the labour market at a monthly frequency. We extend the Shimer (2012) code, publicly available on his webpage. To avoid the breaks in the survey that are recurrent until 1995, we start our sample in 1996, but for comparison with the European countries, we report the results for the 2003-2018 period in the main text.

4.2.3 Definition of public jobs

In our view, the defining characteristic of the public-sector is that its goods or services are not sold, but are provided directly to the population. It uses the power of taxation to finance the production of public goods, rival or non-rival, and governmental services. There are two main government decisions that affect its employment level. First, governments decide the scope of the public sector - which goods and services they want to provide. Second, they decide whether to supply them directly by hiring workers - in-house production - or by outsourcing it to private sector firms. These decisions are usually the outcome of a political process and vary drastically across countries. As a consequence, the extent of the operation of the public sector in different industries varies. It is important to bear in mind that, in this paper, we do not focus on particular industries, i.e. public administration, but the entire sphere of public-sector employment, even if it involves different weights on particular industries. Given this conceptual view, we exclude from our definition of public-sector employment, public enterprises, or state-owned enterprises, that provide various private goods and services for sale and usually operate on a commercial basis.

The distinction between public- and private-sector jobs is based on a self-reported variable, which is in accordance with how official statistics are drawn. During the survey, the interviewer asks the individual to classify his employer. In the UK, we include the following categories in our definition of public-sector employment : i) Central Government, Civil Service; ii) Local government or council (incl. police, fire services and local authority controlled schools or colleges); iii) University or other grant-funded educational establishment; iv) Health authority or NHS trust; and v) Armed forces. We exclude from our definition every private organization, as well as: i) Public company; ii) Nationalised industry or state corporation; iii) Charity, voluntary organisation or trust; and iv) other organisation. A similar definition is used for France[4]. For Spain, the survey asks directly whether respondents work for the public or the private sector. For the United States, the definition of public sector is working for the government (federal, state or local government)[5].

The shortcoming of a such declarative variable is that it could be subject to misclassification of the sector of work. Misreporting of the sector is not a serious problem in computing the overall stock of public and private sector employment, but it might overstate the transitions from public to private sector (and vice versa). Given that, for the unemployment decomposition in Section 4.4, we compute a time-aggregation bias correction; the overstating of flows between the two sectors can introduce noise or bias in all transition rates. A similar problem exists for the flows in between unemployment and inactivity and was addressed by Elsby et al. (2015a). To solve this problem, we check whether the transitions between the sectors are spurious by controlling for the tenure of jobs. We validate a direct transition between the two sectors only when the respondent states that he has been working for the same employer for less than three months. Bradley et al. (2017) use a similar method. Unfortunately, the CPS does not report the tenure on the job, so we cannot apply the same adjustment for spurious transitions for the United States. We use a different approach similar to Elsby et al. (2015a). We calculate the three-period transitions and calculate and remove the fraction of moves between one sector and the other that revert to the initial sector on the following month (remove the P-G-P from P-G flows, and the G-P-G out of the G-P flows).

The percentage of flows between public and private sector that are consider spurious varies across countries. In the US, France, the UK and Spain, 17, 32, 55 and 87 percent of the flows, respectively are spurious. Although the number for the Spain looks high, one should put it in perspective. The error is relatively large, partly because the number of transitions is very small. If we measure them relative to total employment, this high number

[4]We include: i) État; ii) Collectivités territoriales; iii) Hôpitaux publics; and iv) Sécurité sociale. We exclude: i) Particulier; ii) Entreprise publique; and iii) Entreprise privée.

[5]Defining the sphere of the public sector is hard and we opted for a conservative definition. Both the UK and the US surveys distinguish the "not-for-profit" private employment. This employment, which is non-negligible - 6 percent in the US and 4 percent in the UK - is attached to the private sector despite having different features. Publicly owned firm that represent 5.7, 2.6 and 0.9 percent of employment in France, the UK and Spain is also attached to the private sector.

in Spain could be explained if 0.6 percent of the employees make a mistake in reporting their sector. Still, one should be cautious about the quality of the Spanish data.

4.3 Worker gross flows

4.3.1 Average gross flows

Figure 4.1 summarizes the average quarterly (monthly) worker flows over the 2003-2018 period for the three European countries (United States). It reports the stocks of workers in thousands (t) and as a percentage of the working-age population (p), as well as the number of people that change status every quarter (month) as a percentage of the working-age population (p) and as a transition probability or hazard rate (h). We restrict our analysis to the working-age population (16 to 64 years old). The public sector employs 17.0 percent of the working-age population in the UK, 13.7 percent in France, 12.0 percent in the US and 7.8 percent in Spain. It represents 23, 21, 16 and 16 percent of total employment, respectively.

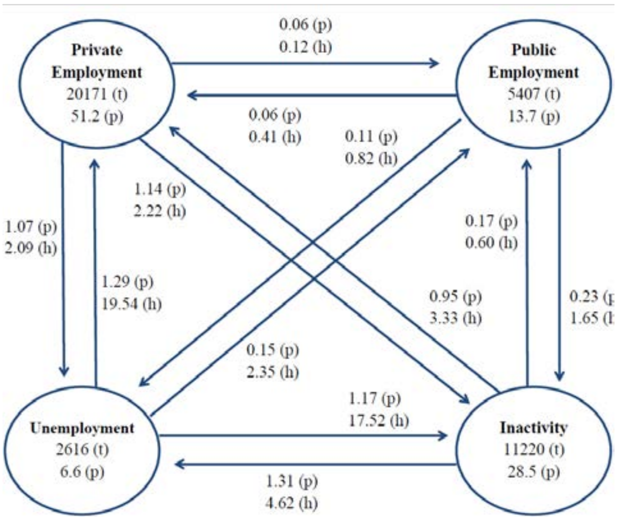
The main difference between the two sectors is their turnover. Labour turnover, between employment and non-employment, is lower in the public sector. In each quarter in the UK and France, flows in and out of private-sector employment represent around eight percent of its stock, while for the public sector, they are around 4.5 percent of its stock. In the United States, monthly turnover represents seven percent in the private sector and 4.6 percent in the public. In Spain, the turnover is larger, with 15.4 percent in the private sector and 9.3 percent in the public sector.

Fewer people separate from the public sector. The probability of moving from employment to unemployment is more than two times higher if working in the private sector in the four countries. It is almost three times in the UK, where the probability is 1.47 percent in the private sector and only 0.52 in the public sector. In all countries, the probability of moving from employment to inactivity is around 30 percent higher in the private relative to the public sector. Fewer separations imply that there are fewer hires. In the three European countries, while roughly 20 percent of the unemployed find a job in the private sector each quarter, only two to three percent find one in the public sector. In the United States, each month, 20.73 percent of the unemployed find a job in the private sector, while only 1.88 percent find a public-sector job.

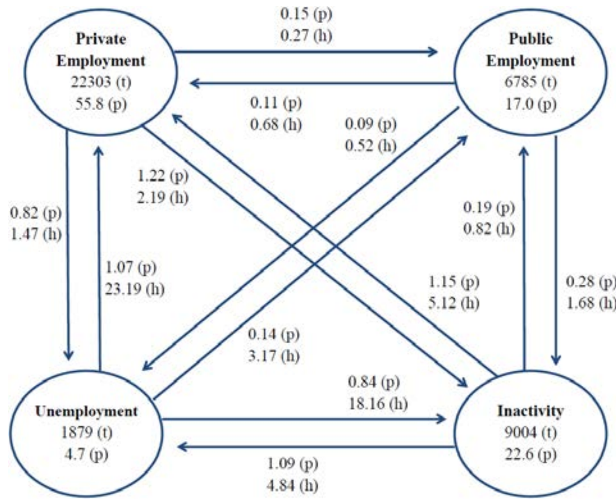
When leaving public-sector jobs to non-employment, workers are more likely to withdraw from the labour force. In France, 67 percent of out flows from the public sector (to nonemployment) are directed to non-participation. The corresponding statistic for the private sector amounts to 51 percent. The finding is stronger in the UK and the US, where

Figure 4.1: Average worker flows, 2003-2018

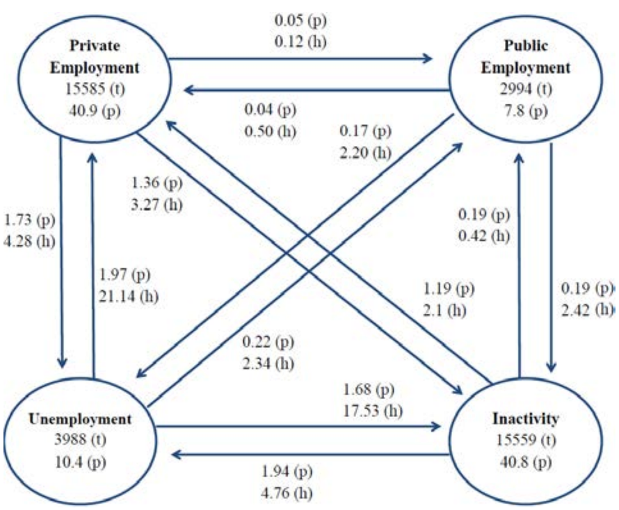
(a) France, quarterly flows



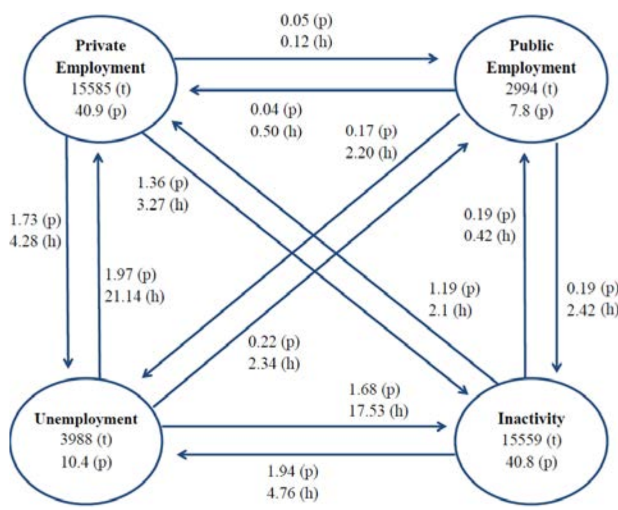
(b) UK, quarterly flows



(c) Spain, quarterly flows



(d) US, monthly flows



*Note: the worker stocks and flows are expressed as total number of people in thousands (t), as a percentage of the working-age population (p) or as a hazard rate (h). Data extracted from the French, UK and Spanish Labour Force Survey, and the CPS. * For the US, flows between private and public employment were adjusted with a different methodology.*

more than 72 percent of public-sector separations are to inactivity, but weaker in Spain, at 52 percent. Likewise, returns to public jobs from non-participation are also more frequent. In France and the UK, more than 50 percent of new hires in the public sector come from inactivity, whereas in the private sector, that number is less than 50 percent. In Section 4.5, we use a multinomial logit model to re-evaluate these differences in separation probabilities between sectors, controlling for observable characteristics.

There are few direct transitions between employment in the two sectors. Each quarter in the France and Spain, only 0.12 percent of private-sector workers switch sector without a measured spell of unemployment. This represents less than 15 percent of all inflows into the public sector. In the UK and US these flows seem more important. In each quarter, 31 and 38 percent of the new hires in the public sector come directly from private employment[6]. Understanding the importance of the direct transitions across the two sectors has implications for the theoretical literature on the effects of public-sector employment. While Bradley et al. (2017) model the direct transitions across the two sectors, most of the literature - including Gomes (2018) or Albrecht et al. (2019) - ignores these. We find that, although transitions between the two sectors are not negligible, most of the in ow into public-sector employment comes from non-employment. These results are also consistent with the view, described in Chassamboulli et al. (2018), that Spain and French public sectors are more segmented, requiring competitive entry exams, which is not the case for the majority of public-sector jobs in the UK and US.

The industries having the highest share of public-sector employment vary by country. In France and the UK (see Table 4.4 in Appendix A) public-sector employment represents 85-90 percent of total employment in "Public administration and defence". With around 75-80 percent of public-sector employment, "Education" is the sector with the second-highest fraction of public-sector employment. "Health and social work" has also a very high number of public-sector workers, but they represent only 55 percent of the total workers in the industry in the UK and 36 percent in France. Other industries where the public sector is relevant include "Water supply, sewerage, waste", "Arts, entertainment and recreation" and "Extraterritorial organizations". In the SLFS, the industries "Public Administration, education and health activities" are not disaggregated, but within this group, 73 percent of employment is in the public sector. In the US, the public sector accounts for all of the employment in the industries of Public administration" and "Armed forces" but only 35 percent of employment in "Educational and health services".

[6]For the US, we have calculated the job-finding rate to public and private sector conditional on previous status. These rates, shown in Appendix E, support the conclusion that the choice of sector is persistent, even after an unemployment spell. The unconditional job-finding rate in the public sector is only 1.8 percent, but conditional of being in the public sector in the month preceding unemployment it is close to 30 percent. Curiously, the job-finding rate conditional on being previously employed in the private is 1.4 percent, roughly equal to the rates conditional of previously being unemployed or inactive. For the private sector, again we see the attachment of workers with a conditional job-finding rate of more than 40 percent. Being previously employed in the public sector does not raise the job-finding rate in the private sector relative to the ones that were unemployed or inactive (with job-finding rates of around 16 percent).

4.3.2 Disaggregated worker flows

The tables in Appendix C show the average stock and flows of different subgroups of workers, disaggregated by gender, education and age. Public-sector employment is particularly relevant for women. On average, 16.5 and 22.2 percent of all women are working in the public sector in France and in the UK, respectively. However, given than women's labour market participation is lower than men's, public-sector employment corresponds to 27 and 33 percent of total employment for women in the two countries, roughly double than for men. For Spain and the US, the gender differences are smaller. The Spanish and US public sectors hire 19 percent of all working women, and only 12 percent of all working men. In the four countries, the probability of a woman finding a job in the public sector is twice as high as for men.

Job-finding rates are increasing and job-separation rates are decreasing in education in both sectors. In France, the fraction of the job-finding rate accounted for by the public sector increases from ten percent for primary-educated workers to 13 percent for college graduates. In the other countries, the differences are larger. This fraction increases from seven to 22 percent in the UK, from eight to 17 percent in Spain and from two to 16 percent in the US. In the US, the public sector does not play any role in the labour market for primary-educated workers, but it accounts for one fifth of all new hires of college graduates.

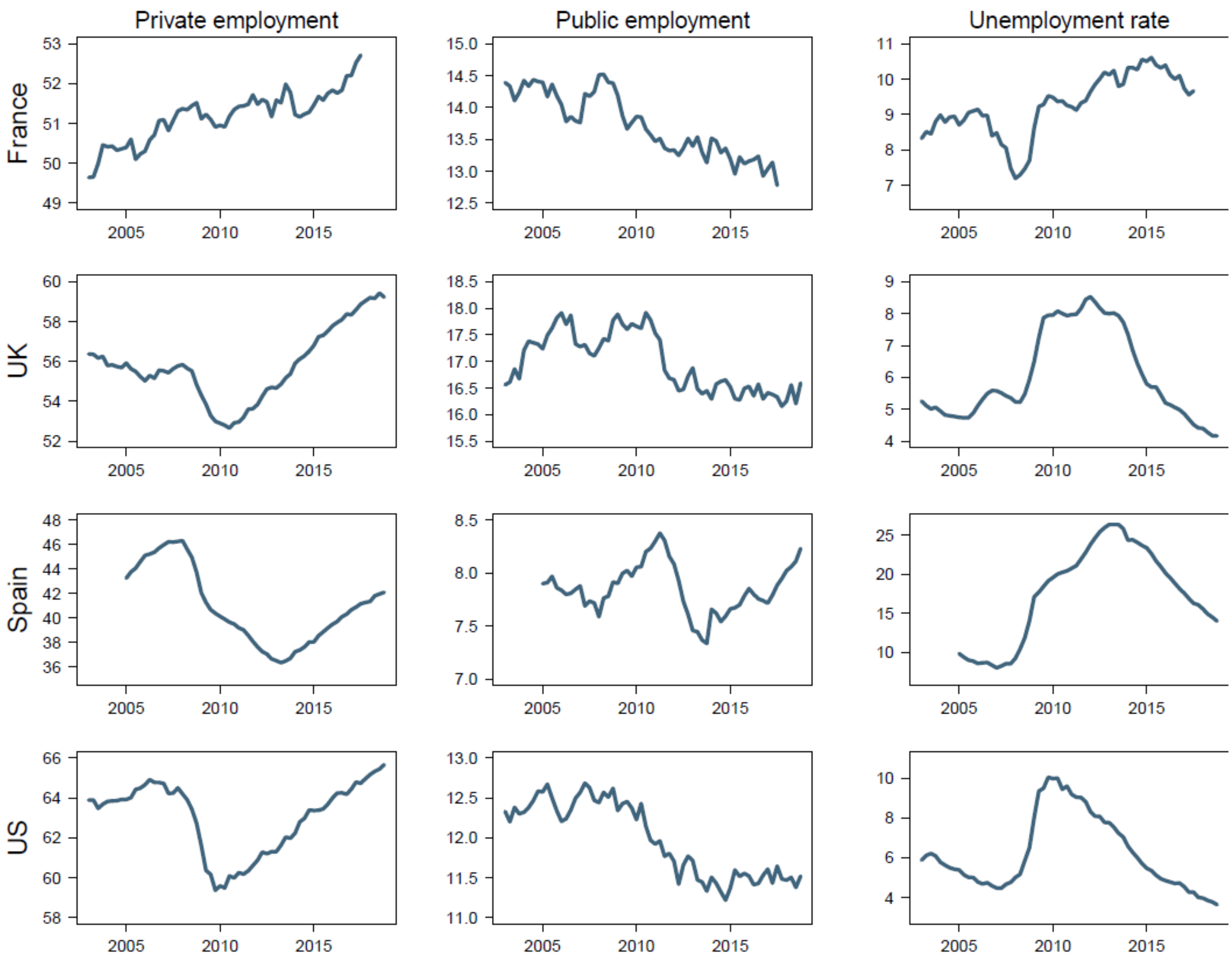
The public sector hires few young workers. Out of all employed workers aged 16 to 29, the public sector accounts for only 16 percent in France and the UK, about eight percent in Spain and 10 percent the US. In France and the UK, most public-sector employment is concentrated on prime-age workers. The French and UK's public sectors employ 17.6 and 20.9 percent, respectively, of all workers aged 39-49. However, as a fraction of total employment, the public sector is more significant for older workers (age 50-64), accounting for 24 and 27 percent of their employment. This means that, in the private sector, older workers leave the labour force at a faster pace. This age profile is even stronger in Spain and the US, where the public sector employs around 15 percent of prime-age employed workers and 22 percent of older employed workers.

4.3.3 Evolution of labour market stocks and flows

Figure 4.2 displays the evolution of the public and private employment rates and the unemployment rate, while Figure 4.3 shows the transition probabilities between unemployment and employment in both sectors. All the gross worker series were previously seasonally adjusted. The graphs with the remaining transition probabilities are shown in Appendix A.

Our sample covers the period of the Great Recession. In France, from 2003 until 2008, the unemployment rate fell to seven percent. After that, it increased regularly until it peaked at the end of 2015. In the UK, prior to the Great Recession, the unemployment rate was stable at five percent. In 2008, it increased sharply, hit its peak in 2012 at 8.5 percent and has fallen since. In Spain, the unemployment rate increased from less than ten percent before 2008 to 25 percent in 2013. In the US, the unemployment rate increased sharply between 2008 and 2010, but then began to decline, reaching pre-crisis levels by the end of the sample.

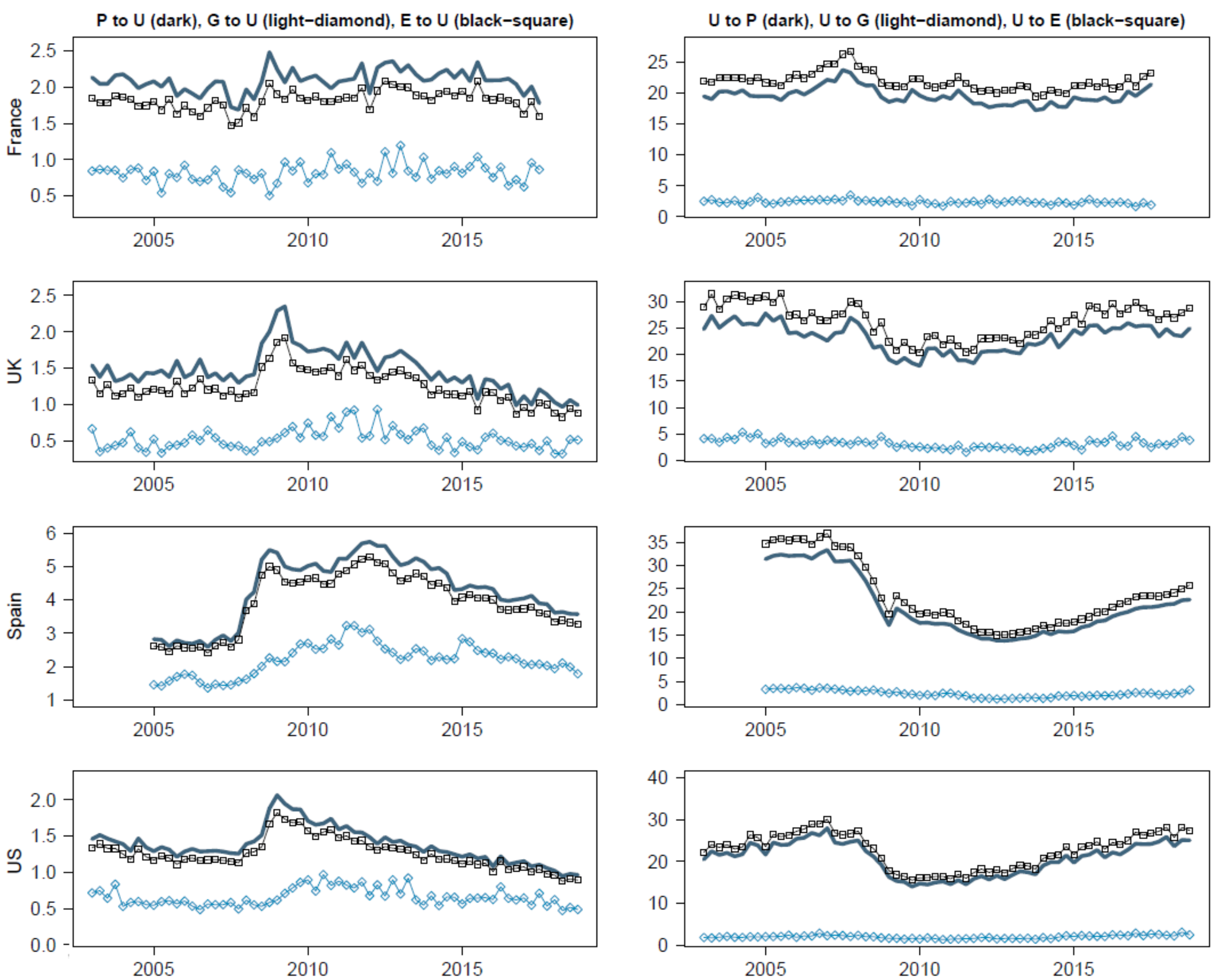
Figure 4.2: Labour market stock



Note: private- and public-sector employment are expressed in percentage of the working-age population. The unemployment rate is in percentage of the labour force.

One can observe that the size of the public sector diminished in all countries in the last years of the sample, apart from Spain. In France, starting in 2008, it decreased by 300,000 workers - 1 percentage point of the working-age population. This means that the government did not carry a countercyclical policy. On the contrary, in the UK, the government initially increased the number of public-sector workers between 2008 and 2010, by 1 percentage point of the working-age population. The fact that there was no increase in job-finding rate nor a visible decrease in job-separation rate is because the change was in large the consequence of a sharp fall in the direct flows to private employment. The reduction of public-sector employment started only after 2010, with a decline equivalent to two percentage points of the working-age population - equivalent to half a million workers. This sharp reduction in public-sector employment since 2010 was achieved mainly with increases in outflows. Compared to the first half of the sample, there were five thousand more workers that moved to unemployment and 7.5 thousand more that move to inactivity from public employment in each quarter.

Figure 4.3: Transition rates between employment and unemployment



In Spain, from its peak in 2011, public employment fell by 400,000 workers in less than three years (1 percent of the working-age population), recovering almost entirely by the end of the sample period. The job-separation rate to unemployment increased from 1.5 percent in the beginning of the sample and reached 3.5 percent in 2011. Also, the job-finding rate in the public sector fell from 3.5 percent at the beginning of the sample to 1.5 percent at the end. In the US, public-sector employment declined as a fraction of the working-age population between 2008 and 2018.

4.3.4 Cyclicality of worker flows

To have a more precise measure of the cyclicality of the hazard rate, we run an ordinary least squares regression of the log of each transition rate on a linear trend and the unemployment rate. This follows Baker (1992), who undertakes a similar procedure to analyse the cyclical movements of unemployment duration. The results are shown in Table 4.1[7]. The table also shows the cyclicality of several measures of the public-sector employment stock. We consider the largest sample available for the four countries.

The regression of different measures of stocks of public-sector employment confirms the differences in cyclicality across the four countries, over the last recession. When we measure public-sector employment in levels (logs) or as a fraction of the working-age population, it is procyclical in France, countercyclical in the US and acyclical in Spain and the UK. Naturally, when we measure it as a fraction of total employment or private employment, as the denominator is very procylical, it makes the ratio more countercyclical.

The hazard rates into and out of public-sector employment are very cyclical, with signs similar to those of its private sector counterparts. The separation rates from employment in both the public and private sectors to unemployment are strongly countercyclical, while the job-finding rates are strongly procyclical. There is, however, a substantial asymmetry between the coefficients. For example, the separation rate to unemployment from the public sector is more cyclical than from the private sector in France and UK, but not in Spain or the US. The hazard rates between the two sectors are also strongly procyclical, except in the US. In expansions, there are more direct transitions between the two sectors. These might justify some of the asymmetry between the cyclicality of public-sector employment across countries. The other explanation might be the cyclicality of flows between employment and inactivity. In the US, the hazard rate goes down in recessions, but not in France. In the UK and Spain the procyclicality of separation rate to inactivity is only present in the private sector. In all countries, in flows into employment from inactivity (public or private)

[7] Appendix A contains similar table with the results with the gross flows as a fraction of the working-age population.

Table 4.1: Cyclical variation of public sector employment stock and hazard rates

	France		**UK**		**Spain**		**US**	
Stock of public-sector employment								
$\log G$	-0.015**	(-4.22)	0.005	(-1.27)	0.000	(0.00)	0 .008**	(7.17)
$\frac{G}{W}$	-0.195**	(-4.86)	-0.006	(-1.30)	-0.007	(-1.19)	0 .021*	(2.26)
$\frac{G}{P+G}$	-0.115*	(-2.02)	0.167*	(2.13)	0.148**	(12.72)	0 .238**	(20.42)
$\frac{G}{P}$	-0.185*	(-2.03)	0.287*	(2.15)	0.210**	(12.62)	0 .338**	(20.41)
Hazard rates								
$P \to U$	0.046**	(2.99)	0.077**	(10.09)	0.038**	(10.33)	0 .072**	(23.65)
$G \to U$	0.082*	(2.30)	0.120**	(8.82)	0.033**	(10.02)	0 .066**	(9.88)
$P \to I$	0.016	(1.46)	-0.020**	(-4.32)	-0.016*	(-12.72)	-0.026**	(-12.06)
$G \to I$	0.032	(1.45)	0.004	(0.54)	-0.003	(1.12)	-0.018**	(-4.57)
$U \to P$	-0.067**	(-6.21)	-0.0072**	(-17.14)	-0.045**	(-31.03)	-0.108**	(-48.07)
$U \to G$	-0.041	(-1.44)	-0.142**	(-11.02)	-0.049**	(-15.87)	-0.109**	(-16.14)
$I \to P$	-0.036**	(-3.11)	-0.043**	(-6.48)	-0.036**	(-20.82)	-0.051**	(23.94)
$I \to G$	-0.056*	(2.16)	-0.056**	(-5.76)	0.010**	(-2.45)	-0.030**	(-6.51)
$U \to I$	0.011	(0.58)	-0.063*	(-15.99)	-0.035**	(-22.53)	-0.044**	(21.50)
$I \to U$	0.155**	(6.34)	0.080**	(22.22)	0.029**	(16.93)	0 .096**	(47.41)
$P \to G$	-0.150**	(-3.50)	-0.109**	(-9.76)	-0.064**	(-8.40)	-0.007	(-1.34)
$G \to P$	-0.171**	(-2.88)	-0.052**	(-3.37)	-0.040**	(-7.06)	0 .010	(-1.64)

*Note: the cyclicality of the hazard rates is the coefficient on unemployment rate in a regression of the series in logs on a time trend and the unemployment rate. The cyclicality of the stock is the coefficient on unemployment rate in a regression of the indicated measure on a time trend and the unemployment rate. T-statistics are in brackets.** denotes significant at 1% and * significant at 5%. The sample is: France (between 2003:1 and 2017:4, 59 observations), UK (between 1994:4 and 2018:4, 97 observations), Spain (between 2005:1 and 2018:4, 56 observations), US (between 1996:1 and 2018:12, 276 observations).*

are moderately procyclical. We now analyse in more detail the importance of inflows and outflows into public-sector employment for unemployment fluctuations.

4.4 The role of the public sector in driving unemployment

4.4.1 Why does the public sector matter?

To understand the effects of ignoring the public sector when decomposing unemployment fluctuations, consider the following example of an economy with a public sector that has extremely low turnover. By this, we mean a separation rate λ^{GU} very close to zero, as well as the hiring rate λ^{UU}. There are also no movements between public and private sector. This scenario translates into a public sector with fixed size $\bar{G}$, unresponsive to the economic cycle. If one were to do a standard two-state decomposition, between total employment (E)

and (U), the measured job-finding and job-separation rates would be:

$$\lambda^{UE} = \lambda^{UP},$$
$$\lambda^{EU} = \frac{N^{PU}}{P + \bar{G}} = \frac{\lambda^{UP}}{1 + \frac{\bar{G}}{P}},$$

where N^{PU} is the total number private sector workers that lost their jobs. We get the second equality by dividing both the numerator and denominator by P. Notice that the presence of the public sector would not affect the job-finding rate, but it would reduce the job-separation rate by a factor of $(1 + \frac{\bar{G}}{P})$. This can be seen clearly in Figure 4.3 - the overall job-finding rate is the sum of the job-finding rates in the two sectors, but the job-separation rate is a weighted average of the sectoral job-separation rates. The main problem for the unemployment decomposition is that, in a scenario with fixed public-sector employment, the ratio $\frac{\bar{G}}{P}$ will have a cyclical pattern. Consider a recession driven simultaneously by a decrease in job-finding and an increase in job-separation from the private sector. As $\frac{\bar{G}}{P}$ goes up, λ^{PU} would go up by less than the separation rate in the private sector, so one would underestimate the true contribution of separations.

The role of the public sector is more complex than this example shows because, in reality, its employment has a cyclical pattern. As we have seen, it can be procyclical as in France, countercyclical as in the US, or acyclical, as in Spain and the UK. Furthermore, whether this cyclicality happens because the government increases or decreases hirings in recessions or because there are fewer or more separations, could either reinforce or mitigate this bias in the unemployment decomposition.

4.4.2 Unemployment decompositions

The starting point for all unemployment decompositions is the equation of the steady-state unemployment u_t^{ss}. With four states, the equilibrium unemployment is a function of all 12 transition probabilities. See Appendix B for the exact formula and the comparison between equilibrium and actual unemployment in the four countries. We perform two decomposition methods, one based on Shimer (2012) and the other on Fujita and Ramey (2009). In this section, all the transition probabilities were previously corrected for time-aggregation bias using the methodology applied by Shimer (2012). Other exercises, such as alternative variables, no detrending, 3-states decomposition, and a non-steady-state decomposition, are shown in Appendix B.

Table 2 displays the importance of each transition probability for the four countries and the two methodologies. The bottom part of the table provides the relative split of the contribution of different rates to fluctuations in the unemployment rate. Out of the total contribution of flows in and out of employment, 20 percent are attributed to the public sector in the UK, 15 percent in France, while only ten percent in Spain and the US. Out of these, the inflows to public employment are more important than the outflows, with a relative split of around 70-30.

Table 4.2: 4-states unemployment decompositions

	Shimer				Fujita & Ramey			
	France	**UK**	**Spain**	**US**	**France**	**UK**	**Spain**	**US**
$P \to U$	0.24	0.24	0.23	0.22	0.25	0.22	0.21	0.22
$G \to U$	0.03	0.04	0.03	0.02	0.04	0.04	0.02	0.02
$P \to I$	-0.02	-0.02	-0.04	-0.03	-0.02	-0.02	-0.04	-0.02
$G \to I$	0.00	0.01	-0.00	-0.00	0.00	0.01	0.00	-0.00
$U \to P$	0.39	0.32	0.47	0.38	0.40	0.30	0.47	0.39
$U \to G$	0.06	0.09	0.08	0.0	0.06	0.08	0.08	0.04
$I \to P$	0.08	0.10	0.08	0.07	0.08	0.10	0.08	0.06
$I \to G$	0.02	0.03	-0.00	0.01	0.02	0.03	-0.00	0.02
$I \to U$	0.14	0.08	0.05	0.13	0.14	0.07	0.04	0.12
$U \to I$	0.06	0.10	0.11	0.13	0.06	0.10	0.10 0	.13
$P \to G$	0.02	0.02	0.00	-0.00	0.02	0.01	0.00	-0.00
$G \to U$	-0.01	-0.01	-0.00	0.00	-0.01	-0.01	-0.00	0.00
Relative contribution (sum to 100)								
Private employment vs. Public employment								
	86-14	79-21	88-12	91-9	85-15	80-20	88-12	90-10
Public job-finding rate vs. Public job-separation rate								
	63-37	67-33	75-25	64-36	60-40	67-33	76-24	69-31
Private job-finding rate vs. Private job-separation rate								
	62-38	57-43	67-33	63-37	62-38	58-42	69-31	64-36
Job-finding rate vs. Job-separation rate [3-states]								
	62-38	61-39	67-33	66-34	61-39	62-38	70-30	66-34

Note: the gross flows series are previously seasonally adjusted using the X13 Census programme and the transition probabilities are corrected for time-aggregation bias using the methodology applied by Shimer (2012). The series are then detrended with an HP filter with smoothing parameter of 100000. Number in the top half panel of the table reports the variance contributions of transition rates to changes in steady-state unemployment. For instance, the first number of column 2 reads as follows: private job separation rate accounts for 24% of the variations in French steady-state unemployment.

Consistent with the literature, private sector job-finding rate is more important than its job-separation rate, with a rough 60-40 split. In Appendix B, we show the usual three-state decomposition. Given the cyclicality of the stocks and transition probabilities in this sample, accounting for the public sector barely changes the relative importance of job-finding and job-separation rates in France, but it matters marginally for the UK, Spain and the US, where the ratio of public to private employment is more strongly countercyclical.

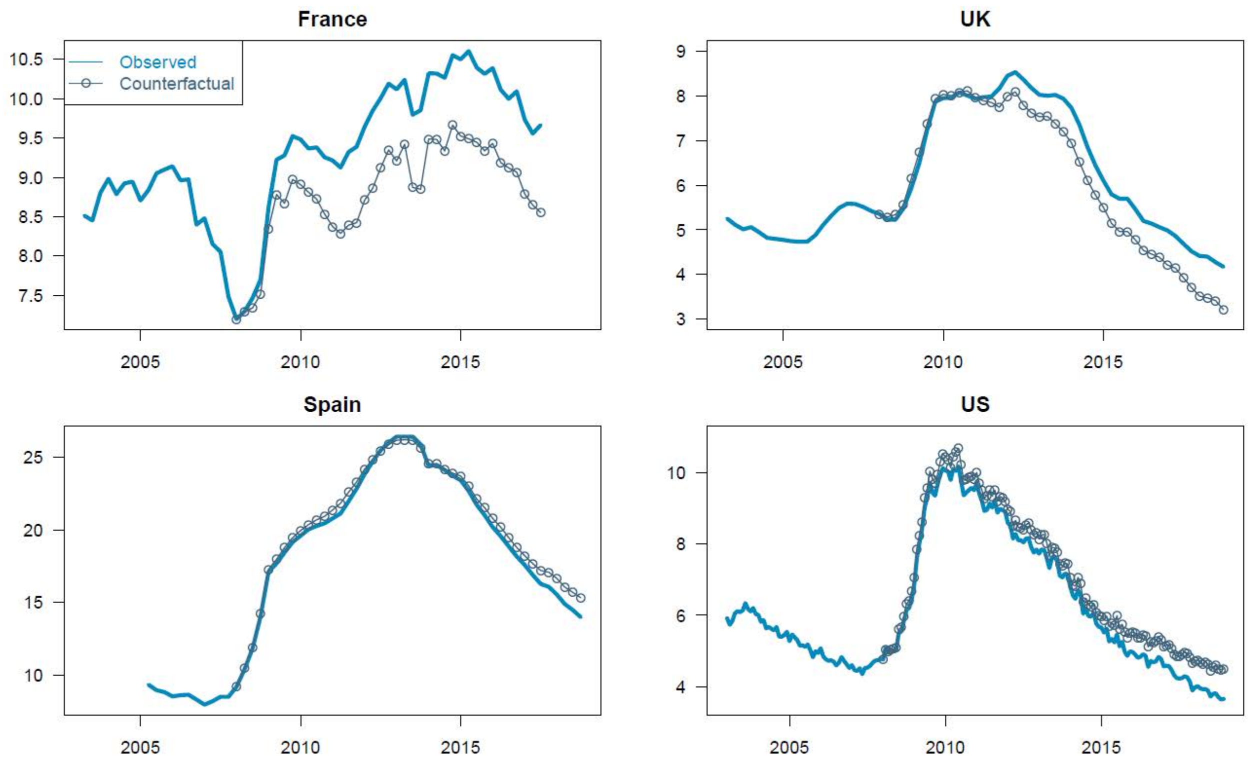
As in Elsby et al. (2011) or Hertweck and Sigrist (2015), we perform the unemployment decomposition for different sub-groups of the population, based on gender, age and education. We show the complete tables in Appendix C. In general, the contribution of the public sector to fluctuations in unemployment is proportional to its size. In France and the UK, the transition rate in and out of public-sector employment contributes to around 25 percent of women's unemployment, compared to less than ten percent of the male unemployment rate. In the European countries, the public sector accounts for a larger fraction of fluctuations in the unemployment rate of prime-age workers, with 29, 20 and 11 percent for France, UK and Spain. Finally, the public sector accounts for more than 20 to 30 percent of the fluctuation in the unemployment rate of college graduates in the three European countries.

4.4.3 Unemployment during the Great Recession: a counterfactual

While the previous sub-section is based on an analysis of the transition rates, we now perform an alternative analysis based on the level of worker gross flows. From the first quarter of 2008, we calculate what the unemployment rate would have been if the number of people hired and separated from the public sector had been equal to the average of the sample until 2007. We assume that the number of people that transited between the other three states (private-sector employment, unemployment and inactivity) are equal to the actual ones.

Figure 4.4 shows the actual and counterfactual unemployment rates. In France, from 2010 onwards, the unemployment rate would have been 1.1 percentage points lower if the hirings and separations in the public sector had been kept constant. In the UK, since 2012, the unemployment rate would have fallen faster if the government had not reduced public-sector employment. The difference is 0.9 percentage points. Spain and the US have the opposite pattern. By the end of the sample, the unemployment rate would have been higher without a change in policy, by 1.3 percentage points in Spain and 0.8 in the US. While the government employment component of American Recovery and Reinvestment Act of 2009 contributed to reduce unemployment, the government employment component of the austerity policies followed by France and UK generated higher unemployment.

Figure 4.4: Counterfactual unemployment rate



4.5 How safe are public-sector jobs?

The argument that public-sector jobs are safer is often used in policy discussions over public-sector wages. According to Gomes (2015b), the optimal design of the public-sector wage schedule should take job security into account. Safer jobs raise a job's expected duration of a job and reduce the expected time spent in unemployment. Thus, the government should offer lower wages in order to keep the value of a public-sector job in line with that of the private-sector job. Hence, the estimation of the differences in job-loss probabilities between the two sectors is extremely relevant from a policy perspective, but to the best of our knowledge, there are no available estimates of value of the job safety that government provides.

4.5.1 Conditional job-separation rates

The evidence on the average gross flows provided in Section 4.5 suggests that jobs in the public sector are indeed safer than those in the private sector[8]. However, we also documented a significant amount of heterogeneity along gender, education and age, so the lower aggregate job-separation rates might be due, in part, to composition effects. In this section, using a multinomial logit model, we estimate the probabilities of transiting out of employment conditional on observable characteristics. Conditional on being employed, a worker can keep his job, become unemployed or become inactive. We consider staying employed as the base outcome and compute the probabilities of becoming unemployed or inactive as:

$$\lambda_i^U = \frac{exp(x_i\beta_U)}{1 + exp(x_i\beta_U) + exp(x_i\beta^I)} \tag{4.5}$$

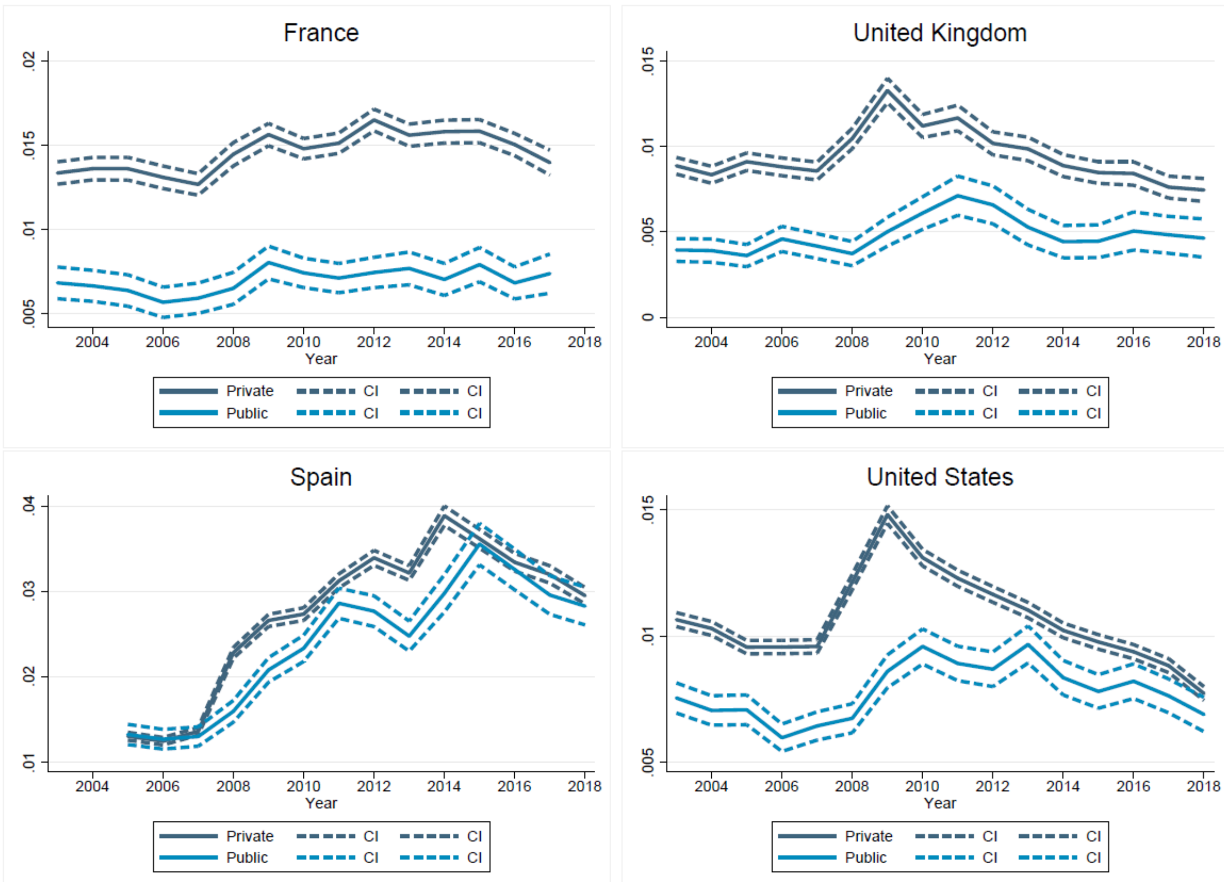
$$\lambda_i^I = \frac{exp(x_i\beta_I)}{1 + exp(x_i\beta_U) + exp(x_i\beta^I)} \tag{4.6}$$

where x_i includes, as control variables, dummies for education, region, gender, occupation and age. It also includes year dummies and year dummies interacted with being previously employed in the public sector. Using the estimates, we are able to compute the evolution of the predicted transition probabilities in both sectors over time, for an employee with the average characteristics in the economy. Figure 4.5 shows the predicted probability of moving to unemployment.

There are still large differences in the probability of moving to unemployment in the two sectors, even controlling for observable characteristics. However, they are smaller than the difference in unconditional separation rates, suggesting that a significant part is due to composition effects. These differences are particularly large in France and the UK, where the job-separation rates are twice as high in the private sector. The differences are smaller in the United States, where the probability of moving to unemployment is 36 percent higher in the private sector, and even smaller in Spain, where it is only 15 percent higher. In all countries, job-separation rates in the private sector increased in the first years of the crisis. However, they also increased in the public sector, but in later years, thus reducing the gap

[8] We associate the lower job-separation rate to safer jobs. The difference between the job-separation rates in the two sectors might not only reflect on differences in job-riskiness, but could also encompass differences in quit rates. For instance, if public-sector wages are higher relative to the private sector, quit rates might be lower. The UK Labour Force has a question differentiating between involuntary separations, quits and other voluntary separations. We have computed the shares of job-separation flows into these groups for private and public employment. The fraction of involuntary job-separations out of the total is similar across public and private sector, around the 50 percent found in Gomes (2012), meaning that both involuntary and voluntary separations are lower in the public sector by the same proportion.

Figure 4.5: Transition probability from employment to unemployment, by sector



Note: Based on estimation of equations 5 and 6 using a multinomial logit. For France, there were 1,884,703 observations and a pseudo R-squared of 0.090. For the UK, there were 1,678,331 observations and a pseudo R-squared of 0.130. For Spain, there were 2,522,803 observations and a pseudo R-squared of 0.094. For the US, there were 7,571,635 observations and a pseudo R-squared of 0.070. For France, the UK and Spain, the transition rate was quarterly, while in the US, it was monthly. We used as controls regional, gender, age, education and occupation dummy variables. The predicted probability is calculated based on an individual with the average characteristics of the employed population. The sample covers 2003-2018 for UK and US, 2005-2018 for Spain and 2003-2017 for France. The dashes lines report the 95 percent confidence interval on the prediction.

with the private sector by the end of the sample. In Appendix D, we show the predicted probabilities of moving to inactivity, but for the transition to inactivity difference between the two sectors is small in all countries - between 10 to 16 percent higher - and, in general, the confidence intervals overlap.

4.5.2 The value of safety in the public sector: a back-of-the-envelope calculation

What do these differences represent? We use a metric to perform a back-of-the-envelope calculation, based on the Bellman equation of employment and unemployment, stipulated by search models in continuous time:

$$rV^e = \frac{w^{1-\sigma}}{1-\sigma} - \delta(V^e - V^u) \tag{4.7}$$

$$rV^u = \frac{(z \times w)^{1-\sigma}}{1-\sigma} + f(V^e - V^u) \tag{4.8}$$

where the V^e and V^u are the value of employment or unemployment, w the wage rate, z the flow value of unemployment expressed as a replacement rate of the wage, f the job-finding rate, δ the job separation rate, σ the degree of risk aversion and r the discount rate. Using these two equations, we can calculate the value of a lower job-separation rate. The exercise is to calculate what fraction of their wage private-sector workers would be willing to give up to have the same job-separation rate as public-sector workers.

We consider two cases. In the first case, workers are risk-neutral ($\sigma = 0$), meaning that the value from job security comes only from spending a smaller fraction of time unemployed. This provides a lower bound on the value of job security. In the second case, we consider risk-averse workers ($\sigma = 2$) with no method of savings, which we interpret as an upper bound.

Using the two equations, we calculate V^e and V^u and substitute back in equation 4.7 in order to get the value of employment as a function of wage, separation rate, job-finding rate, unemployment replacement rate, risk aversion and interest rate. For two different separation rates, δ^1 and δ^2, the ratio of wages that equate the value of employment is given by:

$$\frac{w^2}{w^1} = \left[\frac{(r + \delta^2 + f) + (r + \delta^1 \times z^{1-\sigma} + f)}{(r + \delta^1 + f) + (r + \delta^2 \times z^{1-\sigma} + f)}\right]^{\frac{1}{1-\sigma}} \tag{4.9}$$

which, under risk neutrality, collapses to:

$$\frac{w^2}{w^1} = \frac{(r + \delta^2 + f) + (r + \delta^1 \times z + f)}{(r + \delta^1 + f) + (r + \delta^2 \times z + f)} \tag{4.10}$$

The ratio of the two wages depends on the value of unemployment - in particular, how bad it is relative to employment replacement rate) and how persistent it is (job-finding rate). Notice that when the replacement rate is 1, the four terms cancel out, meaning that workers would not be willing to sacrifice any wage for a lower job-separation rate. Naturally, if the flow value on unemployment is exactly the same as the value of working, differences in job-separation rates do not matter.

For the back-of-the-envelope calculation, we have five scenarios for the value of unemployment, created with different values for the replacement rate ($z = 0.3$, $z = 0.5$ and $z = 0.7$) and for the job-finding rate (the mean, minimum and maximum of the sample for each country). The results are in the Table 4.3, using the average conditional rates in Figure 4.5. The lower bound of the value of job security varies between 0.1 and 2.5 percent

Table 4.3: Back-of-the-envelope calculation on public-sector job-security premium

	Scenario for value of unemployment					**Government budget** (medium scenario)		
	Very low	Low	Medium	High	Very high			
	$z = 0.3$	$z = 0.3$	$z = 0.5$	$z = 0.7$	$z = 0.7$	Millions	% of GDP	% of Gov Spending
	$f = min$	$f = mean$	$f = mean$	$f = mean$	$f = max$			
Lower bound: risk neutrality ($\sigma = 0$)								
France	2.5%	2.2%	1.6%	0.9%	0.8%	4422 (€)	0.20	0.39
UK	1.5%	1.2%	0.8%	0.5%	0.4%	1430 (£)	0.08	0.19
Spain	1.3%	0.9%	0.6%	0.4%	0.2%	716 (€)	0.07	0.16
US	1.4%	0.8%	0.5%	0.2%	0.1%	9963 ($)	0.05	0.16
Upper bound: risk neutrality ($\sigma = 2$) and no insurance								
France	6.9%	6.3%	2.9%	1.3%	1.1%	8241 (€)	0.38	0.72
UK	4.5%	3.5%	1.6%	0.7%	0.6%	2741 (£)	0.15	0.37
Spain	2.8%	2.1%	1.0%	0.5%	0.3%	1241 (€)	0.11	0.28
US	3.7%	2.2%	1.0%	0.3%	0.2%	18854 ($)	0.10	0.30

Note: The first five columns of table report the fraction of the wage that a private-sector worker is willing to forgo to have the same conditional job-separation rate as a public-sector worker in each country, depending on the replacement rate and job-finding rate. The discount rate r is set to 0.005 for France, the UK and Spain and to 0.0017 for the US. We calculate the budgetary value of job-security based on 2015 data on wage compensation of government workers, GDP and total government spending provided by AMECO and FRED datasets.

of the wage for this range of realistic scenarios across the four countries, and the upper bound varies between 0.2 and 6.9 percent of the wage. For the medium scenario for the value of unemployment, workers would value this job security between 1.6 and 2.9 percent for France, 0.8 to 1.6 percent for the UK and 0.5 to 1.0 percent for Spain and the US. We redo the exercise using the unconditional job-separation rates in Figure 4.1, as well for the different education levels, and show them in Appendix D[9].

To have an alternative metric, we get national accounts data from AMECO and FRED datasets on "Compensation of employees: general government" for 2015. The compensation

[9]Using the unconditional rates, the job-security premium is roughly double from the baseline numbers. In France, the UK and the US, workers with less education are willing to pay more for the job safety of the public sector. On the other hand, the Spanish public sector has a lower separation rate for only college graduates.

to government employees represents, respectively, 12.8, 9.1, 11,1 and 10.3 percent of GDP in France, the UK, Spain and the US. The numbers from national accounts will bias the size of the public-sector wage bill downward, because they only account for a subset of the total number of public-sector workers. Using the medium value of unemployment scenario and risk neutrality, the value of a lower job-separation rate is equivalent to between 0.05 to 0.2 percent of GDP, or, alternatively, 0.16 to 0.4 percent of total government spending. The upper bound is roughly double: between 0.10 to 0.37 percent of GDP or 0.3 to 0.72 percent of total government spending.

This exercise provides only an interval for the value of job-security in the public sector, as we are considering two extreme scenarios. In the lower bound, with risk-neutral workers, the value arises from differences in expected duration of the match. In the upper bound, we do not allow any self-insurance mechanism. A more precise answer would require considering several insurances mechanisms, but that would require a more complicated framework. We leave such calculations for future work.

4.6 Conclusion

The objective of this paper was to establish a number of key facts about public- and private sector labour market flows. It provides a picture of a wide range of information about worker gross flows from different angles, improving our understanding of the workings of these two labour markets. The main findings of this paper can be summarised as follows:

- In France and the UK, the public sector represents 21 and 23 percent of total employment, respectively. Spain and the US have smaller public sectors, representing 16 percent of total employment.
- There is 30 to 50 percent less turnover in the public sector relative to the private sector.
- In each quarter (month in the US), the probability of a worker losing his job is 2-3 times higher in the private sector. Part of the difference is due to composition effects.
- In each quarter (month in the US), an unemployed worker has a 20 percent probability of finding a job in the private sector and only a two to three percent chance of finding a public-sector job.
- There are few direct transitions between the public and private sectors: 60 to 85 percent of the new hires in the public sector come from non-employment.

- The French and UK public sectors accounts for around 30 percent of total employment of women. The Spanish and US public sectors account for 20 percent. In all countries, the probability of women finding a job in the public sector is twice as high as for men.

- Public sectors hire predominantly college graduates, accounting for between 20 and 40 percent of their employment. The public sector is not relevant for workers with only a primary education.

- The public sector represents a larger fraction of employment of older workers, accounting for 25 percent of their employment in France and the UK and 22 in Spain and the US. The public sector hires few young workers.

- Public-sector employment has been countercyclical in the US, procyclical in France and acyclical in Spain and the UK.

- Public-sector employment explains 20 percent of the fluctuations in the unemployment rate in the UK, 15 percent in France and ten percent in Spain and the US.

- Public-sector employment explains a larger fraction of the fluctuations in unemployment rate of women, college graduates and older workers.

- Public-sector employment policies contributed to higher unemployment rate in France and UK between 2010 and 2015, by 1.1 and 0.9 respectively. On the other hand, they contributed to lower unemployment rate in Spain and US by 1.3 and 0.8 percentage points.

- Private-sector workers would be willing to forgo 0.5 to 2.9 percent of their wage to have the same job security as in the public sector.

This paper is starting point of a larger research agenda to study the effects of public sector employment using structural models, focussing on the heterogeneity across education (Chassamboulli et al. (2018)), gender (Gomes and Kuehn (2019)) and age (Gomes et al. (2020)).

4.7 Appendix

Appendix A. Extra material: Section 4.3

Table 4.4: Most representative public sector industries, thousands

	France		United Kingdom	
Industry	Private sector	Public sector	Private sector	Public sector
E Water supply, sewerage, waste	155	34 (18%)	166	42 (20%)
O Public administration and defence	275	2220 (89%)	282	1585 (85%)
P Education	423	1471 (78%)	739	2363 (76%)
Q Health and social work	2291	1299 (36%)	1691	2035 (55%)
R Arts, entertainment and recreation	308	74 (19%)	571	142 (20%)
U Extraterritorial organisations	12	8 (67%)	20	23 (52%)

Note: For the UK, it is the average number of workers between 2009 and 2016. For France, it is the average number of workers between 2008 and 2015. The fraction of public sector employment is in brackets. For both the UK and France, all the remaining industries have less than 10 percent of public sector employment industries (A Agriculture, forestry and fishing; B Mining and quarrying; C Manufacturing; D Electricity, gas, air cond supply; F Construction, G Wholesale, retail, repair of vehicle; H Transport and storage; I Accommodation and food services; J Information and communication; K Financial and insurance activities; L Real estate activities; M Prof, scientific, technical activ.; N Admin and support services; S Other service activities; T Households as employers).

Table 4.5: Cyclical variation of labour market flows gross rates

	France		UK		Spain		US	
Rates								
$P \to U$	0.039*	(2.53)	0.063**	(9.06)	0.026**	(6.60)	0.057*	(18.50)
$G \to U$	0.068	(1.92)	0.120**	(8.58)	0.032**	(8.02)	0.068**	(10.19)
$P \to I$	0.009	(0.82)	-0.034**	(-7.65)	-0.028**	(-23.94)	-0.041**	(-19.56)
$G \to I$	0.018	(0.80)	0.004	(0.45)	-0.004	(-1.32)	-0.016**	(-3.99)
$U \to P$	0.050**	(4.65)	0.081**	(16.71)	0.018**	(14.09)	0.045**	(19.43)
$U \to G$	0.076**	(2.70)	0.011	(0.90)	0.013**	(3.41)	0.044**	(6.76)
$I \to P$	-0.042**	(-3.60)	-0.042**	(-7.84)	-0.039**	(-18.94)	-0.043**	(-20.97)
$I \to G$	-0.062*	(-2.38)	-0.056**	(-5.75)	-0.012**	(-3.24)	-0.022**	(-4.70)
$U \to I$	0.128**	(7.12)	0.091**	(20.65)	0.028**	(24.14)	0.109**	(44.26)
$I \to U$	0.109**	(5.90)	0.080**	(19.74)	0.026**	(17.55)	0.104**	(46.25)
$P \to G$	-0.157**	(-3.20)	-0.123**	(-10.77)	-0.076**	(-9.96)	-0.023**	(-4.20)
$G \to P$	-0.185**	(-3.12)	-0.052**	(-3.54)	-0.041**	(-7.46)	-0.009	(-1.29)

*Note: the cyclicality of the series is the coefficient on unemployment rate in a regression of the flows as percentage of the working-age population in logs on a time trend and the unemployment rate. T-statistics are in brackets.** denotes significant at 1% and * significant at 5%. The sample is between 2003:1 and 2018:4.*

Appendix B. Extra material: Section 4.4

Equilibrium unemployment with four-states transitions

In steady-state, there are no changes in the stocks so we set equations (1)-(4) to zero. Normalizing the working-age population to 1, we can substitute $I^{ss} = 1 - P^{ss} - G^{ss} - U^{ss}$, and write a system of the remaining states in matrix form

$$A \times \begin{pmatrix} P^{ss} \\ G^{ss} \\ U^{ss} \end{pmatrix} = B$$

where

$$A = \begin{pmatrix} (\lambda^{PG} + \lambda^{PU} + \lambda^{PI} + \lambda^{IP}) & (\lambda^{IP} - \lambda^{GP}) & (\lambda^{IP} - \lambda^{UP}) \\ (\lambda^{IG} - \lambda^{PG}) & (\lambda^{GP} + \lambda^{GU} + \lambda^{GI} + \lambda^{IG}) & (\lambda^{IG} - \lambda^{UG}) \\ (\lambda^{IU} - \lambda^{PU}) & (\lambda^{IU} - \lambda^{GU}) & (\lambda^{UP} + \lambda^{UG} + \lambda^{UI} + \lambda^{IU}) \end{pmatrix}$$

and

$$B = \begin{pmatrix} \lambda^{IP} \\ \lambda^{IG} \\ \lambda^{IU} \end{pmatrix}$$

The solution of this system is then given by:

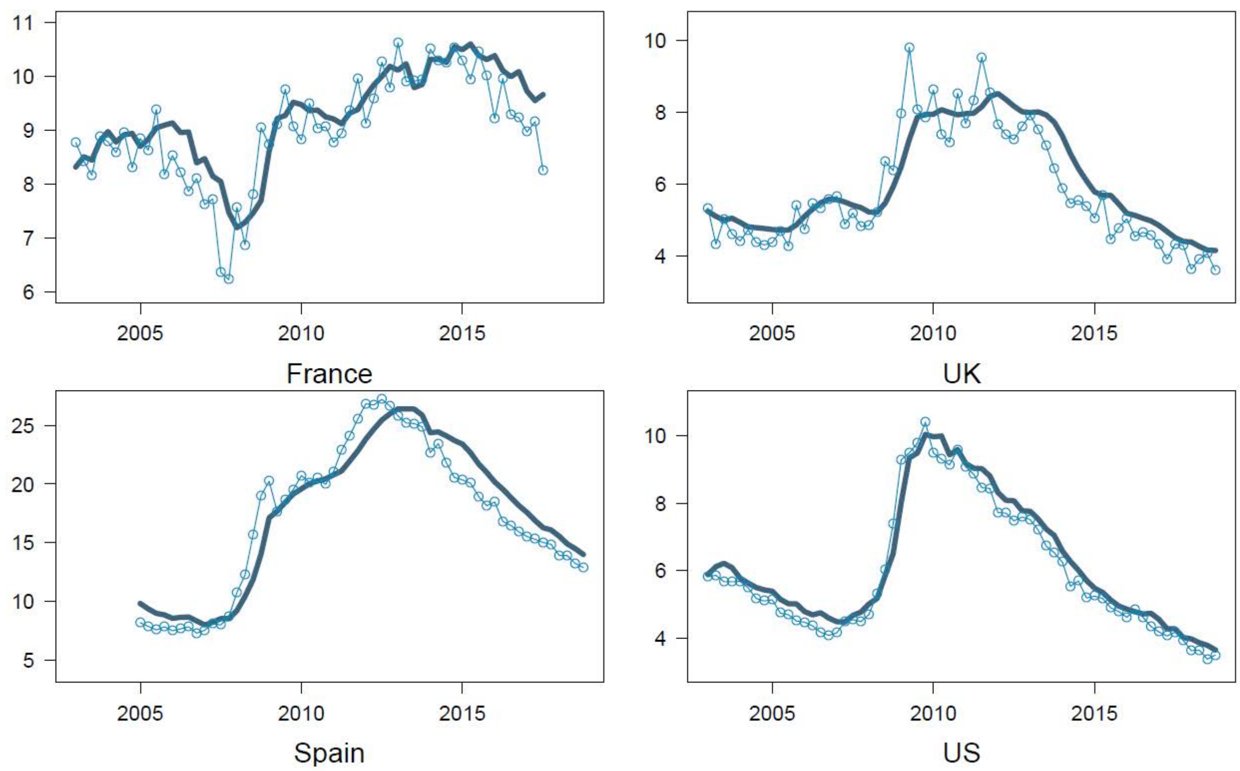
$$\begin{pmatrix} P^{ss} \\ G^{ss} \\ U^{ss} \end{pmatrix} = A^{-1} \times B$$

To calculate the unemployment rate we need to compute $\frac{U^{ss}}{P^{ss}+G^{ss}+U^{ss}}$.

Continuous time-aggregation bias correction

We can record the transitions rates λ^{ij} in a 4×4 discrete time Markov transition matrix with columns summing to 1. Let μ denote a diagonal matrix of eigenvalues and p the matrix with corresponding eigenvectors of the discrete transition matrix. Suppose now that the transitions occur in a continuous time environment. Let $\tilde{\lambda}$ be the 4×4 continuous time Markov transition matrix that records in the off-diagonal the Poisson continuous arrival rate, λ^{ij} from state $i \in \{P, G, U, I\}$ to state $j \neq i$. We can retrieve the continuous time transition matrix from the limit of the discrete transition matrix:

Figure 4.6: Unemployment rate (blue lines) and its steady state counterpart (dotted lines)



$$\tilde{\lambda} = \lim_{\Delta \to 0} \frac{p\mu^{\Delta}p^{-}1 - I}{\Delta} \tag{4.11}$$

Table 4.6: 3-states unemployment decompositions

	Shimer				Fujita & Ramey			
	France	**UK**	**Spain**	**US**	**France**	**UK**	**Spain**	**US**
$E \to U$	0.28	0.28	0.26	0.23	0.30	0.26	0.24	0.22
$E \to I$	-0.03	-0.04	-0.04	-0.02	-0.03	-0.03	-0.04	-0.02
$U \to E$	0.46	0.44	0.54	0.43	0.48	0.42	0.55	0.43
$I \to E$	0.10	0.12	0.08	0.07	0.10	0.11	0.08	0.07
$I \to U$	0.13	0.09	0.05	0.13	0.14	0.08	0.04	0.12
$U \to I$	0.06	0.10	0.11	0.15	0.06	0.09	0.10	0.15
Relative contribution								
Job-finding vs Job separation	62-38	61-39	67-33	66-34	61-39	62-38	70-30	66-34

Note: the gross flows series are previously seasonally adjusted using the X13 Census programme and the transition probabilities are corrected for time aggregation bias using the methodology applied by Shimer (2012). The series are then detrended with an HP filter with smoothing parameter of 100000.

Table 4.7: Shimer's 4-states unemployment decompositions, no detrending

	France	**UK**	**Spain**	**US**
$P \rightarrow U$	0.21	0.23	0.19	0.17
$G \rightarrow U$	0.04	0.04	0.02	0.02
$P \rightarrow I$	0.03	-0.02	-0.07	-0.04
$G \rightarrow I$	0.01	0.01	-0.01	-0.01
$U \rightarrow P$	0.34	0.30	0.50	0.35
$U \rightarrow G$	0.07	0.08	0.09	0.03
$I \rightarrow P$	0.04	0.10	0.10	0.07
$I \rightarrow G$	0.03	0.02	0.01	0.01
$I \rightarrow U$	0.30	0.08	0.04	0.14
$U \rightarrow I$	-0.04	0.09	0.12	0.09
$P \rightarrow G$	0.02	0.02	0.00	-0.00
$G \rightarrow P$	-0.01	-0.01	-0.00	0.00
Relative contribution (sum to 100)				
Private employment vs. Public employment				
	81-19	80-20	86-14	91-9
Public job-finding rate vs. Public job-separation rate				
	64-36	67-33	78-22	68-32
Private job-finding rate vs. Private job-separation rate				
	63-37	57-43	73-37	68-32

Note: the gross flows series are previously seasonally adjusted using the X13 Census programme and the transition probabilities are corrected for time aggregation bias using the methodology applied by Shimer (2012).

Table 4.8: Shimer's 4-states unemployment decompositions, no adjustment by tenure for job-to-job transitions

	France	**UK**	**Spain**	**US**
$P \to U$	0.24	0.23	0.24	0.22
$G \to U$	0.03	0.05	0.02	0.02
$P \to I$	-0.02	-0.02	-0.04	-0.03
$G \to I$	0.00	0.01	0.00	0.00
$U \to P$	0.39	0.32	0.49	0.38
$U \to G$	0.06	0.08	0.07	0.03
$I \to P$	0.08	0.11	0.08	0.07
$I \to G$	0.02	0.02	0.00	0.01
$I \to U$	0.14	0.08	0.05	0.13
$U \to I$	0.06	0.10	0.11	0.13
$P \to G$	0.02	0.02	0.00	0.00
$G \to P$	-0.01	-0.01	-0.01	0.00
Relative contribution (sum to 100)				
Private employment vs. Public employment				
	86-14	80-20	90-10	91-9
Public job-finding rate vs. Public job-separation rate				
	63-37	63-37	77-23	63-33
Private job-finding rate vs. Private job-separation rate				
	62-38	57-43	67-33	63-37

Note: the gross flows series are previously seasonally adjusted using the X13 Census programme and the transition probabilities are corrected for time aggregation bias using the methodology applied by Shimer (2012). The series are then detrended with an HP filter with smoothing parameter of 100000.

Table 4.9: Elsby et al. (2015a) non-steady state decomposition, 4-states

	France	**UK**	**Spain**	**US**
$P \rightarrow U$	0.19	0.10	0.19	0.16
$G \rightarrow U$	0.03	0.06	0.02	0.01
$P \rightarrow I$	-0.02	-0.01	-0.01	-0.03
$G \rightarrow I$	0.01	0.02	0.01	-0.00
$U \rightarrow P$	0.36	0.32	0.51	0.45
$U \rightarrow G$	0.07	0.09	0.06	0.03
$I \rightarrow P$	0.02	0.05	0.04	0.05
$I \rightarrow G$	0.00	0.01	-0.01	0.00
$I \rightarrow U$	0.23	0.10	0.08	0.14
$U \rightarrow I$	0.13	0.23	0.18	0.16
$P \rightarrow G$	0.00	0.00	0.00	0.00
$G \rightarrow P$	0.00	0.01	0.00	-0.00
Relative contribution (sum to 100)				
Private employment vs. Public employment				
	83-17	73-27	90-10	93-7
Public job-finding rate vs. Public job-separation rate				
	67-33	61-39	76-24	70-30
Private job-finding rate vs. Private job-separation rate				
	65-25	76-24	73-27	74-26

Note: the gross flows series are previously seasonally adjusted using the X13 Census programme and the transition probabilities are corrected for time aggregation bias using the methodology applied by Shimer (2012).Series are "smoothed" with a 3-order moving average for France, UK and Spain, and a 9-order moving average for the US.

Figure 4.7: Counterfactual exercise, France

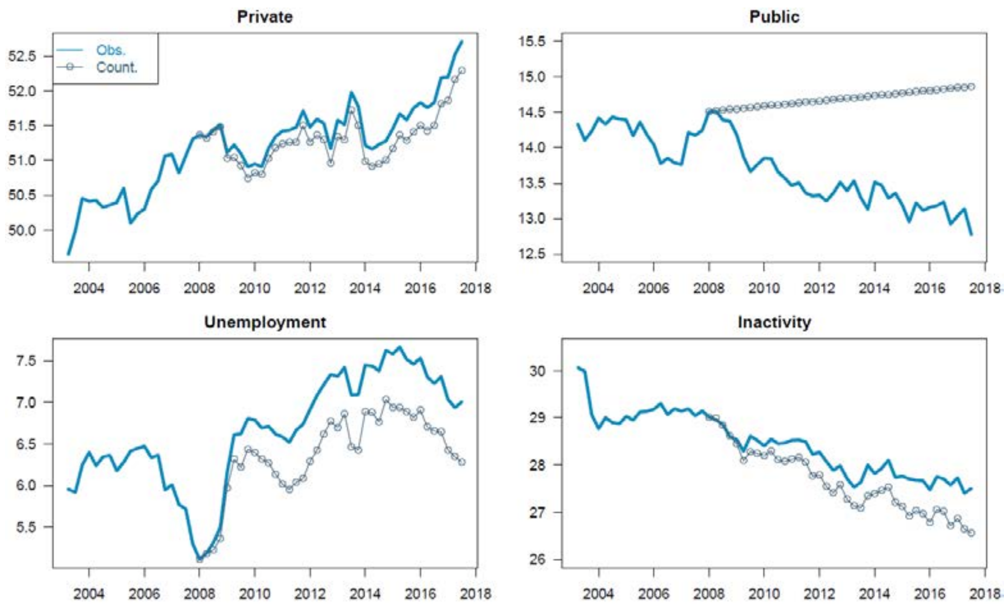


Figure 4.8: Counterfactual exercise, UK

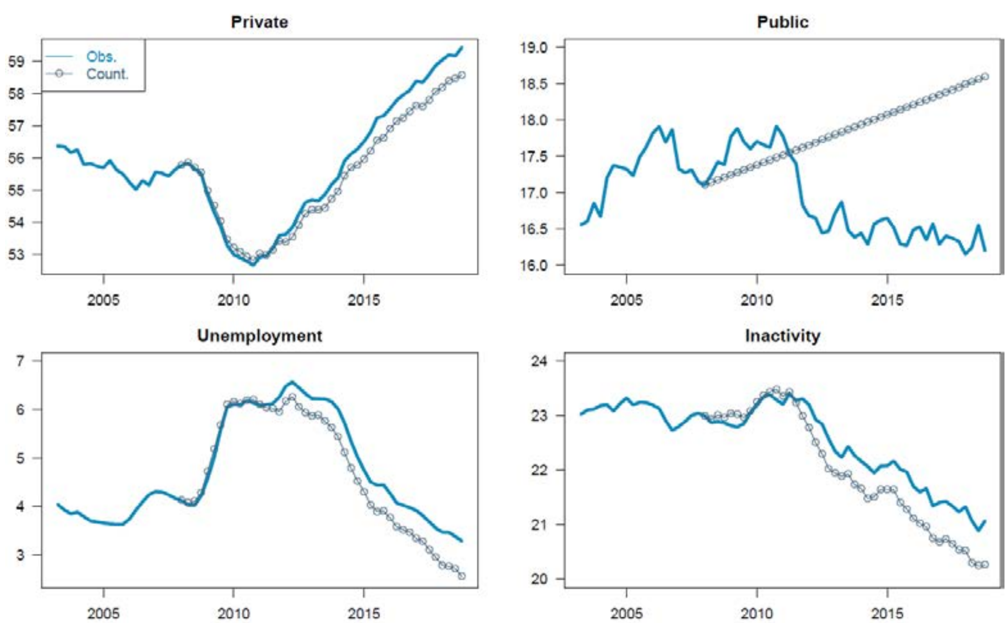


Figure 4.9: Counterfactual exercise, Spain

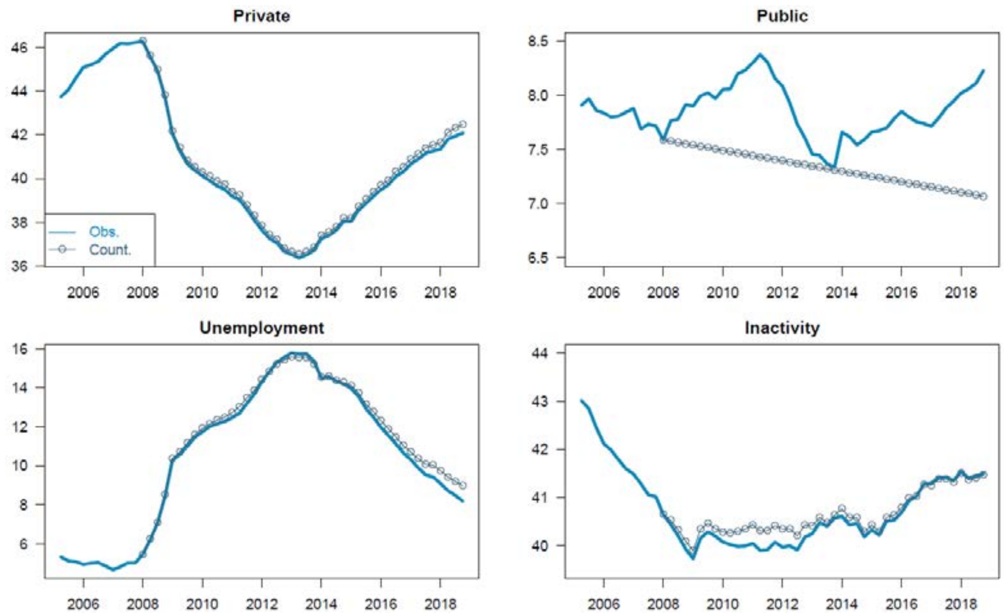
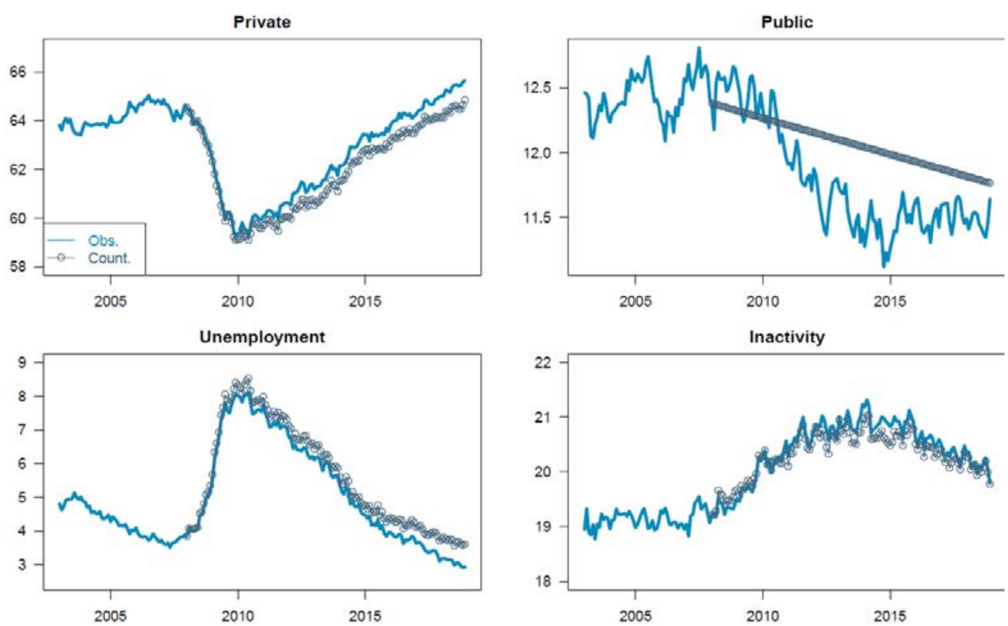


Figure 4.10: Counterfactual exercise, US



Appendix C. Extra material: Different subgroups

Table 4.10: Unemployment decompositions of subgroups (2003-2017). France

	Shimer								
	All	Men	Women	15-29	30-49	50-64	Primary.	Secondary	Tertiary
$P \to U$	0.24	0.39	0.11	0.28	0.24	0.26	0.32	0.20	0.26
$G \to U$	0.03	0.04	0.05	0.04	0.07	0.01	-0.02	0.05	0.05
$P \to I$	-0.02	-0.02	0.02	-0.02	0.04	0.05	-0.03	0.03	0.03
$G \to I$	0.00	0.01	0.01	0.02	0.06	0.01	0.02	0.01	0.01
$U \to P$	0.39	0.32	0.44	0.41	0.31	0.26	0.42	0.36	0.32
$U \to G$	0.06	0.02	0.12	0.03	0.06	0.02	0.04	0.11	0.06
$I \to P$	0.08	0.08	0.07	0.06	0.04	0.04	0.05	0.05	0.05
$I \to G$	0.02	0.01	0.06	0.02	0.08	0.03	0.02	0.02	0.06
$I \to U$	0.14	0.11	0.10	0.07	0.08	0.31	0.08	0.09	0.16
$U \to I$	0.06	0.03	0.05	0.07	0.01	0.00	0.08	0.07	0.03
$P \to G$	0.02	0.01	0.02	0.02	0.02	0.00	0.01	0.01	0.01
$G \to P$	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	-0.02

Note: the gross flows series are previously seasonally adjusted using the X13 Census programme and the transition probabilities are corrected for time aggregation bias using the methodology applied by Shimer (2012). The series are then detrended with an HP filter with smoothing parameter of 100000.

Table 4.11: Unemployment decompositions of subgroups (2003-2018). UK

	Shimer								
	All	Men	Women	15-29	30-49	50-64	Primary.	Secondary.	Tertiary
$P \to U$	0.24	0.33	0.09	0.22	0.26	0.15	0.28	0.11	0.17
$G \to U$	0.05	0.02	0.05	0.05	0.07	0.03	-0.02	0.02	0.05
$P \to I$	-0.02	-0.01	-0.01	-0.03	-0.01	0.04	0.04	0.05	0.01
$G \to I$	0.00	0.01	0.00	0.00	-0.01	0.02	0.02	0.01	0.05
$U \to P$	0.32	0.34	0.33	0.40	0.34	0.31	0.51	0.53	0.34
$U \to G$	0.09	0.06	0.13	0.07	0.11	0.07	0.02	0.11	0.20
$I \to P$	0.10	0.10	0.10	0.09	0.06	0.10	0.09	0.07	0.04
$I \to G$	0.03	0.01	0.05	0.02	0.03	0.03	0.01	0.05	0.01
$I \to U$	0.07	0.04	0.07	0.06	0.03	0.08	-0.03	-0.10	0.04
$U \to I$	0.10	0.10	0.12	0.09	0.12	0.16	0.12	0.15	0.08
$P \to G$	0.02	0.00	0.03	0.01	0.01	0.00	0.01	0.01	0.01
$G \to P$	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	-0.01

Note: the gross flows series are previously seasonally adjusted using the X13 Census programme and the transition probabilities are corrected for time aggregation bias using the methodology applied by Shimer (2012). The series are then detrended with an HP filter with smoothing parameter of 100000.

Table 4.12: Unemployment decompositions of subgroups (2005-2018). Spain

	Shimer								
	All	Men	Women	15-29	30-49	50-64	Primary.	Secondary.	Tertiary
$P \to U$	0.23	0.29	0.17	0.22	0.30	0.21	0.25	0.26	0.18
$G \to U$	0.03	0.03	0.02	0.01	0.04	0.03	0.01	0.01	0.05
$P \to I$	-0.04	-0.01	-0.10	-0.05	-0.03	-0.03	0.01	-0.05	-0.03
$G \to I$	0.00	-0.01	0.01	-0.01	0.00	0.02	0.00	0.00	0.00
$U \to P$	0.47	0.46	0.50	0.54	0.41	0.36	0.45	0.50	0.43
$U \to G$	0.08	0.05	0.10	0.04	0.07	0.09	0.03	0.05	0.13
$I \to P$	0.08	0.06	0.11	0.11	0.04	0.07	0.04	0.08	0.05
$I \to G$	0.00	0.01	-0.02	0.01	0.00	-0.05	-0.01	0.00	0.02
$I \to U$	0.05	0.04	0.07	0.03	0.06	0.14	0.07	0.05	0.03
$U \to I$	0.11	0.09	0.13	0.09	0.10	0.16	0.12	0.12	0.11
$P \to G$	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01
$G \to P$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: the gross flows series are previously seasonally adjusted using the X13 Census programme and the transition probabilities are corrected for time aggregation bias using the methodology applied by Shimer (2012). The series are then detrended with an HP filter with smoothing parameter of 100000.

Table 4.13: Unemployment decompositions of subgroups (2003-2018). US

	Shimer								
	All	Men	Women	15-29	30-49	50-64	Primary.	Secondary.	Tertiary
$P \to U$	0.22	0.26	0.11	0.17	0.25	0.21	0.06	0.21	0.24
$g \to U$	0.02	0.02	0.03	0.01	0.03	0.04	0.01	0.01	0.02
$P \to I$	-0.03	0.00	-0.02	-0.01	-0.01	0.01	0.06	-0.02	0.00
$G \to I$	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00
$U \to P$	0.38	0.40	0.38	0.46	0.38	0.31	0.56	0.42	0.33
$U \to G$	0.03	0.03	0.05	0.02	0.03	0.06	0.01	0.03	0.07
$I \to P$	0.07	0.05	0.06	0.08	0.03	0.03	0.03	0.07	0.03
$I \to G$	0.01	0.01	0.02	0.01	0.01	0.01	0.00	0.01	0.02
$I \to U$	0.13	0.09	0.13	0.09	0.11	0.12	0.03	0.10	0.12
$U \to I$	0.13	0.12	0.18	0.14	0.14	0.16	0.19	0.15	0.13
$P \to G$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$G \to P$	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00

Note: the gross flows series are previously seasonally adjusted using the X13 Census programme and the transition probabilities are corrected for time aggregation bias using the methodology applied by Shimer (2012). The series are then detrended with an HP filter with smoothing parameter of 100000.

Table 4.14: Average quarterly worker flows. France 2003-2017

	Men			*Women*			*15-29*			*30-49*			*50-64*			*Primary*			*Secondary*			*Tertiary*		
	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)
Stocks																								
P	11340	58.54	–	8831	44.04	–	3995	37.73	–	10355	64.7	–	5822	45.32	–	10170	47.71	–	3837	50.29	–	6165	58.3	–
G	2100	10.85	–	3307	16.5	–	784	7.41	–	2819	17.61	–	1803	14.07	–	2051	9.6	–	987	13.05	–	2369	22.69	–
U	1328	6.84	–	1288	6.42	–	984	9.29	–	1107	6.91	–	526	4.08	–	1610	7.62	–	486	6.32	–	520	4.94	–
I	4602	23.76	–	6617	33.03	–	4828	45.58	–	1726	10.78	–	4660	36.53	–	7453	35.08	–	2306	30.33	–	1461	14.07	–
Flows																								
$P \to U$	230	1.19	2.03	191	0.95	2.17	182	1.72	4.55	176	1.1	1.7	63	0.49	1.07	234	1.1	2.31	90	1.17	2.33	97	0.92	1.57
$G \to U$	17	0.09	0.79	28	0.14	0.83	20	0.19	2.54	17	0.11	0.62	7	0.05	0.39	22	0.1	1.07	9	0.12	0.94	13	0.12	0.54
$P \to I$	211	1.09	1.86	237	1.18	2.69	178	1.68	4.46	126	0.79	1.22	144	1.12	2.49	237	1.12	2.34	111	1.45	2.89	101	0.95	1.63
$G \to I$	30	0.15	1.42	59	0.3	1.79	30	0.28	3.85	20	0.13	0.73	39	0.3	2.15	37	0.17	1.83	23	0.3	2.32	29	0.28	1.22
$U \to P$	267	1.37	20.24	242	1.21	18.86	227	2.14	23.22	215	1.34	19.48	67	0.52	12.63	272	1.28	16.99	110	1.43	22.76	126	1.2	24.43
$U \to G$	21	0.11	1.58	40	0.2	3.14	28	0.27	2.89	24	0.15	2.21	8	0.07	1.62	28	0.13	1.76	14	0.18	2.97	19	0.18	3.62
$I \to P$	170	0.88	3.7	203	1.01	3.07	226	2.13	4.68	95	0.6	5.54	52	0.41	1.12	173	0.81	2.32	114	1.5	4.94	87	0.83	5.92
$I \to G$	22	0.12	0.49	45	0.22	0.68	40	0.38	0.83	18	0.11	1.02	10	0.08	0.21	23	0.11	0.3	22	0.29	0.96	22	0.22	1.54
$U \to I$	207	1.06	15.41	254	1.27	19.67	179	1.69	18.13	173	1.08	15.56	109	0.84	20.57	292	1.39	18.06	93	1.2	18.93	76	0.72	14.59
$I \to U$	226	1.16	4.9	292	1.45	4.42	235	2.22	4.87	186	1.16	10.78	96	0.74	2.08	316	1.5	4.26	111	1.44	4.78	90	0.86	6.16
$P \to G$	8	0.04	0.07	15	0.07	0.17	12	0.11	0.3	9	0.06	0.09	2	0.02	0.04	9	0.04	0.08	7	0.09	0.17	8	0.08	0.13
$G \to P$	9	0.05	0.41	13	0.07	0.4	10	0.1	1.32	9	0.06	0.32	3	0.02	0.16	8	0.04	0.37	5	0.07	0.53	9	0.09	0.39

Note: France Labour Force Survey.

Table 4.15: Average quarterly worker flows. UK 2003-2018

	Men			*Women*			*15-29*			*30-49*			*50-64*			*Primary*			*Secondary*			*Tertiary*		
	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)
Stocks																								
P	13179	66.71	–	9122	45.38	–	6345	56.12	–	10576	60.96	–	5381	48.01	–	4085	48.79	–	13152	61.45	–	7243	55.21	–
G	2327	11.79	–	4458	22.19	–	1166	10.31	–	3635	20.95	–	1984	17.74	–	628	7.24	–	3498	15.43	–	3840	29.96	–
U	1058	5.35	–	799	3.97	–	957	8.43	–	609	3.5	–	291	2.6	–	546	6.53	–	930	4.45	–	359	2.73	–
I	3190	16.14	–	5713	28.47	–	2850	25.14	–	2531	14.58	–	3524	31.66	–	3111	37.44	–	3799	18.68	–	1598	12.1	–
Flows																								
$P \to U$	203	1.03	1.55	122	0.61	1.34	159	1.41	2.53	112	0.65	1.07	54	0.48	1.01	73	0.86	1.78	195	0.92	1.5	81	0.62	1.13
$G \to U$	15	0.08	0.65	20	0.1	0.45	12	0.11	1.05	14	0.08	0.38	9	0.08	0.47	4	0.05	0.7	20	0.09	0.57	17	0.13	0.44
$P \to I$	214	1.08	1.62	274	1.36	3.01	196	1.74	3.09	117	0.67	1.11	175	1.56	3.26	106	1.26	2.59	297	1.42	2.31	120	0.91	1.65
$G \to I$	34	0.17	1.45	80	0.4	1.8	25	0.22	2.15	28	0.16	0.77	61	0.55	3.07	14	0.16	2.24	60	0.27	1.74	58	0.45	1.51
$U \to P$	249	1.26	24.11	177	0.88	22.77	241	2.13	25.89	129	0.75	21.88	56	0.5	19.39	91	1.08	16.87	261	1.2	28.17	110	0.83	31.07
$U \to G$	21	0.1	2.05	36	0.18	4.76	25	0.22	2.77	22	0.13	3.9	9	0.08	3.22	7	0.08	1.21	31	0.14	3.26	28	0.22	8.41
$I \to P$	195	0.98	6.11	266	1.32	4.67	282	2.49	9.97	93	0.54	3.7	85	0.76	2.44	87	1.05	2.82	295	1.41	7.76	96	0.72	5.94
$I \to G$	23	0.11	0.71	51	0.26	0.9	35	0.31	1.25	21	0.12	0.81	18	0.16	0.5	7	0.09	0.23	41	0.19	1.06	33	0.25	2.12
$U \to I$	150	0.76	14.56	184	0.92	23.56	173	1.52	18.42	103	0.59	17.4	59	0.52	20.4	96	1.15	17.97	198	0.93	21.36	56	0.42	15.74
$I \to U$	196	0.99	6.14	240	1.2	4.21	267	2.35	9.33	117	0.68	4.64	53	0.47	1.51	121	1.45	3.88	266	1.24	6.91	72	0.55	4.54
$P \to G$	22	0.11	0.17	39	0.19	0.43	30	0.26	0.47	24	0.14	0.23	7	0.06	0.13	5	0.06	0.13	36	0.17	0.27	27	0.21	0.39
$G \to P$	18	0.09	0.77	28	0.14	0.63	18	0.16	1.54	20	0.11	0.55	8	0.07	0.41	4	0.05	0.69	25	0.11	0.76	23	0.18	0.6

Note: UK Labour Force Survey.

Table 4.16: Average quarterly worker flows. Spain 2005-2018

	Men			*Women*			*15-29*			*30-49*			*50-64*			*Primary*			*Secondary*			*Tertiary*		
	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)
Stocks																								
P	9151	49.21	–	6587	33.74	–	3009	40.31	–	9102	62.39	–	3502	41.96	–	1943	17.74	–	8579	48.34	–	5215	53.87	–
G	1280	6.88	–	1561	7.99	–	264	3.54	–	1581	10.84	–	974	11.58	–	99	0.89	–	897	5.06	–	1846	19.13	–
U	2059	11.01	–	1960	9.99	–	1264	17.6	–	1998	13.58	–	751	8.75	–	721	6.92	–	2449	13.59	–	849	8.59	–
I	6128	32.9	–	9417	48.28	–	2795	38.55	–	1921	13.19	–	3108	37.71	–	7844	74.45	–	5908	33.01	–	1792	18.41	–
Flows																								
$P \rightarrow U$	377	2.02	4.2	283	1.45	4.31	215	2.94	7.61	355	2.42	3.91	89	1.05	2.51	100	0.93	5.54	411	2.3	4.84	150	1.54	2.87
$G \rightarrow U$	29	0.15	2.25	37	0.19	2.39	18	0.25	7.38	36	0.24	2.26	12	0.14	1.18	7	0.07	8.72	32	0.18	3.53	27	0.28	1.47
$P \rightarrow I$	222	1.2	2.4	292	1.5	4.44	159	2.12	5.18	191	1.32	2.1	128	1.57	3.74	110	0.99	5.41	300	1.71	3.47	104	1.09	2.01
$G \rightarrow I$	27	0.15	2.12	45	0.23	2.9	16	0.21	6.04	26	0.18	1.65	24	0.28	2.45	10	0.09	10.43	31	0.17	3.43	32	0.33	1.73
$U \rightarrow P$	415	2.22	23.11	339	1.73	18.96	270	3.7	23.38	394	2.69	21.92	89	1.05	13.46	103	0.97	15.85	466	2.6	21.51	185	1.89	23.88
$U \rightarrow G$	35	0.19	1.91	49	0.25	2.73	24	0.33	2.06	44	0.3	2.54	15	0.17	2.17	9	0.08	1.3	39	0.22	1.8	36	0.37	4.78
$I \rightarrow P$	185	1	3.07	268	1.38	2.82	189	2.54	6.78	159	1.09	8.12	88	1.08	2.83	82	0.74	1.01	269	1.53	4.7	101	1.06	5.79
$I \rightarrow G$	22	0.12	0.37	44	0.23	0.46	23	0.31	0.84	25	0.17	1.31	15	0.18	0.48	9	0.08	0.11	27	0.15	0.48	30	0.31	1.7
$U \rightarrow I$	243	1.3	13.13	397	2.03	21.65	216	2.99	17.94	256	1.75	14.69	163	1.92	24.19	127	1.21	19	393	2.19	17.62	120	1.23	15.48
$I \rightarrow U$	280	1.5	4.56	460	2.35	4.9	293	4.05	10.51	286	1.95	15.45	158	1.87	5.14	136	1.29	1.73	453	2.53	7.72	152	1.56	8.47
$P \rightarrow G$	9	0.05	0.09	11	0.06	0.16	8	0.1	0.25	10	0.07	0.11	3	0.04	0.1	3	0.03	0.19	8	0.04	0.09	11	0.11	0.2
$G \rightarrow P$	7	0.04	0.56	8	0.04	0.51	6	0.09	2.43	7	0.05	0.45	3	0.04	0.35	3	0.03	4.23	7	0.04	0.77	7	0.07	0.36

Note: Spanish Labour Force Survey.

Table 4.17: Average monthly worker flows. US 1996-2018

	Men			*Women*			*15-29*			*30-49*			*50-64*			*Primary*			*Secondary*			*Tertiary*		
	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)	(t)	(p)	(h)
Stocks																								
P	57996	67.25	–	54832	57.35	–	34272	60.35	–	47663	67.16	–	31004	57.1	–	7804	59.15	–	66952	61.78	–	40240	64.34	–
G	8806	10.22	–	12730	13.33	–	3617	6.37	–	9487	13.36	–	8283	15.4	–	294	2.22	–	8714	8.04	–	11634	18.74	–
U	4913	5.69	–	4201	4.39	–	3966	6.97	–	3230	4.56	–	1998	3.67	–	862	6.49	–	6659	6.12	–	2020	3.24	–
I	14565	16.84	–	23838	24.92	–	14973	26.3	–	10584	14.92	–	12915	23.82	–	4238	32.14	–	26114	24.06	–	8568	13.68	–
Flows																								
$P \to U$	896	1.04	1.56	640	0.67	1.17	704	1.24	2.07	555	0.78	1.17	300	0.55	0.98	193	1.45	2.47	1144	1.05	1.71	311	0.5	0.78
$G \to U$	50	0.06	0.57	92	0.1	0.72	47	0.08	1.32	53	0.08	0.56	42	0.08	0.5	4	0.03	1.55	77	0.07	0.88	58	0.09	0.5
$P \to I$	1053	1.22	1.81	1445	1.51	2.63	1362	2.4	3.97	661	0.93	1.39	507	0.93	1.63	254	1.93	3.25	1829	1.69	2.73	521	0.83	1.29
$G \to I$	126	0.15	1.43	246	0.26	1.93	134	0.24	3.72	110	0.16	1.16	131	0.24	1.58	13	0.1	4.51	202	0.19	2.32	158	0.25	1.36
$U \to P$	981	1.14	21.24	758	0.79	19.03	865	1.53	22.85	600	0.84	19.75	299	0.55	16.07	206	1.55	24.99	1288	1.19	20.58	360	0.58	18.85
$U \to G$	56	0.07	1.22	105	0.11	2.6	60	0.11	1.59	58	0.08	1.89	43	0.08	2.35	5	0.04	0.62	85	0.08	1.35	70	0.11	3.65
$I \to P$	898	1.04	6.21	1248	1.31	5.25	1231	2.17	8.28	557	0.79	5.27	385	0.71	2.98	243	1.84	5.73	1559	1.44	6	448	0.71	5.21
$I \to G$	104	0.12	0.72	203	0.21	0.85	124	0.22	0.83	96	0.13	0.9	90	0.17	0.7	12	0.09	0.29	169	0.16	0.65	128	0.21	1.51
$U \to I$	839	0.97	17.66	947	0.99	22.91	939	1.65	24.06	531	0.75	17.02	326	0.6	16.89	182	1.37	21.87	1358	1.25	20.95	310	0.49	15.65
$I \to U$	768	0.89	5.28	889	0.93	3.73	906	1.59	6.06	473	0.67	4.46	288	0.53	2.22	169	1.27	3.97	1246	1.15	4.77	302	0.48	3.53
$P \to G$	130	0.15	0.22	189	0.2	0.34	106	0.19	0.31	128	0.18	0.27	86	0.16	0.27	5	0.04	0.07	167	0.15	0.25	143	0.23	0.35
$G \to P$	108	0.13	1.23	157	0.16	1.24	84	0.15	2.32	105	0.15	1.11	78	0.14	0.94	5	0.03	1.55	136	0.12	1.57	123	0.19	1.05

Note: US Current Population Survey .

Appendix D. Extra material: Section 4.5

Figure 4.11: Transition probability from employment to inactivity, by sector

Note: Based on estimation of equations 5 and 6 using a multinomial logit. For France, there were 1,884,703 observations and a pseudo R-squared of 0.090. For the UK, there were 1,678,331 observations and a pseudo R-squared of 0.130. For Spain, there were 2,522,803 observations and a pseudo R-squared of 0.094. For the US, there were 7,571,635 observations and a pseudo R-squared of 0.070. For France, the UK and Spain, the transition rate was quarterly, while in the US, it was monthly. We used as controls regional, gender, age, education and occupation dummy variables. The predicted probability is calculated based on an individual with the average characteristics of the employed population. The sample covers 2003-2018 for UK and US, 2005-2018 for Spain and 2003-2017 for France. The dashes lines report the 95 percent confidence interval on the prediction.

Table 4.18: Public-sector job-security premium, unconditional job-separation rates

	Scenario for value of unemployment					Government budget (medium scenario)		
	Very low	Low	Medium	High	Very high			
	$z = 0.3$	$z = 0.3$	$z = 0.5$	$z = 0.7$	$z = 0.7$	Millions	% of GDP	% of Gov
	$f = min$	$f = mean$	$f = mean$	$f = mean$	$f = max$			Spending
Lower bound: risk neutrality ($\sigma = 0$)								
France	4.0%	3.6%	2.5%	1.5%	1.3%	7161 (€)	0.33	0.63
UK	3.1%	2.4%	1.7%	1.0%	0.9%	2979 (£)	0.16	0.41
Spain	7.3%	5.1%	3.6%	2.1%	1.5%	4261 (€)	0.39	0.97
US	3.5%	1.9%	1.4%	0.5%	0.4%	25702 ($)	0.14	0.41
Upper bound: risk neutrality ($\sigma = 2$) and no insurance								
France	10.5%	9.7%	4.6%	2.1%	1.8%	12963 (€)	0.59	1.13
UK	8.8%	7.1%	3.2%	1.4%	1.2%	5599 (£)	0.30	0.76
Spain	14.6%	11.8%	5.9%	2.8%	2.0%	7080 (€)	0.66	1.62
US	9.2%	5.7%	2.7%	0.7%	0.4%	48166 ($)	0.27	0.77

Note: The first five columns of table report the fraction of the wage that a private-sector worker is willing to forgo to have the same conditional job-separation rate as a public-sector worker in each country, depending on the replacement rate and job-finding rate. The discount rate r is set to 0.005 for France, the UK and Spain and to 0.0017 for the US. We calculate the budgetary value of job-security based on 2015 data on wage compensation of government workers, GDP and total government spending provided by AMECO and FRED datasets.

Table 4.19: Public-sector job-security premium, unconditional job-separation rates

	Scenario for value of unemployment				
	Very low	Low	Medium	High	Very high
	$z = 0.3$	$z = 0.3$	$z = 0.5$	$z = 0.7$	$z = 0.7$
	$f = min$	$f = mean$	$f = mean$	$f = mean$	$f = max$
Primary educated workers					
France	2.9%-7.2%	2.6%-6.6%	1.8%-3.2%	1.1%-1.5%	1.0%-1.3%
UK	3.4%-9.1%	1.9%-5.5%	1.3%-2.5%	0.8%-1.1%	0.6%-0.8%
Spain	-	-	-	-	
US	2.8%-5.8%	1.2%-3.3%	0.9%-1.6%	0.3%-0.4%	0.2%-0.3%
Secondary educated workers					
France	2.4%-7.0%	2.1%-6.0%	1.5%-2.8%	0.9%-1.2%	0.7%-1.0%
UK	1.7%-4.8%	1.1%-3.2%	0.8%-1.4%	0.5%-0.6%	0.4%-0.5%
Spain	-	-	-	-	
US	2.2%-5.6%	1.3%-3.6%	0.9%-1.6%	0.4%-0.4%	0.2%-0.3%
Tertiary educated workers					
France	2.1%-6.2%	1.8%-5.2%	1.2%-2.4%	0.7%-1.0%	0.6%-0.9%
UK	1.0%-3.1%	0.7%-2.2%	0.5%-1.0%	0.3%-0.4%	0.2%-0.3%
Spain	2.1%-5.2%	1.2%-3.4%	0.8%-1.6%	0.5%-0.7%	0.3%-0.5%
US	0.7%-2.0%	0.4%-1.2%	0.3%-0.5%	0.1%-0.1%	0.1%-0.1%

Note: The table reports the lower and upper bound of fraction of the wage that a private sector worker is willing to forgo to have the same unconditional job-separation rate as a public sector worker in each country, depending on the replacement rate and job-finding rate The discount rate r is set to 0.005 for France, UK and Spain and to 0.0017 in the US.

Appendix E. Extra material: Conditional transition rates

Table 4.20: Conditional job-finding rates, US (Average 1996-2018)

	U-E rate		*I-E rate*	
	Public	Private	Public	Private
Unconditional	1.83	20.38	0.85	5.90
Conditional				
G	29.48	16.85	26.35	11.19
P	1.39	40.48	1.53	31.91
U	1.48	17.14	1.12	10.63
I	1.53	15.79	0.38	2.89

Note: The table reports the unconditional transition rates from unemployment (inactivity) to employment in a given sector, conditional on the state prior to unemployment (inactivity).

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