Essays on labor market adjustment and earnings growth

by

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Published and submitted content

Chapter 1 of this dissertation, titled *From Bricklayers to Waiters: Reallocation in a Deep Recession*, has been previously shared as a working paper.
URL: https://henryredondo.github.io/index/files/Manuscript.pdf

Abstract

This dissertation aims to enhance our understanding of the factors that shape workers' earnings trajectories. It investigates institutional and exogenous factors that significantly impact workers' earnings and can lead to long-term effects. The dissertation is structured into three distinct chapters, each focusing on a different facet of this topic.

The first chapter investigates the consequences of a significant shock to the Spanish economy, the burst of the construction sector during the Great Recession, and how workers mitigate its pervasive effects. The exploration delves into the reallocation of workers, considering the influence of working in more affected regions on their geographic and sectoral mobility. The chapter identifies factors that contribute to heterogeneous responses among workers, emphasizing the role of sectoral opportunities, which can explain variations in the impact of the construction sector burst.

The second chapter focuses on the duality of the Spanish labor market, characterized by temporary and permanent contracts, and its influence on the returns to experience. Estimating these returns poses challenges due to the non-random sorting of workers into contract types. The chapter exploits variation in the contract expiration timing and permanent contract availability as an exogenous variation for contract-type employment. It sheds light on the long-term effects of gaining experience in low-quality jobs, specifically those associated with temporary contracts.

The final chapter studies the influence of the labor market duality on workers' motivations to relocate geographically within Spain. The primary objective of this chapter is to deepen our understanding of the dynamics of internal mobility and labor market instability. Additionally, it provides a comprehensive analysis of recent trends in internal mobility within Spain, offering valuable insights into the factors shaping workers' decisions to move within the country.

Chapter 1. From bricklayers to waiters: Reallocation in a deep recession. This paper explores how the local sectoral composition influences workers' adjustment to a large economic shock. I exploit the massive burst in the Spanish construction sector during the Great Recession. For identification, I leverage regional variation in the intensity of the employment decline among Spanish provinces and detailed longitudinal administrative data. The construction workers in heavily exposed provinces suffered a significant decline in total earnings between 2007 and 2012, consistent with the workers experiencing long periods of unemployment rather than wage cuts. I find evidence that the short-term labor market adjustment was intersectoral rather than interregional, even under asymmetric exposure. In order to understand the role of sectoral composition in an individual worker's response to the shock, I construct a *reallocation index*. This index captures the degree to which workers from the construction sector can reallocate to other sectors. Then, I examine how sectoral composition contributes to ameliorating the shock's impact. I provide evidence that workers' likelihood of changing sectors depends on having better outside opportunities in other sectors, which varies across provinces and workers' characteristics. Individuals with more evenly distributed characteristics across sectors were less affected by the shock because they were more likely to change sectors. This implies that, on average, workers are less likely to adapt to shocks when a region has a high sectoral concentration.

Chapter 2. Quasi-Random Matched: Evidence from Dual Labor Markets. A fast-growing literature studies how sorting into particular jobs, firms, or locations affects workers. The key challenge when studying such questions is the non-random sorting of workers into jobs. We propose a novel identification strategy that exploits the *timing* of worker-firm matching. We isolate quasi-random variation in matches by interacting high-frequency information on the duration of contracts on the labor supply and transitory fluctuations in job creation on the labor demand side. We apply this method to address a central question in *dual labor markets*: how do different contract types – fixed-term or open-ended contracts – affect workers' careers? We find that transitory variation in the opening of permanent contracts is highly predictive of individual promotion probabilities and has long-lasting effects on earnings, employment, and the accumulation of experience in permanent positions.

Chapter 3. Internal migration and job instability. The lack of promotion opportunities in permanent positions is a major concern for young workers in Southern European countries. Career advancement uncertainty can discourage potential migrants from seeking opportunities in other regions. These individuals may find themselves on an unfavorable career trajectory if they end up in a potential migration destination that offers only a series of temporary contracts. To shed light on this issue, this study focuses on the Spanish provinces as a case study, analyzing how job uncertainty, as measured by changes in the proportion of fixed-term contracts, impacts internal mobility. By utilizing comprehensive longitudinal data from administrative records, I track all workers' movements between Spanish provinces. The first part of the paper provides descriptive evidence of recent trends in internal migration rates in Spain. Subsequently, I examine short-term and long-term migration, presenting novel findings on the connection between employment stability and migration. The results indicate that an increase in work flexibility encourages short-term migration but discourages long-term migration.

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Chapter 1

From bricklayers to waiters: Reallocation in a deep recession

1.1 Introduction

In recent years, workers have experienced the pervasive consequences of two deep economic crises— the Great Recession and the COVID-19 pandemic— along with the emergence of large economic shocks that have transformed entire occupations and sectors. A growing body of literature quantifies the impact of those shocks on the labor market. Well-known examples include Chinese import competition and industrial robots' effect on the US manufacturing sector (Acemoglu and Restrepo 2022; Autor et al. 2013; Autor et al. 2014). Still, little is known about how workers' heterogeneity affects their ability to adapt to such shocks. To create effective policies that support workers in a job loss event, it is necessary to understand how to mitigate earnings and employment losses and to develop methods to identify the most vulnerable workers during hard times.

To that end, this paper studies the massive decline of the Spanish construction sector during the Great Recession. The article is divided into two main sections. First, I study the impact of the shock on workers' earnings trajectories and employment adjustment. For identification, I leverage regional variation in the intensity of the employment decline and exploit detailed longitudinal administrative data, which allows me to disentangle the effect of the shock from other possible confounders. Second, I examine the role of sectoral composition in determining workers' mitigation responses. To analyze adjustment paths, I construct a *reallocation index* that incorporates two potential sources of frictions in worker reallocation: differences in a sector's suitability based on worker characteristics and heterogeneity in the availability of jobs across different regions as a consequence of spatial specialization patterns of economic sectors.

There are several different mechanisms through which workers adapt to economic fluctuations in their labor market outcomes. Two important mechanisms are geographical and sectoral mobility. In a classic contribution, Blanchard et al. (1992) found that the impacts of local labor demand shocks on unemployment and participation disappear in less than ten years, indicating geographical mobility is the dominant regional adjustment mechanism. Recent studies, however, have found that regional disparities last longer (Amior and Manning 2018; Dao et al. 2017) and that workers' migration responses are limited (Autor et al. 2014; Dix-Carneiro and Kovak 2017).

In light of this small migration response, sectoral mobility should be further explored. This mechanism may also help to mitigate individual-level consequences of negative shocks as workers reallocate to a less affected or growing sector. However, large outflows from the most affected sectors into other sectors remain uncommon. One reason is that workers accumulate sector-specific human capital (Neal 1995; Rogerson 2005), making it more costly for them to leave the shrinking sectors for another sector.[1] A growing body of literature examines this mechanism, mainly in the context of trade shocks.[2] For example, Yi et al. (2016), Artuç et al. (2010), and Dix-Carneiro (2014) found that as a result of trade shocks, workers reallocating from the manufacturing sector reported fewer earnings disruptions than those who changed jobs but remained in manufacturing. However, sectoral mobility may be a relevant adjustment mechanism in other contexts. Additionally, I study geographical and sectoral mobility as adaptation mechanisms to a large shock and how worker characteristics influence each worker's response.

In the first part of my analysis, I explore how local labor demand changes, induced by the shrinking of the construction sector, heterogeneously affect workers' earnings and employment. I exploit variation in the employment contraction of the construction sector, across Spanish provinces, as an economic shock.[3] I define workers' exposure as the relative change in the employment share of the construction sector between 2007 and 2012 in the workers' initial province of residence. The identifying assumption is that local employment contraction of the construction sector is as good as randomly assigned, conditional on observable characteristics.

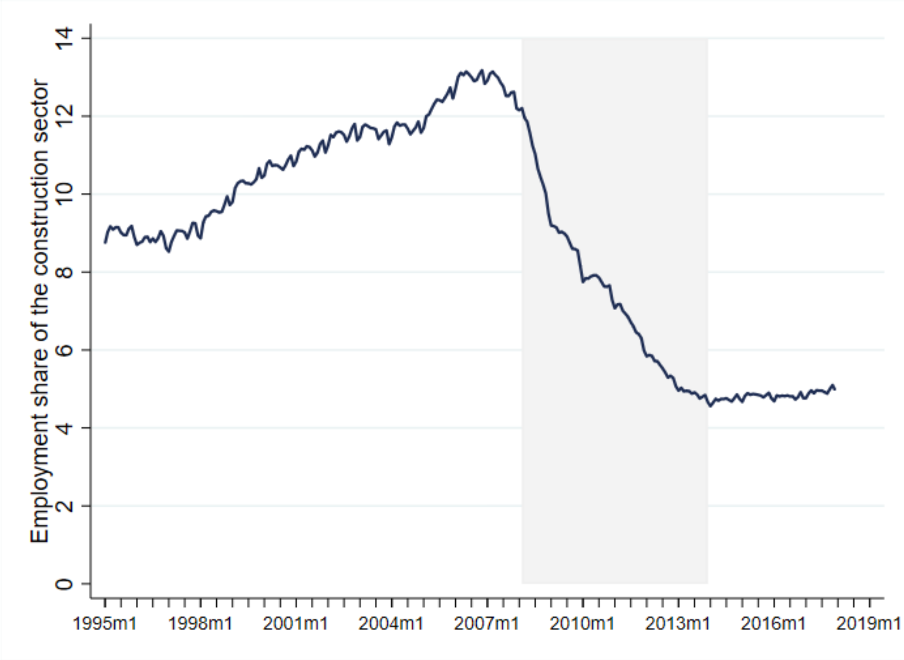
The second part of the paper exploits shock variation across provinces and administrative panel data that tracks all the worker's labor market history to investigate local sectoral compositions' contribution to attenuating job loss's consequences. I construct a *reallocation index* that reflects the likelihood of transitioning from construction to another industry. It captures the imperfect substitutability of workers

[1] Sectoral reallocation has been widely discussed, mainly as part of the trade literature (Mayer 1974; Kambourov 2009), and less often but equally important, as an adjustment mechanism to large economic shocks (Carrington 1996; Arntz et al. 2022).

[2] Sectoral mobility reduces the impact of negative shocks on workers' labor market outcomes, compared with continuity in the same sector.

[3] Here I follow the approach by Autor et al. (2014) and Yagan (2019), who studied the impact of the Great Recession and the China shock on workers' earnings and employment trajectories, respectively.

Figure 1.1 Employment share of workers in the Spanish construction sector, 1995-2017



Notes: Presents the proportion of workers in Spain's construction sector from January 1995 to December 2017. The data is restricted to monthly observations of workers aged 20-60 employed during the referenced period. The shaded area comprises the years of the Great Recession in Spain, between 2008 and 2014.

across different sectors by exploiting variation in each province's sectoral composition and worker characteristics.

My analysis relies on longitudinal data covering a worker's entire labor market history and unique characteristics. The Continuous Sample of Working Lives (MCVL) includes the working history of 4% of the workers affiliated with Spain's Social Security. This rich data source tracks earnings and contract changes before and after the crisis, allowing me to compare the shock's consequences to pre-recession earnings and employment trajectories.

Through this paper, I contribute further evidence on the impact of economic shocks on workers' labor market outcomes (Autor et al. 2014; Dix-Carneiro and Kovak 2017) and the long-term consequences of job loss (Jacobson et al. 1993; Gulyas et al. 2019). I also examine the dynamics of the shock's impact on workers' earnings and employment, providing additional evidence on workers' reactions. Similar to Autor et al. (2014), I find large employment losses immediately after the shock. However, the employment differentials related to the asymmetric exposure to the shock disappear over time, partly explained by an increasing worker reallocation into other sectors.

I also extend the literature on workers' labor market adjustment by providing evidence that a worker's reaction depends on the interaction between the worker's characteristics and the sectoral composition. To clarify that relationship, I build on the literature on occupation/sector similarity estimation (Schubert et al. 2019;

Beaudry et al. 2012; Caldwell and Danieli 2018; Costa Dias et al. 2021) and construct a reallocation index, which captures the match between the worker characteristics and the composition of jobs in the region. A related idea is also explored by Yi et al. (2016) and Macaluso et al. (2017), who noted that the worker's initial sector or occupation may affect the posterior adjustment. My paper is distinct from those studies as the reallocation index varies between regions and workers' characteristics. Therefore, it allows researchers to explore changes in the relevant worker's labor market, even within the same region. At the end of this section, I provide a more comprehensive review of related literature.

My results show that individuals initially employed in the construction sector and working in more exposed provinces earned less and remained employed for fewer days between 2007 and 2012 compared to those in less exposed provinces. Conditional on the initial province of residence, the difference between the 75th and 25th percentiles of exposure results in an additional cumulative earnings loss of 20% of the initial annual earnings between 2007 and 2012. This impact is mainly due to a decline in employment rather than wages. Compared to those in the five most affected provinces, workers in the five least affected provinces accumulated, on average, 290 extra days of employment during the recession. According to the heterogeneity analysis, native and young workers suffered the largest employment declines.

Furthermore, I demonstrate that workers adjusted mainly through intersectoral mobility rather than geographical mobility. As of 2015, four times as many workers who initially worked in construction had switched sectors compared to those who changed provinces. In addition, workers in the worst-hit provinces were less likely to remain in the construction sector after the Great Recession. In contrast, there was no significant impact on their likelihood of moving into a new province. In line with the recent empirical literature, sectoral mobility tends to be more prevalent than geographical reallocation.

In light of this insufficient adjustment via geographical migration, I found a statistically significant relationship between exposure to the shock and the likelihood of reallocating to another sector. A worker with an average value on the *reallocation index* suffered a 40% weaker average impact on cumulative earnings between 2007 and 2012. Moving from the second to the third quartile of the *reallocation index* results in a 33% milder shock to earnings and employment. Sectoral composition plays an important role in explaining the heterogeneous impact of the employment decline on worker outcomes. Because the value of certain skills differs based on the sectoral composition of the local economy, it is important to consider the size and variance of the shock by worker and region.

Finally, the results in this paper are robust to several sensitivity tests. A falsification exercise indicates no relative downward employment trend in severely shocked areas before the recession, corroborating the identification. The results on the reallocation index are robust to using transition probabilities while constructing the index, as I find similar results compared to the main specification. Furthermore, the results remain mostly unaffected when the sector's cumulative growth before the recession instruments the shock.

Related literature and contribution: I contribute primarily to two strands of the literature: research on the consequences of job loss on workers' labor market outcomes, and research on the role of outside options in reemployment opportunities.

Several studies have shown that job losses have long-term effects on workers' earnings and employment trajectories in the context of mass layoffs (Jacobson et al. 1993; Neal 1995; Farber 2017; Gulyas et al. 2019), economic downturns (Yagan 2019; Mian and Sufi 2014; Bachmann et al. 2015; Nagore García and van Soest 2017), and the growth of import competition from developing countries (Autor et al. 2014; Dix-Carneiro and Kovak 2017; Dauth et al. 2014). Despite this extensive research, we know little about why the earnings differentials are so persistent and how workers specifically respond to negative shocks.[4] This paper contributes to filling that gap by taking advantage of a massive construction shock in Spain. Having a well-defined group of workers affected by the shock allows comparison of its consequences and adjustment margins for directly and indirectly affected workers. Additionally, I compare how different degrees of exposure to the shock affected workers' prospects by using high-quality administrative data. This data allows me to track the earnings and employment impact before and after the Great Recession providing novel evidence on the heterogeneity of the shock by worker's and regional characteristics and the dynamics of the impact.

In the aftermath of adverse economic events, why are there large earnings and employment differentials between exposed and less exposed workers? Relocating workers to less-affected regions could mitigate the impact of negative demand shocks (Topel, 1986). Blanchard et al. (1992) argues that regional differences in exposure to adverse shocks trigger a migration response among workers, equalizing differences in employment and wages among regions.[5] Amior and Manning (2018) found that despite a strong migratory response, adjustment to shocks is incomplete within a decade. Dix-Carneiro and Kovak (2019), studying trade liberalization in Brazil, emphasized the importance of geographic location for explaining outcome differentials, implying that the workers' adjustment to economic shocks occurs primarily within the region. Following previous evidence, I demonstrate that workers in more exposed regions are not more likely to migrate to less affected regions, a trend that

[4]Some groups of workers have been documented to be highly responsive to negative conditions, such as college graduates (Wozniak 2010) and foreign workers (Cadena and Kovak 2016). As a result of negative conditions in these studies, more mobile individuals moved to less affected regions.

[5]Monras 2018 studied the consequences of the Great Recession across locations, documenting that around 60 percent of the initial differences potentially dissipate across space within ten years.

persists even after controlling for individual and regional characteristics.

Previous research supports the equalizing role of geographical mobility in reducing regional disparities. At the worker level, however, the efficacy is less clear. In particular, when comparing regions affected differently by economic shocks, it has been found that the primary effect is a decline in in-migration rates (Dustmann et al. 2017; Gathmann et al. 2020), despite claims in classical references that increased out-migration rates is the equalizing force (Blanchard et al., 1992). Additionally, Marinescu and Rathelot (2018) and Manning and Petrongolo (2017) found that workers' job searches are discouraged by the distance to open vacancies, contributing to the low geographical mobility observed during economic downturns. It is also important to study additional sources of adjustment, which may significantly affect the workers' adjustment. Sectoral mobility is one such alternative. Utar (2018) in Denmark, Dix-Carneiro (2014) in Brazil, and Walker (2013) in the U.S. found that even though adjustment through sectoral mobility is small compared to the number of workers hit by a shock, sectoral mobility plays a significant role in the labor market adjustment of workers, supporting earlier documentation by Carrington (1996). Using regional and detailed worker characteristics, I contribute to this debate by documenting the relevance of adjustment through geographical and sectoral mobility after a large shock.

Furthermore, I contribute to the growing literature estimating the similarity of job requirements between occupations (or industries). Previous papers exploited mobility flows among occupations/industries (Shaw 1987; Schubert et al. 2020), skill and task similarities (Macaluso et al. 2017; Gathmann and Schönberg 2010, and worker composition and qualification similarity (Caldwell and Danieli, 2018). Instead, I estimate a reallocation index, which captures the most likely transitions by exploiting worker similarities between sectors. At the regional level, this measure estimates how changes in the composition of jobs could affect employment opportunities.

Identifying the relevant labor market for each worker is crucial to assessing how job composition affects employment opportunities. Worker flows were used by Schubert et al. (2019) to identify local job opportunities. According to their study, labor market concentration has a significant effect on wages. In their analysis, worker flows capture asymmetrical transition probabilities. However, this approach relies on the stability of job transitions between occupations and industries, which may be violated during recessions. I capture industry similarity by comparing the sector's workforce, as in Caldwell and Danieli (2018), who constructed an index of the value of workers' outside options in Germany. I create a reallocation index, which reproduces the most likely changes by capturing the suitability of each sector conditional on the local specialization and worker characteristics.

Beaudry et al. (2012) showed that changes in the availability of high-wage jobs within a region have considerable wage spillover effects. Those changes impact workers' outside options and compensation through wage bargaining. I propose that variation in the local sectoral composition may also affect workers' adjustment opportunities, which influence wages immediately and have a persistent influence as workers struggle to recover their previous earnings trajectories.

Two papers that are closely related to mine are Macaluso et al. (2017), which examined how laid-off workers' outcomes differ based on the similarity of local occupations, and Yi et al. (2016), which used labor market transitions to demonstrate that workers in inflexible labor markets, i.e., those in regions where the sectors with a similar skill requirement are scarce, will have a larger impact from mass layoffs. The latter study estimated an index that captures the potential reallocation of workers from a particular sector and focuses on the relevance of skill transferability among sectors. However, both articles concentrate on regional differences rather than considering how workers within the same labor market may respond differently to the same shock. As a contributor to this literature, I demonstrate that sector composition affected the likelihood of finding a good match, based on the characteristics of the worker and other relevant regional characteristics, during the Great Recession.

1.2 Theoretical framework

To motivate my empirical analysis, I present a simple model in which workers may switch their initial sector in response to direct shocks. I capture how a worker's reaction is influenced by the regional composition of sectors, affecting their set of relevant employment options.

Workers and firms: Consider an economy characterized by S sectors (indexed by s) and R regions (indexed by r). In this scenario, workers are mobile across sectors but not between regions.[6] They are identified by the vector of characteristics X, and firms are grouped into J sectors. Following this notation, X_i represents the characteristics of a worker i and j_f the sector of firm f.

Workers live for T periods after labor market entry, and firms live forever. Workers in the construction sector are identified by $(s = 1)$ and face a region-specific probability of losing their job μ_r. When faced with this situation, workers search for jobs and may receive offers from construction and other sectors.

Matching: Firms and workers are brought together through a search process, which takes time and is random. In order to fill the vacancy, firms publish job opportunities that contain a take-it-or-leave-it wage offer. For construction workers, the posted wages are the average for workers with the same characteristics X_i. The function $w(X_i)$ captures the wage of a worker in the construction sector with

[6] For expositional purposes, I focus on sectoral mobility. However, I also allow geographical mobility in the empirical results.

characteristics X_i. Finally, I assume the earned wage in other sectors is the same regardless of their characteristics and region, which I normalize to one.[7]

In the spirit of Burdett and Mortensen (1980), I assume job seekers randomly receive job offers within their labor market.[8] As in Schubert et al. (2020), I follow a probabilistic definition of the worker's relevant labor market. By defining this as a region, the set of possible jobs would be overestimated. Thus, I consider that workers receive random offers based on their likelihood of finding employment in that industry, conditional on their characteristics.

For simplicity, I first present the framework considering that workers have the option to reallocate into another sector and receive offers with probability $\mathbb{P}(X_i, r)$, which depends on their region,r, and their characteristics X_i. I then expand this measure to explicitly account for changes in the composition of workers and firms in each local labor market.

Timing: Employed workers receive their earnings at the beginning of the period. Similarly, unemployed workers are randomly given job offers based on their region and characteristics.[9] Suppose the probability that worker i will receive an offer from the construction sector is captured by the sector's employment share (σ^r_{cs}). I use it as a proxy for the local labor demand in the construction sector.[10] Also, the probability that the worker receives an offer from another sector is represented by $\mathbb{P}(X_i, r)$. Lastly, if the workers are not matched, I assume they receive a zero payoff.

Framework: The period utility of worker i at time t is represented by the value function $V_t(X_i, r)$:

$$V_t(X_i, r) = w(X_i) + (1 - \mu_r)V_{t+1}(X_i, r) + \mu_r\tilde{V}_{t+1}(X_i, r),$$

$$\tilde{V}_{t+1}(X_i, r) = \sigma^r_{cs}V_{t+1}(X_i, r) + (1 - \sigma^r_{cs})\mathbb{P}(X_i, r),$$

where $\tilde{V}(X_i, r)$ denotes the continuation value if the shock hits the worker, this function captures the reemployment probability and the probability of the workers finding a job in another sector.[11] The employment share of the construction sector in a region influences the probability of workers receiving offers from the sector. Additionally, job offers from other sectors are caught by $\mathbb{P}(X_i, r)$, which depends not only on employment shares but also on the likelihood that workers with char-

[7]This assumption is later relaxed in the empirical results allowing earnings to differ by sector and region.

[8]Hall and Krueger (2012) find evidence consistent with wage posting mainly for low-skilled workers, which in the case of the construction sector are most of the employed workers.

[9]It is assumed that in unemployment, the workers get a zero payoff, so the outside option of the worker, in this case, is zero. In a more realistic environment, we could assume workers receive unemployment benefits, which are strictly less than the payoffs in any other sector.

[10]Schubert et al. (2020), and Caldwell and Danieli (2018) apply a similar assumption to their estimation.

[11]If the worker gets a job in another sector, the contract lasts until the worker dies. Therefore, the present value of their earnings is just the sum of earnings until period T.

acteristics X_i are matched to a firm in each sector. If the worker did not receive an offer from a construction firm or another company, they remain unemployed and have a payoff equal to zero during that period.

Combining expression (1.2) and (1.2):

$$V_t(X_i, r) = \underbrace{w(X_i) + V_{t+1}(X_i, r)}_{\text{Utility in absense of shock}} \underbrace{-\mu_r(1-\sigma^r_{cs})V_{t+1}(X_i, r)}_{\text{Impact of the shock}} + \underbrace{\mu_r(1-\sigma^r_{cs})\mathbb{P}(X_i, r)}_{\text{Attenuation of the shock}}.$$

Equation (1.2) shows that the shock attenuation depends on the possibility of reallocating and the reemployment opportunities in the same sector. In the absence of the shock, workers in the construction sector know how much they will earn, as it evolves along with their characteristics over their life cycle profile. As a result, if workers cannot switch sectors, the shock's impact is just the future earnings discounted by the probability of losing their current job.

Equation (1.2) has a representation in terms of pre-shock earnings. Let $W_0(X_i)$ be the initial earnings of an individual i. Then, dividing both sides of the equation by $W_0(X_i)$, the following equation is obtained:

$$\frac{V_t(X_i, r)}{W_0(X_i)} = \frac{w(X_i) + V_{t+1}(X_i, r)}{W_0(X_i)} - \mu_r(1-\sigma^r_{cs})\frac{V_{t+1}(X_i, r)}{W_0(X_i)} + \mu_r(1-\sigma^r_{cs})\frac{\mathbb{P}(X_i, r)}{W_0(X_i)}.$$

The previous expression presents the future worker's earnings as a function of their characteristics X_i, the intensity of the shock μ_r, the reemployment probability σ^r_{cs}, and the worker's attenuation through sectoral mobility $\mathbb{P}(X_i, r)$. Additionally, the normalization by the worker's current earnings allows for assessing the impact of the shock in terms of the initial earnings. This equation is the starting point in the empirical exploration of the impact of the employment decline in the construction sector on workers' earnings trajectories. Next, I will re-express the previous equation in a way that can be estimated.

$$E_i = X_i\beta + Shock^r_i\delta + EmplShare^{cs}_i\gamma + Shock_i Prob_i\Gamma.$$

In the previous expression, E_i is the normalized future earnings of worker i, X_i is the vector of a worker's characteristics. $Shock^r_i$ represents the intensity of the shock on the worker's province. $EmplShare^{cs}_i$ and $Prob_i$ are the construction and other sectors' reemployment probabilities, respectively. The parameters of interest are δ and Γ, which measure the impact of pre-shock earnings on the labor market trajectories and the worker's attenuation of the shock.

Studying the interaction between workers' characteristics and the local sectoral composition requires estimating the probability of finding a job in another sector. Therefore, I propose a reallocation index. In this approach, workers' opportunities are defined by the size and likelihood of transitioning between sectors. This measure, which will later be used in the empirical analysis, will be briefly discussed below.

Reallocation probabilities: As mentioned before, I follow a probabilistic definition of the relevant labor market similar to Schubert et al. (2020). The job opportunities are a function of workers' matching probabilities to each sector and the sector's size locally. I assume that workers receive offers as a function of how well their characteristics match the other sector's workforce,[12] which I capture with the term:

$$p_{j,i} = \frac{P(X = X_i, J = j)}{P(X = X_i)P(J = j)}$$

Equation (1.2) represents the likelihood that a worker i is hired in a firm in sector j. $P(X = X_i, J = j)$ is the probability of observing a match between a worker with characteristics X_i and a job in sector j. $P(X = X_i)P(J = j)$ is the product of the marginal distributions for worker characteristics and the firm sector. This product is the probability of observing a match with such characteristics under a random assignment. The basic intuition for this result is that the probability of observing i matched with j depends on the frequency and accountability for the total measure of workers and jobs with such observables.

I add up the propensities across all the sectors and weigh them by their employment share ($P(J = j|R = r)$). Based on the worker's characteristics X_i, employment shares capture the framework's random matching aspect as their chances of being offered a job in the sector depend on its size. Finally, by rearranging terms, I get the following expression for the reallocation index:

$$\begin{aligned} Reallocation(X_i, r) &= \sum_j \frac{P(J = j, X = X_i)}{P(X = X_i)P(J = j)} P(J = j|R = r) \\ &= \sum_j \frac{P(J = j, X = X_i)}{P(X = X_i)} \frac{P(J = j|R = r)}{P(J = j)} \\ &= \sum_j P(J = j|X = X_i) \frac{Share_j^r}{Share_j} \end{aligned}$$

1.2.1 Empirical predictions

1. Based on the characteristics of workers, reallocation probabilities differ between and within regions. Available jobs may vary based on worker characteristics and local sectoral composition.

2. The shock may have a large impact on workers, but if they have good prospects in other sectors, i.e., if they have a large $\mathbb{P}(X_i, r)$, then the shock will only have a minor impact.

[12] In Section 1.7, I apply another measure that exploits the transition probabilities conditional on the worker's characteristics.

3. Worker valuations of their characteristics may differ, which impacts shock attenuation. Different reallocation probabilities explain this.

1.3 Data

The primary data sources are the 2006 to 2017 editions of the *Muestra Continua de Vidas Laborales* (MCVL), best translated as "Continuous Sample of Working Lives." The raw data represents 4% of the Spanish population registered with Social Security (workers, recipients of unemployment benefits, and pensioners). The observational unit tracks any change in the individual's job status or variation in their characteristics.

This rich dataset is built from Spanish administrative files matching Social Security, income tax, and census records. The data has a longitudinal design: those initially sampled are also selected yearly, as long as they still have a relationship with Social Security. The benefit of using multiple waves of the MCVL is the expansion of the dataset. Each year, the sample is refreshed by replacing individuals who leave the Social Security rolls with new individuals, thus allowing the tracking of individuals' complete labor market history.

The MCVL also offers earnings information derived from social security and tax records. Earnings information from Social Security records is available from 1980 or the beginning of the worker's career. Earnings from the Social Security Administration are restricted by upper and lower limits and updated based on inflation and general labor market conditions. As for the tax records, they are not bound but are only available between 2006 and 2017. The limited availability of the tax information is only a minor concern, as my main analysis focuses primarily on 2007-2013 earnings. For this reason, I rely on earnings from tax records when available. An example of cases where it is not available is the autonomous communities of Basque Country and Navarre, which collect income taxes independently of the Spanish government, so tax records cannot be obtained from those regions. In those cases, I use earnings information from Social Security records instead. [13]

Using the MCVL, I build a monthly panel covering 2000 to 2017. This data combines individual, firm, and job characteristics. It includes information on the worker's gender, educational attainment, date of birth, activity sector at the two-digit level, province of the establishment, occupational contribution group, and monthly earnings or unemployment benefits. The raw data has information on each employment spell's entry and exit date, which I use to compute individual

[13] Bonhomme and Hospido (2017) compares earnings from tax and Social Security records, suggesting the difference is primarily a concern at the top of the distribution, around the 90th percentile. However, construction workers are below the middle of the earnings distribution, making both earnings sources comparable.

experiences and the number of monthly days employed. I use the number of employed days within the month to transform the yearly earnings from tax records into daily earnings, simplifying the comparison with the monthly earnings available from Social Security records.

1.3.1 Sample restrictions

I restricted my analysis to individuals registered in the general regime of Social Security or the special regime for agrarian, sea workers, and mining. This restriction excludes self-employed workers due to unreliable information on earnings and days worked. The regional information considers only the 50 Spanish provinces, excluding the two autonomous cities of Ceuta and Melilla, due to the limited size of those regions.

I construct two sub-samples: i) The complete sample, from which I derive all the descriptive evidence. This dataset is a monthly panel from January 2000 to December 2017, and I limit it to active workers aged 18 to 60. ii) The second sample is labeled the estimation sample, which I limit to native workers employed in the construction sector before the Great Recession. Following their information from January 2007 to December 2013.

To estimate and describe the shock, I restrict the sample to workers with a high attachment to the construction sector. They are defined as individuals employed in the sector for at least one year between 2005 and 2006. Those workers are more likely affected by the sector's employment contraction than those with low attachment. Additionally, for the primary analysis, I calculated the cumulative earnings between 2007 and 2012. To avoid measurement bias due to early retirements in calculating cumulative earnings, I limited the sample to individuals aged 20 to 50 in 2007. Lastly, a price index deflates earnings information to prevent mechanical changes caused by price fluctuations during the business cycle.

1.3.2 Computation of the reallocation index

This section describes the procedure for estimating the reallocation index. This index exploits cross-sectional allocations of observably similar workers across sectors before the Great Recession, and I employ it to estimate the relevant job options for each worker during the recession. The baseline assignment captures workers' suitability for jobs within each sector based on their observable characteristics. This utilizes equation (1.3.2), as explained in Section 1.2. It is necessary to determine the probability of being employed in each sector based on the worker's characteristics and the relative employment size of each sector by province. As a result, I divide the estimation process into two steps.

First, I estimate the likelihood of observing a match between a worker and a firm in each sector, based on a given set of worker characteristics X_i. The MCVL consists of pairs of matches between workers and employers, allowing me approximate workers' employment probabilities in each sector. Second, I weigh the prior probabilities by the sector's employment share in the worker's province of residence before the shock. During the Great Recession, workers' geographical mobility was limited. As a result, the distribution of jobs in their province of residence before the recession is a good proxy for each individual's local labor market.

$$Reallocation(X_i, r) = \sum_{j=1}^{J} \mathbb{P}(J_f = j|X_i) \frac{EmplShare_j^r}{EmplShare_j}.$$

The two-step process is as follows. I use the actual worker allocations in different sectors before the Great Recession, specifically for 2000-2004. In this step, I work with the whole population of workers not employed in the construction sector during those years.[14] I regress an indicator variable of the individual's firm sector on an array of worker characteristics. The control variables are skill level in the occupation, gender, foreign-born status, and interactions of age categories with educational attainment. Based on the estimated coefficients, I get the predicted probabilities in the estimation sample. This step captures the probability of finding a plausible match between a worker i and a sector j. I repeat this process for each sector.[15] In the second step, I combine the predicted values using weights based on the ratio of the employment share of sector j in province r, and on the employment share of sector j in the entire economy. Both weights are measured in 2006, to avoid potential bias caused by employment changes driven by the Great Recession. To simplify the interpretation, the reallocation index is standardized so that the mean is zero and the standard deviation is unitary.

As an example, consider a situation with a random allocation of jobs across regions. Consequently, the sectoral composition of each region's local economy reflects that of the aggregate economy. This implies that similar workers face an equivalent set of relevant labor market options, regardless of their province of residence. In such a case, we expect heterogeneity in the shock's impact based on worker characteristics, but not between provinces. However, in practice, a significant impact heterogeneity is not explained by workers' characteristics. Workers may be more (less) lucky as their characteristics are more (less) valued in their region of residence, i.e., they may have more options close to their observed characteristics since there is variation in the local sectoral composition. Because of this, even under the same exposure to the shock, similar workers may have very different prospects depending on their region of residence.

[14] The results are not significantly different when I use different time windows.
[15] I consider 13 sectors, which are enumerated in Appendix 1.C.

1.4 Description of the Construction Sector

Table 2.6 provides descriptive statistics of construction workers before and after the Great Recession. For this sample of workers, fixed-term contract employees constituted 64.1% of total employment in 2007 but were down 28.6% by 2012.[16] According to Bentolila et al. (2012), fixed-term contracts' hiring flexibility promoted construction sector growth. The reason is that it simplifies hiring workers in an economic activity that relies on pre-specified contract time. In the Spanish labor market, the implementation of temporary contracts increased employer flexibility, a policy to reduce the unemployment rate. However, as a side effect, the decline in employment shares of those workers during the Great Recession shows how vulnerable they are to economic fluctuations.

Additionally, Table 2.6 shows that the proportion of young, low-skilled, and foreign workers decreased during the Great Recession. Despite this, does this evidence suggest that these workers were the most affected by the Great Recession? Not necessarily; workers with those characteristics were the most vulnerable, evident from the employment decline of each group. However, the sector also experienced a change in the composition of newcomers (Table 1.12) as well as leavers (Table 1.13). Fewer young workers enter the sector, and the proportion of those leaving shifted over the years. Additionally, answering who is the most affected requires considering how the workers adjusted to the job loss. Within the following sections, I explore the employment changes experienced by the sector and which individuals were most affected by the employment contraction in more detail.

1.4.1 Employment decomposition

Over the last two decades, the construction sector has experienced large employment fluctuations. To better understand the sector's evolution, I examined the employment shifts in the construction sector from 2004 to 2017. I divide the sector's inflows and outflows into non-employment, unemployment, and outside the sector.

I define the inflows rate to the construction sector at time t as follows:

$$Inflows_{k,t} = \frac{I_{k,t}}{N_{t-1}},$$

where $I_{k,t}$ denotes the number of individuals entering the construction sector from status k, whether inflows come from unemployment, non-employment, or other sectors at time t.

[16]The use of fixed-term contracts in Spain was liberalized early with the labor reform in 1984. Subsequently, it became usual for workers to follow a long sequence of temporary contracts in Spain.

Table 1.1 Descriptive statistics of workers in the construction sector

	2004	2007	2012	2017
Age				
< 24	0.162	0.132	0.043	0.030
24-35	0.452	0.449	0.362	0.237
35-45	0.244	0.272	0.370	0.410
45<	0.143	0.147	0.225	0.323
Average age	33.6	34.3	38.1	40.7
Education				
Below secondary	0.764	0.753	0.661	0.675
Secondary	0.153	0.158	0.195	0.185
Tertiary	0.083	0.089	0.143	0.140
Type of contract				
Part-time	0.038	0.038	0.077	0.092
Fixed-term	0.727	0.666	0.478	0.508
Foreign born	0.157	0.270	0.187	0.191
Occupations				
Very-high skilled occupations	0.020	0.023	0.049	0.043
High skilled occupations	0.043	0.046	0.078	0.069
Medium-high skilled occupations	0.053	0.054	0.084	0.073
Medium-low skilled occupations	0.579	0.599	0.629	0.640
Low skilled occupations	0.305	0.278	0.161	0.175

Notes: In the table above, we find the main characteristics of workers in the construction sector in 2004, 2007, 2012, and 2017.

Similarly, I define the outflows rate from the construction sector at time t as:

$$Outflows_{k,t} = \frac{O_{k,t}}{N_{t-1}},$$

where $O_{k,t}$ denotes the number of individuals leaving the construction sector to status k at time t. k represents whether the worker stays in non-employment, is unemployed, or moved into another sector at time t. In both equations, N_{t-1} is the total of workers in the construction sector at time $t-1$.

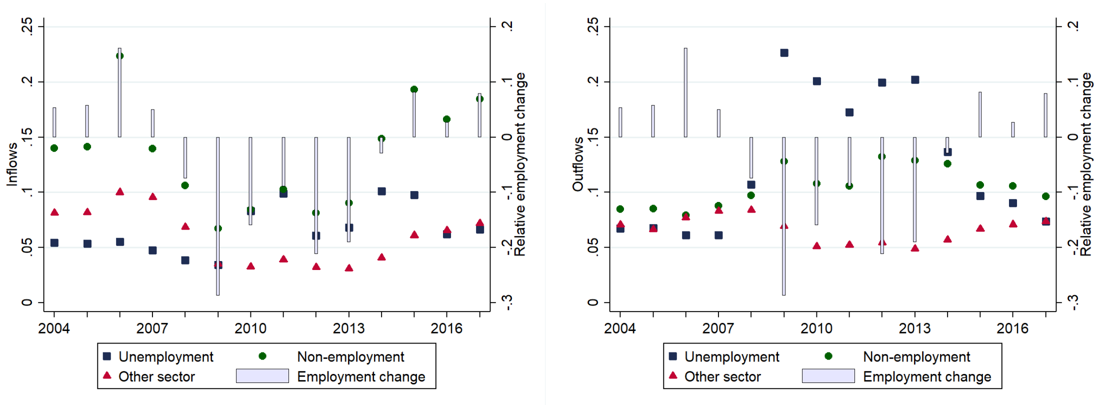
For comparison, I present the yearly employment change in the construction sector. Defined as:

$$EmploymentChange_t = \frac{Empl.Construction_t}{Empl.Construction_{t-1}} - 1.$$

I show the results of this decomposition in Figure 3.11. Panels (a) and (b) present inflows and outflows, respectively. The blue bars in both figures represent the relative changes in construction employment.

According to Panel (a), inflows from unemployment, non-employment, and other sectors had a similar evolution. During this period, inflows from non-employment

Figure 1.2 Aggregate flows from/to the construction sector



(a) Inflows to the construction sector (b) Outflows from the construction sector

Notes: Panel (a) Inflows to the construction sector: individuals that one year before were in another sector, non-employment or unemployment as a proportion of the workers in $t-1$. Panel (b) Outflows from the construction sector that one year before were in another sector, non-employment or unemployment as a proportion of workers in $t-1$. The sample is restricted to yearly observations between 2003 and 2017 of workers aged 18-60.

accounted for most of the employment growth, which was more evident during the construction boom. In 2006, non-employment inflows spiked from 15 to 22 percent of the construction sector's population, primarily explained by an increase in the migrant population at that time. In 2005, there was a large legalization episode of foreign-born workers in Spain (Moraga et al., 2019). This event resulted in a significant increase in the number of immigrants in Social Security records, impacting the number employed in the construction sector. Table 2.6 shows that 15.7% of workers were foreign-born in 2004, increasing to 27.9% right before the Great Recession.

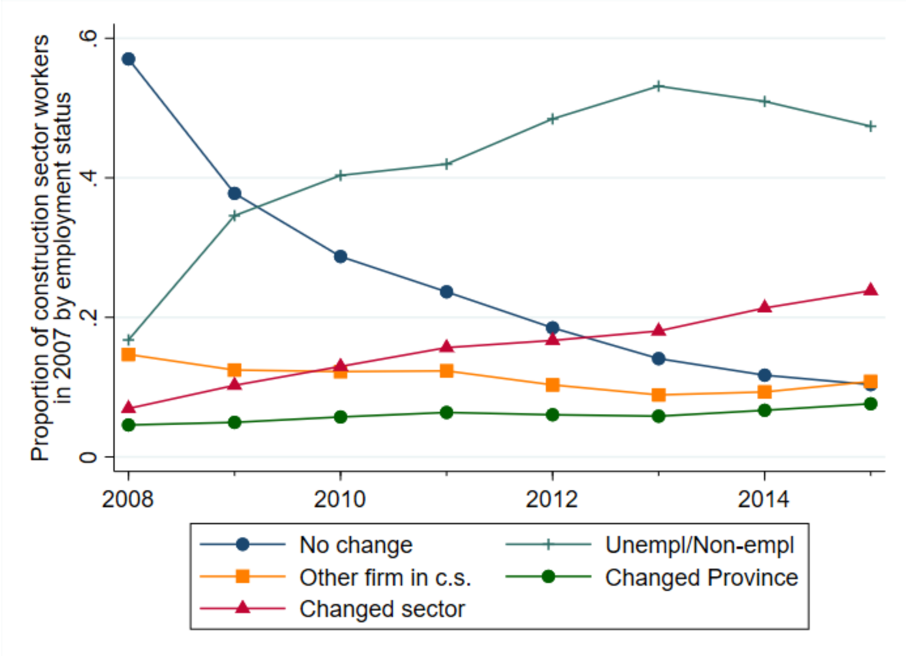
During the expansionary period, relatively high salaries were paid to low-educated workers, resulting in many young individuals dropping out of education and entering the sector (Lacuesta et al., 2020), contributing to the large inflows from non-employment before the Great Recession.

As shown in Figure 3.11, outflows into other sectors do not account for a large fraction of the observed employment decline. However, workers' dynamic decisions are hidden in aggregate flows, making it difficult to gauge the worker's adjustment process. In the following exercise, I restrict my analysis to workers in the construction sector in 2007 and track their working status yearly, considering five scenarios: if they remain in the same firm, work in another firm in the same sector and province, move to another region, move to another sector within the same region, or stayed unemployed/non-employed.

The results are presented in Figure 1.3, in which I emphasize three main points.[17]

[17] I present in appendix 1.20 the same graph for high-skill workers as a comparison group largely unaffected by the shock. Additionally, I present in appendix 1.21 the same graph for a sample of workers in the construction sector in 2003, which compares changes in the working status before

Figure 1.3 Working status of individuals employed in the construction sector in 2007



Notes: The shares are computed based on workers in the construction sector in 2007, and every year I tracked their working status up to 2015. The sample is limited to native workers employed in the construction sector in 2007.

Most construction workers lost their jobs during the housing bubble bust. As of 2015, only 10 percent of workers held the same job as in 2007, and only 20 percent remained employed in the construction sector. Second, 42 percent of workers in the construction sector in 2007 were no longer employed in 2015. Among those individuals are unemployed workers, international migrants, people working in the informal sector, or those out of work.

Finally, the results suggest that moving to another sector becomes more important as overall adjustment increases. About 30% of construction workers found a job outside the sector in 2015, as opposed to the lower percentage of internal migration. Within a year of the housing bubble burst, a large fraction of workers moved to a different province; in 2008, 5.5% of workers lived in a different province than in 2007. After three years, however, this percentage does not change significantly, increasing by only three percentage points, while workers changing sectors increased from 9 to 30 percent of the reference population during the same period.

Different factors are responsible for the employment decline in the construction sector. However, this analysis does not provide information about long-term earnings or employment losses. Job loss is widely documented to have negative and persistent effects on worker outcomes. Identifying the most vulnerable workers and their adjustment is crucial to understanding the impact of negative shocks. In light of this, it is natural to ask which workers are most likely to be found in each em-

the Recession.

FIGURE 1.4 Characteristics of workers initially in the construction sector by employment status in 2013

(a) Average age (b) Share of foreign workers

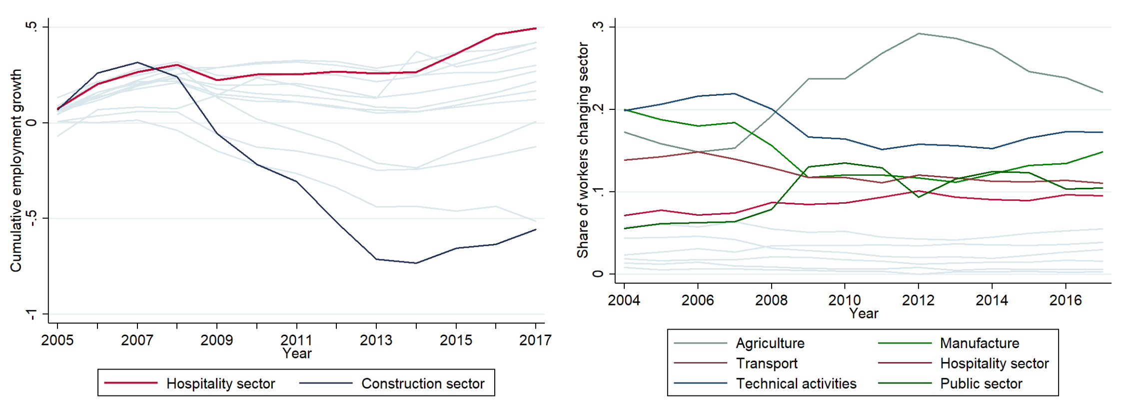
Notes: Panel (a) Average age in 2007 of workers in the construction sector by status in 2013. Panel (b) Share of foreign workers in the construction sector by status in 2012. The sample is restricted to workers in the construction sector in 2007 and aged 20-55 years old.

ployment status after the housing bust.

Figure 1.4 shows the average age and the proportion of foreign-born workers in the different categories of working status in 2013. As above, these results are based on the sample of workers employed in the construction sector in 2007. According to the results, workers who changed regions or sectors are younger than those who stayed in the construction sector or stayed unemployed. Over the past decade, a large fraction of workers have been employed in temporary contracts. The situation is much more prevalent among young workers waiting for permanent positions. Because of this, those workers are more vulnerable to job loss during a recession because they may be dismissed at a much lower cost than similar workers in permanent positions. Still, they also have more flexible human capital due to lower tenure and job-specific experience, which makes them find optimal to change sector or region as the opportunity cost to change is smaller compared to workers with more specific human capital (Neal 1995; Gathmann and Schönberg 2010).

Panel (b) shows that foreign workers are over-represented in non-working conditions and among those who changed regions. It is consistent with foreign workers migrating more frequently (Cadena and Kovak, 2016). I also present evidence in Appendix 1.D that foreign workers in the most exposed regions are more likely to leave administrative records. Spain's data does not track workers who leave the country, which largely explains the higher fraction of unobserved foreign workers during that period, justified by the return migration of this population. After returning to their home country, individuals may have reduced cumulative earnings, not necessarily because they worked less or received a lower wage, but because they are no longer observed. In order to avoid such measurement bias, I restrict the estimation sample to native workers in the rest of the paper.

Figure 1.5 Cumulative employment growth and destination sector of switchers



(a) Cumulative employment growth (b) Movers by destination sector

Notes: Panel (a) Sector of destination as the proportion of total movers by year from the construction sector, 2004-2017. Panel (b) Cumulative yearly employment growth per sector, 2005-2017.

The period of economic expansion in Spain was characterized by many changes, including greater use of temporary contracts, substantial inflows of foreign workers, and increased availability of land for construction, which implied a significant increase in construction employment. During that period, many workers reallocated to another sector, as evidenced above. Panel (a) of Figure 1.5 presents the large employment decrease in the construction sector and the growth in others. For instance, it shows the employment growth in the hospitality sector and the employment stability in many others.

Is there a complete reallocation of workers from the shrinking sector to the hospitality sector? The short answer is no. All Spanish provinces were affected by the contraction in construction employment. Nevertheless, those provinces have a different sectoral composition, which makes exposed workers dependent on the local labor demand. Consequently, the adjustment depends not only on the cost of changing sectors or the likelihood of individual workers switching sectors. In addition, it is dependent on their skill set's relative demand. As an exploratory exercise, panel b) of Figure 1.5 shows how workers initially in the construction sector moved to very different sectors, the heterogeneity I will exploit in the construction of a reallocation index.

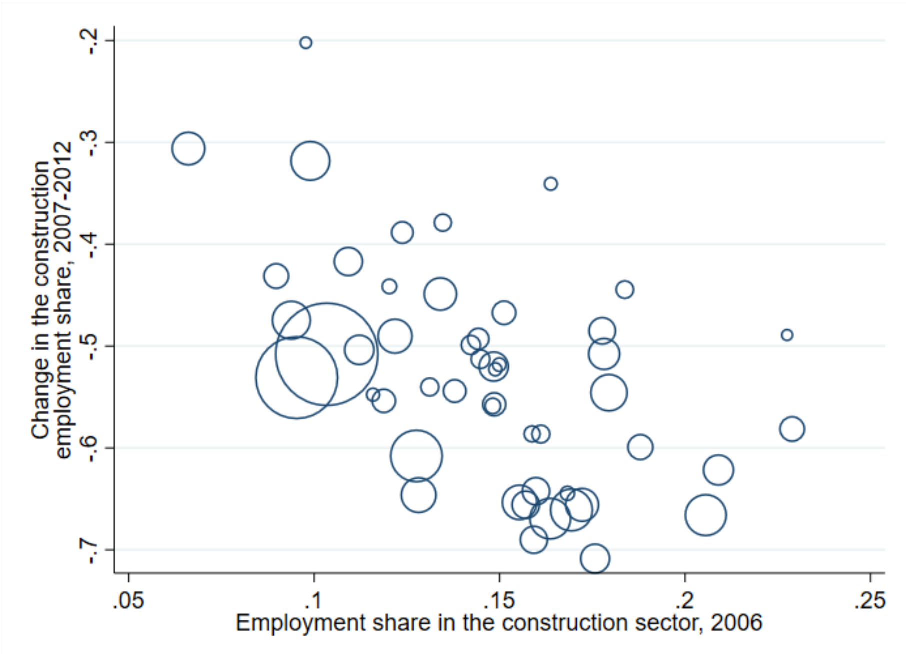
1.4.2 Province level impact

The initial employment share and the employment contraction of the construction sector during the Great Recession differed among the Spanish provinces.[18] My empirical analysis exploits the asymmetric regional decline in job opportunities based on these exposure differences.

[18] I use March of 2006 as my initial period, this is a reasonable time as, at the moment, there are no signs of contraction, this started to be apparent in the fourth quarter of 2007 Figure 1.1.

The initial employment share of the construction sector by province ranges from 6.8 to 24.14 percent (Figure 1.6), such that the employment share is higher in the southern provinces. For example, in Gipuzkoa, Araba, and Barcelona, the construction sector employed less than 10% of workers, while in the southern provinces of Ciudad Real, Huelva, and Malaga, it was more than 20%. Employment contraction also varies significantly by province, ranging between 14.7% and 70.3% of employment in 2007.

Figure 1.6 Employment share of workers in the construction sector by province, 2007-2012.



Notes: Change in the employment share of the construction sector by province between 2007 and 2012 against employment share in 2006. The computation of employment shares is based on yearly data. The sample considers the 50 Spanish provinces and all workers employed in April of each year.

1.5 Worker level impact: Employment decline in the construction sector

This section examines how the shock to the construction sector affected workers' earnings and employment paths. The results are based on the estimation sample, as further described in Section 2.2. This sample consists of native workers highly attached to the construction sector before the Great Recession. Highly-attached workers are individuals employed in this sector for at least 12 months between 2005 and 2006. The identifying assumption is that local employment contraction of the construction sector is as good as randomly assigned, conditional on observables. The estimated impact is based on comparing workers with similar characteristics, except for their province of residence before the Great Recession.

The baseline specification in this section takes the form:

$$y_i = Shock_i^r \beta_0 + \mathbf{X}_i' \Delta + \epsilon_i,$$

where the normalized cumulative earnings of individual i are represented by y_i. Cumulative earnings are non-zero earnings from January 2007 through December 2012, divided by the 2005-2006 average annual earnings. Normalizing by average earnings is equivalent to the approach by Autor et al. (2014) and Yagan (2019), which helps assess the shock's effect on the earnings evolution and interpret the future results in terms of pre-shock earnings.[19]

$Shock_i^r$ represents the change in the employment share in the worker's initial province of residence between 2007 and 2012.[20] X_i represents individual worker and regional characteristics. The full set of controls includes gender, occupational skill level, tenure, experience, an indicator for fixed-term and part-time contracts, and interactions between age categories with educational attainment, all at the worker's 2007 values. Additionally, I consider regional controls, including the construction sector's employment share and the unemployment rate (as of 2006) in the province of worker residence, a Bartik-type variable that accounts for differential demand shocks in the other sectors,[21] and a Herfindahl-Hirschman Index for the employment concentration in the other sectors, used to capture the overall diversity of the local sectoral composition. The results will indicate whether the set of controls differs for each specification.

In Table 1.2, I provide baseline estimates of equation (1.5). Column (1) includes the shock and a full set of age dummies, interacted with the worker's gender and educational attainment to account for variations in their life cycle earnings. On average, workers in the most exposed provinces who were initially employed in the construction sector accumulated fewer earnings between 2007 and 2012, compared to similar workers in the least exposed regions. In the least and most affected provinces, respectively, the cumulative earnings during the Great Recession for an average worker dropped by approximately 0.75 and 2.62 times their initial yearly earnings. In Column (2), I also include variables associated with job characteristics at baseline: occupation skill group, type of contract, tenure, and experience fixed effects. The main coefficient in this regression is attenuated by 35 percent compared to the results in Column (1), but it still suggests a significant impact from the shock.

Column (3) presents my preferred specification. Additionally, I include regional controls and a Bartik-type shock, the latter accounting for demand shocks in other

[19] This measure also avoids the problem of undefined log earnings when earnings are zero.

[20] $Shock_i^r = \frac{emplShare_{2012}^r}{emplShare_{2007}^r}$-1, where $emplShare_t^r$ represents the employment share in the construction sector at region t in period t.

[21] The Bartik shock controls for trends on employment in non-construction sectors. It is constructed as $\sum_{j=1}^{12} ln\left(\frac{Employment_{2012}^j}{Employment_{2007}^j}\right) Share_r^j$. Here, $Employment_t^j$ accounts for the number of workers in sector j at time t and $Share_r^j$ is the share of workers in sector j in region r.

Table 1.2 Cumulative earnings impact from the employment decline of the construction sector, 2007-2012

	(1)	(2)	(3)	(4)	(5)
			OLS		IV
			Cumulative earnings, 2007-2012		
Shock	-3.704***	-2.723***	-1.956***	-2.028***	-2.244***
	(0.458)	(0.306)	(0.274)	(0.299)	(0.598)
Constant	5.574***	6.692***	6.765***	6.810***	6.830***
	(0.277)	(0.306)	(0.229)	(0.234)	(0.271)
Observations	45370	45370	45370	45370	45296
R^2	.1082	.1974	.2009	.2008	.1997
Controls	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses are clustered at the province level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Column (1) adds interactions of age categories with gender and education. Column (2) adds occupational skill group categories, indicators for part-time and fixed-term contracts, tenure, and experience fixed effects. Column (3) adds regional controls: local unemployment rate and employment share of the construction sector in 2006, a Bartik-type shock, and the HHI index. Column (4) considers as a shock the change in total workers in the construction sector between 2007 and 2012. Column (5) instruments the decline of the employment share of the construction sector with the cumulative growth rate of the construction sector between 2000 and 2006.

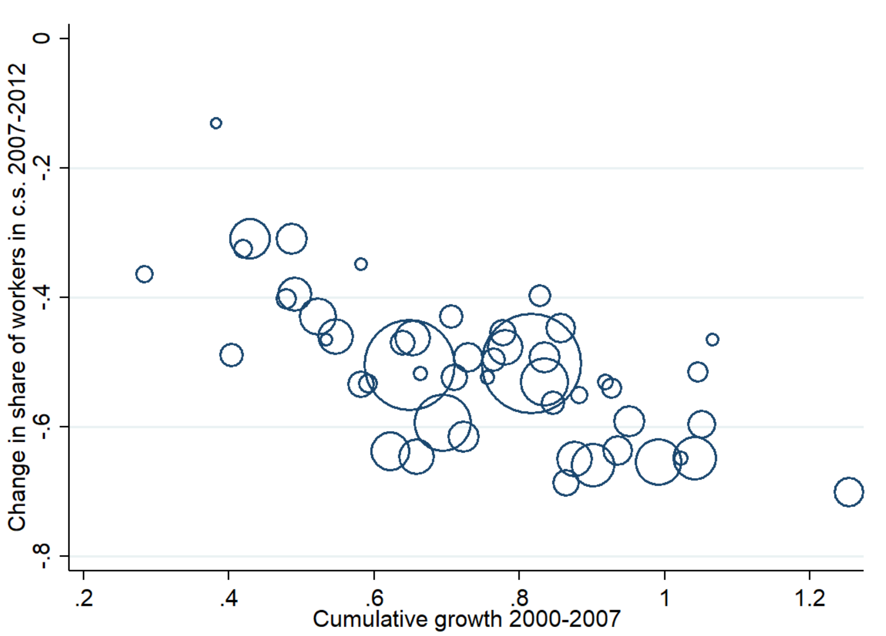
sectors during the Great Recession. Other sectors may experience positive or negative shocks during the study period, which can be captured by the coefficient of the construction sector shock. The Bartik-type variable accounts for such variation, which limits the concern of correlated shocks to other sectors.

To interpret the coefficient estimates of this specification, consider two workers residing in provinces in the 75th and 25th percentile of exposure, respectively: Valencia, where the employment decline in the construction sector was 59.34%, and Badajoz, where it was 45.53%. On average, workers experienced a greater impact due to higher exposure to the construction sector's employment decline. A construction worker in Valencia would accumulate 27% fewer earnings than a similar worker in Badajoz.

Finally, Columns (4) and (5) examine how possible sources of bias may influence the results. First, changes in the province's overall population may affect the estimated employment share in the construction sector, creating a measurement bias. In order to prevent this, I kept constant the number of employed workers by province between 2007 and 2012. Therefore, the shock is the change in employed workers in the construction sector between 2007 and 2012.[22] The results of this estimated measure are presented in Column (4). As a result of this adjustment, the main coefficient is slightly attenuated, with a 3.7% change in the estimated coefficient.

[22]The new shock is: $Shock = \frac{Empl.CS_{2012}}{Empl.CS_{2007}} - 1$. As a result, the shock only captures changes in employment in the construction sector, independent of other sectoral variations in employment.

FIGURE 1.7 The cumulative growth in the construction sector and employment decline of the construction by province



Notes: Monthly share of construction workers, January 2004 to December 2017. The data is restricted to workers aged 20-60 employed during the reference period.

Supply-side factors likely mitigate the contraction effects in the construction sector. Workers who leave the province or leave the formal labor market attenuate the decline in job opportunities for those initially employed in the construction sector. Column (5) presents the results following an instrumental variable approach, which aims to capture the demand-side component of the shock on individual outcomes.

The instrument is constructed using cumulative employment growth in the construction sector between 2000 and 2006 in the worker's province of residence. I take advantage of the fact that regions experiencing a particularly large boost during the housing boom also tend to experience the biggest busts. The construction sector's cumulative growth before the Great Recession is not related to earnings during the Great Recession, satisfying the exclusion restriction. Column (5) shows a 14.7% increase in the coefficient of interest. However, I keep the results from Column (3) as my preferred estimation since the results are very similar. The previous impact may have been caused by changes to the extensive margin (reduced years of work) or the intensive margin (reduced earnings per year). This point is explored in Table 1.3. All the specifications account for the same set of controls as Column (3) of Table 1.2. Column (1) presents the impact on the normalized cumulative earnings as the baseline. Column (2) considers the cumulative days the worker was formally employed between 2007 and 2012, which is transformed into years for ease of interpretation. Column (3) explores the average yearly earnings between 2007 and 2012. To compare the magnitude of these effects, Panel (B) explores the same outcomes

TABLE 1.3 Worker's impact in earnings and employment from the decline in construction employment

	(1) Cumulative earnings	(2) Employment	(3) Average earnings
Panel A: Workers initially employed in the construction sector			
Shock	-1.956***	-1.672***	-0.00176
	(0.274)	(0.177)	(0.00364)
Constant	6.765***	5.235***	0.105***
	(0.229)	(0.0967)	(0.00332)
Observations	45370	45370	45370
R^2	.2009	.2697	.0266
Controls	Yes	Yes	Yes
Panel B: Workers initially not employed in the construction sector			
Shock	-0.349	-0.557***	0.00597
	(0.183)	(0.148)	(0.00419)
Constant	5.605***	4.575***	0.0920***
	(0.135)	(0.0851)	(0.00366)
Observations	301229	301229	301229
R^2	.1387	.2510	.0542
Controls	Yes	Yes	Yes

Robust standard errors in parentheses are clustered at the province level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: In each regression, I control for gender, occupation skill level, education, age, and foreign-born status. (i) Odd columns present evidence for a sample of non-construction sector workers, while (ii) even columns are restricted to workers in the construction sector in 2007. I restrict the sample to workers less than 50 years old in 2007 to avoid complications from workers' early retirement before 2012. Shock measures the relative changes in the share of workers in the construction sector by province. Bartik shock measures trends in employment growth in non-construction sectors.

for a sample of workers not employed in the construction sector.

Panel (A) shows that the average worker in the construction sector in the 25th percentile of exposure accumulated 0.23 fewer years of employment than a worker in the 75th percentile. Column (2) of Panel (B) shows that workers not in the construction sector experienced a negative but small decline in working days between 2007 and 2012 due to the shock. In Column (3), I document no significant impact on average earnings for workers in the construction sector vs. those outside of it. This evidence reveals that the impact on workers' earnings trajectories is explained mainly by workers' non-employment as they experienced a cut in their job opportunities.

1.5.1 Dynamic analysis

In this subsection, I examine the evolution of workers' impact on employment and earnings over time. Figure 1.8 shows a time series of the estimated effects of the construction sector's employment decline on employment and yearly earnings. Each year's t data point equals the coefficients from equation (1.5) on the estimation sample:

$$y_{it} = Shock_i^r \beta_0 + \mathbf{X}_i' \Delta + \epsilon_{it}$$

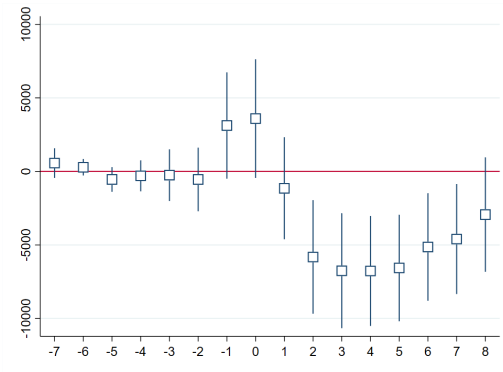
y_{it} is i's labor market outcome: the binary employment status of year t and the yearly earnings at year t. $Shock_i^r$ denotes the local shock to the individual's i initial province of residence. $\mathbf{X}_i$ is a vector of individuals' observable characteristics measured in 2007 and regional characteristics at their 2006 values. Comparing employment outcomes to pre-recession levels allows a transparent comparison of individual employment rate differentials. The sample and independent variable values are fixed across annual regressions; only the outcome varies yearly.

The estimating equations are identical to those in the baseline regression (Table 1.2, Column (3)), except that in place of workers' cumulative earnings over the entire period of 2007–2012, each equation computes the yearly earnings and employment status. Since I am tracking workers over a longer period in this exercise, I now restrict the estimation sample to workers aged 29–45 at baseline, to confine the 2000–2015 analysis to those between typical schooling and retirement ages.

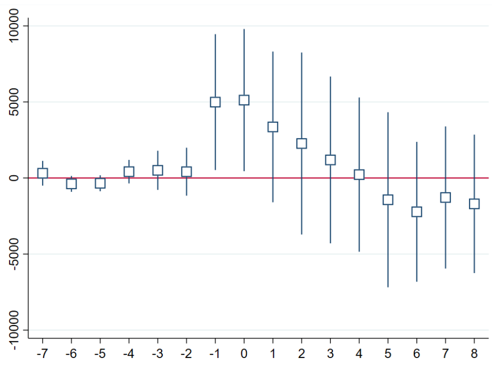
The estimated coefficients are shown in Figure 1.8. First, the pre-recession estimates support the identifying assumption that the local shock was as good as randomly assigned, conditional on controls. Panel (a) shows how the shock affected the workers' annual earnings. There was a negative impact on annual earnings during the Great Recession. This is consistent with previous evidence that workers in more exposed regions accumulated fewer earnings during the Great Recession. However, workers' earnings in the most exposed regions caught up with those in less exposed regions, with no significant differences between them in the last years.

The previously documented consequences may have resulted from workers being unemployed or having lower average earnings during the Great Recession. In order to disentangle these two effects, Panels (b) and (c) examine how the shock affects employment probabilities and earnings on a sample of workers employed each year. In Panel (b), I explore how the shock affects the yearly earnings from a sample of workers with non-zero earnings. Similarly, Panel (c) shows the shock's impact on the probability of being employed. Most of the effect can be attributed to decreased employment probabilities during the Great Recession. Panel (b) shows that there is a positive but insignificant effect on yearly earnings, mainly driven by compositional effects, while Panel (c) shows the same pattern as in Panel (a): a negative impact of the shock on the probability of being employed, which attenuates in the last years of the Great Recession.

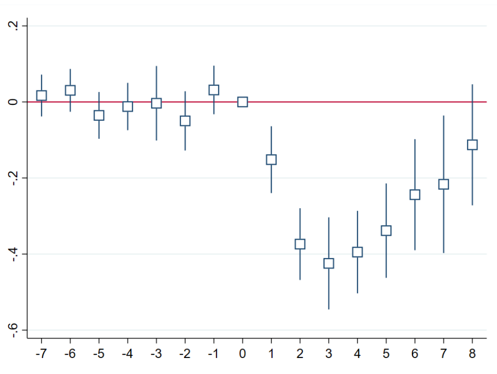
FIGURE 1.8 Impact of the contraction in the construction sector employment



(a) Yearly earnings (Full sample)



(b) Yearly earnings (Only employed)



(c) Binary employment status

Notes: Sample is restricted to workers aged 29-42 and working in the construction sector in 2007. Coefficients of the shock using an outcome variable indicate whether the worker has a valid employment spell each year. (1: the worker appears in the year, 0: the worker is not in the sample). The average earnings are calculated over the non-zero earnings of each year. Additional controls are the initial share of construction sector employment, Bartik type variable, and demographic characteristics.

1.5.2 Heterogeneity of the shock by individual characteristics

According to the previous section, local employment contraction in the construction sector significantly impacted workers' employment and earnings trajectory. In this section, I explore the heterogeneity of impact across individual characteristics. Figure 1.9 explores the consequences of the local shock on cumulative earnings across worker types. Based on the sample of workers initially employed in the construction sector, the figure plots point estimates and 95 percent confidence intervals based on separate regressions for each group of workers. I find that young, low-tenured, and low initial earners bore a proportionally larger incidence of the shock, suggesting that those shocks increased employment inequality across workers of different initial skill levels.

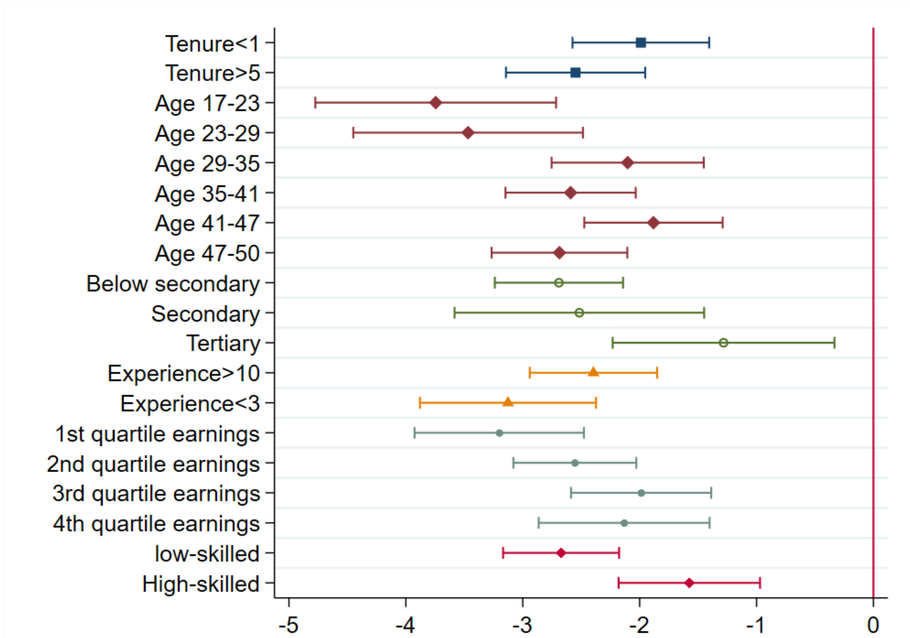
Low initial earners, defined as those at the first two quartiles of the earnings distribution, experienced a worse-than-average impact. In contrast, high initial earners experienced a better-than-average impact. This finding reveals the potential of economic shocks to widen labor market inequalities. There is a marked difference between the economic consequences for young and older workers. It is related to the inequality in employment opportunities between young and old workers. Most workers in Spain start their careers on temporary contracts, which are later upgraded to permanent ones. However, this results in differences in insurance to economic shocks between age groups, as young workers in more unstable jobs are more likely to lose their jobs during bad times. In contrast with what has been shown by Yagan (2019) for the U.S., young workers in Spain are not more resilient to economic fluctuations.

During the Great Recession, earnings inequality in Spain increased significantly. Bonhomme and Hospido (2017) argues that such an increase parallels the employment cyclicality in the lower middle part of the wage distribution. According to them, employment evolution in the construction sector played an important role in explaining this. As a contribution, Figure 1.9 presents that workers initially employed in the construction sector also exhibit considerable impact heterogeneity. Therefore, even within a defined group of workers, economic shocks have the potential to increase regional inequalities as workers across the wage distribution are differently affected.

The following exercise categorizes workers based on their 2007 earnings into quartiles. It quantifies the differential shock exposure conditional on the worker's initial position in the earnings distribution. I study the effects of shocks on normalized cumulative earnings, employment, and average yearly earnings. The regressions controlled by all the worker and regional characteristics used in the previous section.

Results are presented in Table 1.6. A test of equality for the four coefficients

Figure 1.9 Heterogeneity of the shock's impact on employment and earnings by characteristics



Notes: The sample is restricted to native workers aged 20-50 years old in 2007 and working in the construction sector; cumulative variables are computed between 2007 and 2012. Wage is standardized by the average wage in 2006 for months with non-zero earnings. Every regression controls by: gender, age, education, skill group, foreign status, and interactions between age and education. Bartik is computed without considering the construction sector. Each coefficient is obtained from separate regressions for each subgroup.

rejects the null hypothesis that they are equal to each other. According to the results, there is a significant difference based on the worker's initial earnings. The shock is more severe for those with low initial earnings. As a result, national-wise earnings inequality increases, and regional disparities widen. Thus, workers in most affected regions are also differentially affected. There is a 20 percent difference in impact between the beginning in the third quartile of the earnings distribution and the fourth quartile.

Such a difference could be explained by a milder impact on employment or earnings. This is explored in columns (2) and (3). Similar to the results of previous sections, most of the impact is explained by workers in most exposed provinces staying employed for less time during the Great Recession. As a result, the recession not only has a large and significant effect on earnings distributions but also widens employment inequalities. According to Column (2), high-earning workers experience a 35% milder impact on their employment than those with lower earnings in the same province.

1.5.3 Geographical vs. sectoral reallocation

Transitions across sectors and geographical locations are mechanisms through which workers adapt to the effects of negative shocks. However, there is mixed evidence regarding how geographical mobility responds to negative shocks. Worker adjustment across regions appears slow and incomplete (Autor et al. 2014, Dix-Carneiro 2014). This sluggishness is most pronounced among less-educated workers, a subset of workers who are over-represented in the construction sector. Workers also possess sector-specific human capital, which may prevent them from finding a job in another sector. As a result, a worker's adjustment is not trivial, and both mechanisms must be explored.

This section examines the mobility response of construction workers. The shock is the contraction in construction employment between 2007 and 2012 in the worker's initial province of residence. Figure 1.10 examines how shocks affect the probability of changing provinces or sectors. The results are from separate regressions of a binary variable on changing sectors and regions, conditional on the shock and a wide variety of individual and regional controls. A dynamic approach allows comparisons between coefficients before and during the Great Recession and tests for the absence of differential pre-trends.

Figure 1.10 indicates that workers in the most affected regions are also more likely to change sectors, consistent with there being fewer construction employment opportunities. When comparing magnitudes, a worker in the 75th percentile is 4.03 percentage points more likely to change sectors than a worker in the 25th percentile of exposure to the shock. On the other side, there is no statistically significant

Table 1.4 Heterogeneity of the shock's impact on employment and earnings

	(1) Cumulative earnings	(2) Employment	(3) Average earnings
$Q_1^{earnings} \cdot Shock$	-2.659***	-2.111***	-0.0116**
	(0.267)	(0.186)	(0.00391)
$Q_2^{earnings} \cdot Shock$	-2.271***	-1.798***	-0.00723
	(0.262)	(0.181)	(0.00391)
$Q_3^{earnings} \cdot Shock$	-2.093***	-1.677***	-0.00531
	(0.267)	(0.183)	(0.00382)
$Q_4^{earnings} \cdot Shock$	-1.665***	-1.360***	0.00181
	(0.278)	(0.203)	(0.00380)
Constant	6.727***	5.212***	0.105***
	(0.214)	(0.135)	(0.00338)
Observations	40171	40171	40171
R^2	.2193	.2814	.0347
Controls	Yes	Yes	Yes

Robust standard errors in parentheses are clustered at the province level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

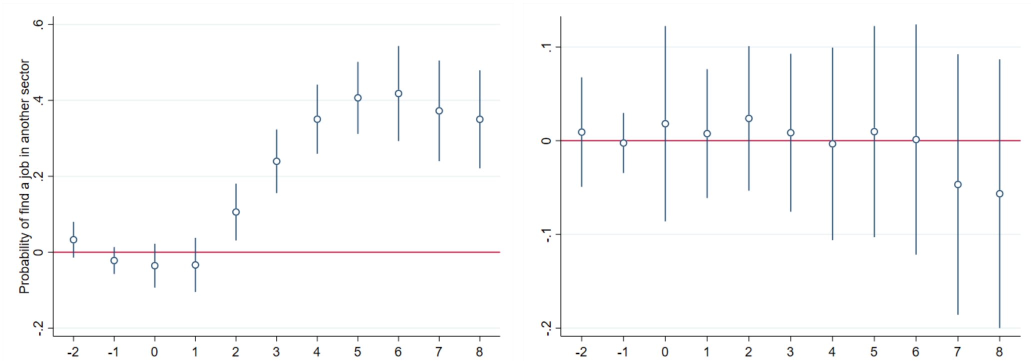
Notes: Dependent variable: Standardized cumulative earnings, 2007–2012, cumulative days employed, 2007-2012, average monthly earnings, 2007-2012. All regressions include a constant and a full set of worker, job, and regional characteristics as additional controls. Demographic control interactions of age group, education, and gender. Initial occupational skill group, type of contract, tenure, experience, and experience squared. Regional characteristics: province-level unemployment rate in 2006, Bartik-type shock, the employment share of the construction sector at 2006. All worker and job characteristics are measured in 2007, and regional controls were measured in 2006. The sample is restricted to workers in the construction sector before the shock, aged 20-50 years old.

relationship between the shock and the probability of changing one's province of residence.

According to Borusyak et al. (2022), spatial correlation of demand shocks attenuates migration responses to negative shocks. Workers consider the local shock as well as the effect on alternative locations, which may affect the estimates. An appropriate strategy is to account for shocks to connected locations. Based on that intuition, I created an adjusted shock measure incorporating migration flows between provinces.

The adjusted shock is shown in equation (1.5.3). $Shock_m$ represents the decline in construction employment from 2007 to 2012 in province m, and $\mu_{r \to k}$ is the probability that a worker from province r migrates to province k, conditional on the worker changing provinces. I construct the adjusted measure in two steps. I start by estimating transition probabilities between provinces, using observed workers'

Figure 1.10 Adjustment to the employment contraction of the construction sector



(a) Shock's impact on the probability of changing sectors

(b) Shock's impact on the probability of changing provinces

Notes: The sample is restricted to workers aged 29-42 and working in the construction sector in 2007. Coefficients of the shock use an outcome variable indicating whether the worker changed residence province or sector on a rolling basis. a) Out of the construction sector; b) in a province different than the worker's residence in 2007. Additional controls are the initial share of construction sector employment, Bartik type variable, demographic characteristics, and interactions.

migration from 2001 to 2006. In the next step, I construct the shock variable by comparing the local shock to the weighted average shock across provinces, based on previously estimated transition probabilities. When determining the effect of a shock on a given province, I compare it against the shock experienced by all other provinces, with more weight placed on provinces that are typical migration destinations.

$$Shock_r^{adj} = Shock_r - \sum_{k \neq r} \mu_{r \to k} Shock_k$$

Table 1.5 shows the impact of the employment decline in the construction sector on the probability of changing sector and province. The first three columns analyze the likelihood that a person will work in a different province in 2012 than in 2007. The fourth to sixth columns examine the likelihood that they will work in a sector other than construction in 2012. As explained previously, Columns (3) and (6) adjust the shock measure to account for shocks in other provinces. The difference in shock between the province of residence and a weighted shock average is based on the likelihood of migrating to each province.

According to Column (1), the shock has a negative but insignificant effect on the likelihood of workers changing provinces. Column (2) includes individual and regional controls, and the results show a positive but insignificant relationship between migration and the shock's impact. Column (3) examines the shock's effect by accounting for shocks in other provinces, as explained above. Despite this, migration and the decline in the construction sector do not appear to be significantly related in this context.

Table 1.5 Geographical vs. sectoral reallocation due to the economic shock

	(1)	(2)	(3)	(4)	(5)	(6)
	Change province			Change sector		
Shock	-0.0421	0.00970		0.383***	0.407***	
	(0.0920)	(0.0561)		(0.0547)	(0.0472)	
AdjustedShock			0.0779			0.349***
			(0.0589)			(0.0769)
Constant	0.252***	0.168***	0.187***	0.321***	0.246***	0.398***
	(0.0477)	(0.0334)	(0.0398)	(0.0439)	(0.0399)	(0.0393)
Observations	30402	30402	30402	30402	30402	30402
R^2	.0365	.1786	.1788	.1405	.1884	.1870
Controls	No	Yes	Yes	No	Yes	Yes

Robust standard errors in parentheses are clustered at the province level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Controls: interactions of age categories with gender and educational attainment, occupational skill group categories, indicators for part-time and fixed-term contracts, tenure and experience fixed effects, local unemployment rate and employment share of the construction sector in 2006, a Bartik type shock, and the HHI index. The shock is the relative employment decline in the construction sector. Adjusted shock compares the shock in the province of residence to the shock in other provinces, weighted by the migration strength between the province and all potential provinces.

Column (4) indicates that workers originally employed in the construction sector were leaving the sector to adjust to the decline in employment opportunities. As shown in Column (5), adding individual and regional controls results in a small increase in the coefficient. Workers in the 75th percentile of exposure are more likely to move into another sector than workers in the 25th percentile. Finally, Column (6) shows the adjusted shock's positive and significant effect on the probability that workers change sectors.

1.6 Sectoral composition and the effect on workers' labor market adjustment

The availability of jobs and the flexibility to change sectors both influence a worker's decision to leave the exposed sector. Individuals with more relevant job options will, on average, be able to sort into better matches and spend less time unemployed. These individuals may also suffer a lower earnings penalty from job loss.

The reallocation index captures the relevant job options available to a given worker within their labor market. In most empirical studies, a local labor market refers to a defined geographic region.[23] Alternatively, they can be defined by exploiting worker flows within a region (Nimczik, 2020). Nevertheless, any binary labor

[23] States: Acemoglu and Angrist (2000); metropolitan areas: Moretti (2004); Commuting zones: Autor et al. (2013).

market definition (i.e., one which treats local jobs as close substitutes and rejects those outside the region) ignores the fact that workers value jobs differently based on their characteristics. I apply a probabilistic definition of the labor market as in Schubert et al. (2020), recognizing that even similar jobs may be valued differently by the workers.

The next section incorporates the reallocation index into the analysis, considering how sectoral composition impacts the workers' job opportunities and easing their adjustment to negative shocks. The reallocation index is constructed by comparing sectors according to the similarity of their workforce. I follow a similar methodology to that used by Caldwell and Danieli (2018) and align with the framework outlined in Section 1.2. I get similar results when constructing the reallocation index using transition probabilities between sectors instead of worker similarity.

1.6.1 Reallocation index

This subsection expands equation (1.5) by incorporating the reallocation index as an additional control. The probability that a worker with characteristics X_i in region r finds a job in another sector plays a role in attenuating the shock's impact. Consistent with that idea, I expect that having a larger reallocation index would capture workers' attenuating the shock's impact on the earnings trajectories of the workers. I test and quantify this hypothesis by examining the adjustment to a large shock.

The results of this exercise are presented in Table 1.6. Column (1) shows that for a worker exposed in provinces at the 25th and 75th percentiles of the shock impact lost 1.19 (-2.35×0.5081) and 1.51 (-2.35×0.6463) times their initial average annual earnings, respectively. The initial average annual earnings impact in high-exposure provinces is almost 21 percent greater than in low-exposure provinces.

In addition, the coefficient in Column (1) shows the effect of the reallocation index on the workers' cumulative earnings. For ease of interpretation, it was standardized to have a zero mean and a unitary standard deviation. Thus, an increase of one standard deviation in the reallocation index corresponds to an increase of 6 percent of the initial annual earnings. Column (2) incorporates the shock's impact and the reallocation index, which are captured by their interaction, to test the relevance of sectoral composition on worker adjustment. Even though the shock impacts all workers in the same province, the results show a positive and statistically significant effect on cumulative earnings of having higher values on the reallocation index.

As described in the framework section, the interaction of the reallocation index and shocks captures the attenuation of adverse conditions, explained by having a better match between the worker's characteristics and the local sectoral composition. According to the analysis, an increase of one standard deviation on the reallocation

Table 1.6 Labor market impact of the employment contraction in the construction sector, 2007-2012

	(1)	(2)	(3)	(4)	(5)	(6)
	Cumulative earnings		Employment		Average earnings	
Shock	-2.358***	-2.420***	-1.832***	-1.871***	-0.00757*	-0.00831*
	(0.239)	(0.233)	(0.166)	(0.161)	(0.00328)	(0.00315)
Reall.Index	0.0592**	-0.183*	0.0432***	-0.109*	0.000153	-0.00274
	(0.0171)	(0.0912)	(0.00950)	(0.0513)	(0.000339)	(0.00149)
$Shock \cdot Reall.Index$		0.432**		0.272**		0.00515*
		(0.144)		(0.0938)		(0.00230)
Constant	6.633***	6.674***	4.998***	5.023***	0.117***	0.118***
	(0.155)	(0.151)	(0.117)	(0.108)	(0.00297)	(0.00319)
Observations	46392	46392	46392	46392	46392	46392
R^2	.2335	.2338	.3230	.3232	.0312	.0314
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses are clustered at the province level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Dependent variable: Standardized cumulative earnings, 2007–2012; cumulative days employed, 2007-2012; average monthly earnings, 2007-2012. All regressions include a constant and a full set of worker, job, and regional characteristics as additional controls. Demographic controls include interactions of age group, education, and gender, along with initial occupational skill group, type of contract, tenure, experience, and experience squared. Regional characteristics are the province-level unemployment rate in 2006, Bartik-type shock, and the employment share of the construction sector in 2006. All worker and job characteristics were measured in 2007, while regional controls were measured in 2006. The sample is restricted to workers in the construction sector before the shock, aged 20-50 years old.

index results in a 17.9% attenuation of the shock's impact (0.432/2.420). As a result, workers would be better off if a large shock occurred in a region where their characteristics are highly valued.

Columns (3) and (4) present the shock and reallocation index's effects on workers' employment between 2007 and 2012. Evidence shows that exposure to the shock negatively impacts workers' employment. However, keeping good prospects in other sectors may help offset the effects of such massive shocks. In other words, outside opportunities counterbalance the decline in employment opportunities in the origin sector.

Column (3) shows that the reallocation probabilities index positively and statistically significantly impacted employment during the Great Recession. An increase by one standard deviation suggests a 4% increase in employment during the reference period. Additionally, Column (4) shows that workers with higher reallocation indexes could better attenuate the shock's impact, the importance of which increases with the shock's magnitude.

Finally, Columns (5) and (6) demonstrate that workers in more exposed areas did not suffer a large impact on their average yearly earnings. The decline in average earnings between 2007 and 2012 for a worker in a province at the 75th percentile of exposure is 84 real Euros compared to the initial annual earnings in 2009.[24] This effect is statistically significant, though the economic magnitude is small.

Heterogeneous impact of the reallocation index

According to the previous section, sectoral composition offers workers differential opportunities to mitigate the impact of economic shocks. This section expands the evidence by considering how the shock impact varies over the distribution of the reallocation probability index.

$$y_i = \sum_{k=1}^{4} \beta_k Q_i^k \cdot Shock_i^r + X_i' \Delta + \epsilon_i,$$

The set of controls remains as in previous specifications but adds dummy variables for each quartile of the reallocation probabilities. The coefficients $\{\beta\}_{k=1}^{4}$ decompose the shock's consequences for different quartiles of the reallocation probabilities, Therefore, a worker's impact differs by the worker's characteristics and region.

The results are presented in Table 1.7. Columns (1) and (3) show the impact of the shock without considering the reallocation index, which indicates that the decline in construction employment between 2007 and 2012 had a significant and statistically significant impact on the cumulative earnings and employment of workers initially employed there. Column (2) and (4) shows how those consequences vary with the degree of mismatch between their characteristics and the job opportunities in other sectors within the region. According to column (2), the workers experience a stronger shock on their earnings trajectories as they have a lower reallocation index, i.e., lower quality or better jobs are scarce in the region because of the sectoral composition. An equality test for the four coefficients is rejected at the 0.2% confidence level.

Regarding economic significance, moving a worker from the first quartile to the third quartile of the reallocation probabilities index would result in a 20% lower shock. In the same way, switching a worker from the first to the last quartile results in a 40% less intense shock. Similar results are presented in Column (4) for workers in the lowest quartile, experiencing a 35% stronger shock from the decline of the construction sector compared to those in the highest quartile.

Next, I assess whether sectoral composition influences workers' willingness to change sectors. Adaptation to economic shocks may occur by relocating to a less affected region or by changing sectors. In Section 1.5.3, I present evidence that workers adjusted mainly through sectoral reallocation. In line with that, I present suggestive evidence that sectoral composition influences the probability of changing

[24] 0.0857*0.6463*1596; the average monthly real earnings are 1596 real Euros.

Table 1.7 Sectoral composition and the consequences from the contraction of the construction sector

	(1)	(2)	(3)	(4)	(5)	(6)
	Cumulative earnings		Employment		Average earnings	
Shock	-2.006***		-1.891***		0.0005	
	(0.198)		(0.177)		(0.0009)	
$Q_1 \cdot Shock$		-2.569***		-2.417***		0.0003
		(0.318)		(0.297)		(0.0016)
$Q_2 \cdot Shock$		-2.038***		-1.867***		-0.00002
		(0.231)		(0.223)		(0.0012)
$Q_3 \cdot Shock$		-1.832***		-1.712***		-0.00001
		(0.214)		(0.204)		(0.0013)
$Q_4 \cdot Shock$		-1.666***		-1.645***		0.0008
		(0.246)		(0.253)		(0.0012)
Observations	46244	46244	46244	46244	46244	46244
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses are clustered at the province level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Dependent variable: Standardized cumulative earnings, 2007–2012, cumulative days employed, 2007-2012, average monthly earnings, 2007-2012. All regressions include a constant and a full set of worker, job, and regional characteristics as additional controls. Demographic control interactions of age group, education, and gender. Initial occupational skill group, type of contract, tenure, experience, and experience squared. Regional characteristics: province-level unemployment rate in 2006, Bartik-type shock, the employment share of the construction sector at 2006. All worker and job characteristics are measured in 2007, and regional controls were measured in 2006. The sample is restricted to workers in the construction sector before the shock, aged 20-50 years old.

sectors, then affecting the worker's labor market adjustment. The composition of local economic activities shapes reemployment opportunities, affecting the worker's adjustment to economic shocks.

A relevant discussion is on how local economic performance is influenced by sectoral concentration, where two main theories arise. According to Marshall (1890), agglomeration forces improve local economic performance, the proximity of related industries facilitates intra-industry knowledge transfer, reduces the cost of transportation, and allows firms to benefit from more efficient labor markets. Jacobs and Jane (1969) argues that diversity fosters innovation and prosperity by promoting knowledge exchange. Related to that discussion, I focus on how the composition of local activities affects the worker's labor market adjustment, where a more diverse labor market benefits a broader group of workers who find themselves with a more diverse set of options in a case of a negative shock. My research contributes to that debate by examining how sectoral composition affects workers' adjustment.

As a result of a major shock, workers may have more options if the labor market is diverse. The HHI index is a common way to measure diversity, but it counts concentration as if all sectors were equally viable from the worker's perspective. The reallocation index gives more weight to sectors closest to the worker's characteristics, so this measure of diversity accounts for the distance between local options and the worker's characteristics, better capturing the worker's relevant labor market.

I estimate a probit regression model to analyze the probability that a worker will switch sectors. The reallocation index is my coefficient of interest. I consider the HHI index additionally to compare the effect of the standard measure of diversity on the probability of changing the sector. Then, I contrast the effect of local diversity of job opportunities on the probability that workers change sectors using both measures.

Table 1.8 presents estimates of the probability of workers in the construction sector changing sectors between 2007 and 2012. There is a statistically significant positive relationship between the employment decline in the construction sector and the probability of leaving it. The HHI does not show a statistically significant relationship between sectoral mobility and sectoral concentration.

Column (2) in Table 1.8 includes the reallocation index, which, as explained earlier, considers the distance between the worker's characteristics and the available options. The probability of changing sectors and the reallocation probabilities are positively related. Mobility into another sector is more likely in a province that matches worker characteristics and sectoral composition. Column (3) presents a decomposition of the into quartiles, enabling a more in-depth study of the heterogeneity and easing the interpretation of the coefficients. An equality test rejects the null hypothesis of equality among the three coefficients. Comparing the coefficients shows that the highest quartile accounts for the most variance.

Workers who move from the third to the fourth quartile of reallocation probabilities are 10% more likely to change sectors. However, those in the first quartile are not more likely to leave the construction sector due to greater exposure to the decline in employment.

1.6.2 Residualized reallocation probabilities

The previous results raise the concern that specific individual characteristics induced the observed attenuation. In other words, the reallocation index may only capture the effect of the worker's attributes on the adjustment. In this section, I examine a residualized reallocation index. I calculated this measure based on the residuals of a regression of the reallocation index on the characteristics used to calculate it. In this experiment, I subtract the variation explained by the individual characteristics. Consequently, the remaining part captures only the interaction of individual characteristics with local conditions.

Table 1.8 Sectoral composition and the probability of change sector

	(1)	(2)	(3)
		Change sector	
Shock	0.489*	0.574**	
	(0.219)	(0.198)	
HHI	2.642	4.492*	4.391*
	(2.275)	(1.998)	(1.993)
Reall. Prob.		0.0602**	
		(0.0197)	
$Q_1 \times Shock$			0.371
			(0.212)
$Q_2 \times Shock$			0.543**
			(0.210)
$Q_3 \times Shock$			0.548**
			(0.192)
$Q_4 \times Shock$			0.603**
			(0.192)
Constant	0.109	-0.114	-0.0546
	(0.193)	(0.180)	(0.177)
Observations	46288	46288	46288
Controls	Yes	Yes	Yes

Robust standard errors in parentheses are clustered at the province level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Coefficients from a probit model of indicator variables if workers changed province, sector, or firm within the same sector between 2008 and 2012. Each regression controls education, age, interactions between education and age, foreign status, occupational skill group, the decrease in the construction sector's local employment share, the initial employment share of the construction sector, the Bartik variable, and the Outside option measure. A sample is constrained to individuals in the construction sector in 2007 and is based on a yearly panel with observations from 2005 to 2017.

Table 1.9 provides the results of adding the residualized reallocation index into the estimating equation. Column (1) presents the results of the 2007-2012 worker's cumulative earnings as a function of the reallocation index and the full set of controls. For ease of interpretation, I standardized the residualized reallocation index to have a zero mean and unitary standard deviation. As a result, an increase of one standard deviation in the reallocation index reduces the average shock's impact by 12.4%. Compared to the baseline results, the reallocation index coefficient is slightly attenuated, dropping by 9.8%. However, the magnitude remains statistically significant and economically relevant. Results in columns (3) and (4) indicate that a high reallocation probability positively affects workers' employment prospects during the Great Recession.

Table 1.9 Residualized reallocation probabilities

	(1)	(2)	(3)	(4)	(5)	(6)
	Cumulative earnings		Employment		Average earnings	
Shock	-2.329***	-2.367***	-1.819***	-1.844***	-0.00736*	-0.00777*
	(0.240)	(0.232)	(0.162)	(0.159)	(0.00335)	(0.00323)
Resid.Reall	0.0534***	-0.110	0.0359***	-0.0716	0.000283	-0.00147
	(0.0128)	(0.0702)	(0.00872)	(0.0480)	(0.000317)	(0.00136)
Shock × *Resid.Reall.*		0.293*		0.193*		0.00316
		(0.115)		(0.0884)		(0.00213)
Constant	6.620***	6.636***	5.014***	5.024***	0.116***	0.117***
	(0.147)	(0.143)	(0.116)	(0.109)	(0.00295)	(0.00312)
Observations	46386	46386	46386	46386	46386	46386
R^2	.2327	.2329	.3221	.3222	.0313	.0314
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Dependent variable: Standardized cumulative earnings, 2007–2012, cumulative days employed, 2007-2012, average monthly earnings, 2007-2012. All regressions include a constant and a full set of worker, job, and regional characteristics as additional controls. Demographic control interactions of age group, education, and gender. Initial occupational skill group, type of contract, tenure, experience, and experience squared. Regional characteristics: the province-level unemployment rate in 2006, Bartik-type shock, the employment share of the construction sector in 2006. All worker and job characteristics are measured in 2007, and regional controls were measured in 2006. The sample is restricted to workers in the construction sector before the shock, aged 20-50 years old.

1.7 Basic robustness

1.7.1 Falsification of the decline in construction employment

Could reallocating jobs from regions that grew more robustly during the expansion explain the contraction in construction employment? In such a case, it may threaten the exogeneity assumption. The hypothesis is tested by examining whether the employment contraction between 2007 and 2012 predicted worker outcomes before the Great Recession. I constructed a sample of construction workers in 2003 and estimated their cumulative earnings from 2003 to 2007.

Table 1.10 provides evidence neglecting that the shock is related to the prerecession outcomes. Column (1) shows a positive but insignificant effect of the shock on both employment and earnings.

1.7.2 Reallocation index from transition probabilities

This section examines an alternative method to construct the reallocation index. It exploits the sector's transition probabilities instead of the similarity of their work-

Table 1.10 Falsification test of the impact of the employment contraction in the construction sector on cumulative days worked from 2003-2007

	(1) Cumulative earnings	(2) Employment	(3) Average earnings
Shock	0.0737	-0.108	0.00188
	(0.206)	(0.147)	(0.00257)
Constant	4.410***	3.447***	0.106***
	(0.143)	(0.0729)	(0.00201)
Observations	25455	25455	25455
R^2	.0667	.1162	.0626
Controls	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The sample is restricted to native workers aged 20-50 in 2003 and working in the construction sector. I compute the cumulative variables between 2003 and 2007. Earnings are standardized by the worker's average earnings in 2002. Controls: gender, skill group, foreign status, and interactions of age categories and education attainment. Bartik is computed without considering the construction sector. The shock is the employment change in the construction sector between 2007 and 2012

force. It uses the movement between similar workers to capture the likelihood that a worker would find it attractive to move to another sector from the construction sector.

It explores the robustness of the previous results since it does not depend on how the reallocation probabilities are defined. This approach follows Schubert et al. (2019) while exploiting the actual mobility reactions of construction workers between 2000 and 2006.

The estimation follows a two-step approach and depends on sectoral transitions of workers in the MCVL between 2000 and 2006. Define the probability a worker moves from the construction sector to sector s as π^s_{cs}. In particular:

$$\begin{aligned}\pi_{cs\to p} &= \frac{\#\text{ in } cs \text{ in } t \text{ observed in sector } s \text{ in } t+1}{\#\text{ in cs in } t \text{ observed in a new sector in } t+1} \\ &\approx \text{Prob(move from } cs \text{ to sector } s \mid \text{ leave sector).}\end{aligned}$$

The transition probabilities are constructed conditional on the individual leaving the construction sector and as a function of worker characteristics X_i. The vector X_i accounts for occupation skill group, gender, foreign-born status, and interactions of age categories with education attainment.[25]

Then, the transition probabilities will be π^s_{cs}, defined as:

$$\pi^s_{cs} = \text{Prob(move from } cs \text{ to sector } s \mid \text{ leave sector }, X_i).$$

[25] As workers may move from one sector to another just due to seasonal variation throughout the year, which may be transitory in some cases, the probabilities estimation also considers month fixed-effects.

Using a probit model, I compute the transition probabilities between 2000 and 2006 for the group of leavers from the construction sector. The estimation sample is monthly data from 2000 to 2006, and the dependent variable is the sector of individual i after leaving the construction sector, footnoteTherefore, if worker i is in the construction sector in period t and another sector in $t+1$ From this first step, the predicted probabilities are obtained. To calculate the second step, I use the weighted average of transition probabilities based on the size of each sector in each province.

$$\widehat{\pi}_{cs \to j} = \Pr(\widehat{Y=1} \mid X) = \Phi\left(X_i \widehat{\beta}\right)$$

Therefore, the final measure is:

$$\sum_j \widehat{\pi}_{cs \to j} * \frac{EmplShare_j^r}{EmplShare_j}$$

The main analysis finds that workers who were employed in the construction sector and living in a hard-hit province before the Great Recession accumulated substantially lower earnings during the economic downturn than comparable workers in a less affected region. Consistent with labor market frictions preventing workers from smoothly adjusting. This paper, in particular, exploits the friction a particular worker may have during the changed sector. The movement depends on the worker characteristics and the particular match with the province's sectoral composition. The idea is that their profile is attractive for a hiring firm and that the local sectoral composition allows sufficient contracting firms in that particular sector.

In order to capture how likely a worker will move to a firm in a particular sector, the previous section exploits the similarity between the moving worker and workers in the receiving sector. This section, as previously explained, will exploit the actual transitions of similar workers from the construction sector to another sector in the pre-shock period.

Table 1.11 presents the results. Column (1) shows the impact on cumulative earnings from the shock, and column (2) decomposes the shock by quartiles of the reallocation probabilities. An equality test of the four coefficients is rejected, so the shock's impact heterogeneity is conditional on being more likely to move into another sector. The effect, however, is partially attenuated when compared to the reallocation probabilities in the baseline specification. As the labor market changed during the Great Recession, the flow of workers from the construction sector was less informative than during the expansion. However, there is still significant impact heterogeneity in columns (2) and (4) as a result of different transition probabilities.

Table 1.11 Reallocation probabilities from transition probabilities

	(1)	(2)	(3)	(4)
	Cumulative earnings		Employment	
Shock	-2.459***		-1.942***	
	(0.238)		(0.174)	
$Q_1 \times Shock$		-2.590***		-2.016***
		(0.260)		(0.176)
$Q_2 \times Shock$		-2.508***		-1.990***
		(0.251)		(0.172)
$Q_3 \times Shock$		-2.455***		-1.904***
		(0.263)		(0.181)
$Q_4 \times Shock$		-2.341***		-1.868***
		(0.261)		(0.178)
Constant	6.592***	6.560***	4.869***	4.846***
	(0.164)	(0.150)	(0.113)	(0.102)
Observations	46375	46375	46375	46375
R^2	.2366	.2371	.3281	.3284
Controls	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Sample workers aged 20-50 years old in 2007 and working in the construction sector before the crisis. Column (1) makes no additional restriction. Column (2) restricts native workers. The computation of the cumulative variables is from 2007 and 2012. Wage is standardized by the average wage in 2006 from months with non-zero earnings. Every regression controls gender, age, education, skill group, foreign status, and interactions between age and education. Bartik is computed without considering the construction sector, and predicted values for the outside option are from the first stage. **probit model**.

1.8 Conclusion

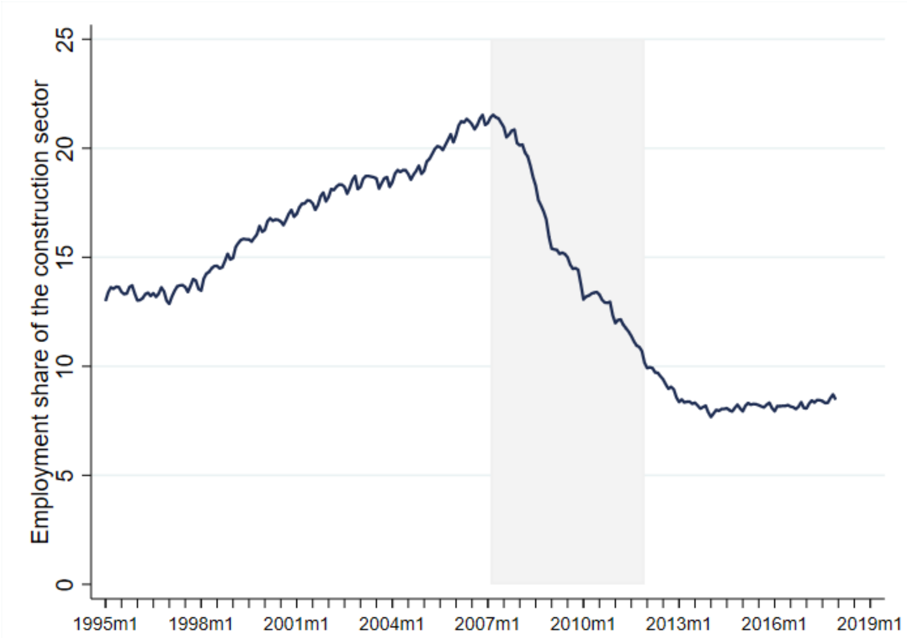
In this paper, I analyzed the effect of the employment decline of the construction sector on Spanish workers between 2007 and 2012. During the Great Recession, Spain was one of the most affected countries. Construction was particularly affected, with contractions unevenly distributed across Spanish provinces. Workers initially employed in the Spanish construction sector suffered large earnings losses due to the burst of the sector. To quantify the impact of the shock on earnings and employment, I estimate a regression model that accounts for regional and individual heterogeneity and relies on the asymmetric employment decline of the construction sector in Spanish provinces. My results reveal that the employment losses were larger during the first years of the Great Recession, and the employment probabilities of workers in the most exposed provinces caught up to those of the least exposed provinces during the Spanish economic recovery. The sectoral change of workers in the most exposed regions partly explains the attenuation of the initial impact. I show that workers' primary adjustment response was from sectoral mobility, with a minor reaction from geographical mobility.

The second part of the paper exploits shock variation across provinces and administrative panel data that tracks all the worker's labor market history to investigate local sectoral compositions' contribution to attenuating job loss's consequences. I aim to account for differences in the sectoral composition, which affects workers' reallocation from two fronts (i) differences in the sector's suitability based on worker characteristics and (ii) heterogeneity in the availability of jobs across different regions as a consequence of spatial specialization patterns. I construct a *reallocation index* that reflects the likelihood of transitioning from construction to another industry. It captures the imperfect substitutability of workers across different sectors by exploiting variation in each province's sectoral composition and worker characteristics.

Finally, the previous results are consistent even after several robustness tests. Importantly, falsification exercises using the Great Recession shock, but a sample and outcomes computed years before the Great Recession show no statistically significant relationship. The relevance of the reallocation probabilities in alleviating the bust's impact on construction sector employment is robust to applying a similar definition of reallocation probabilities and instrumenting the shock on the construction sector's cumulative growth in expansionary years.

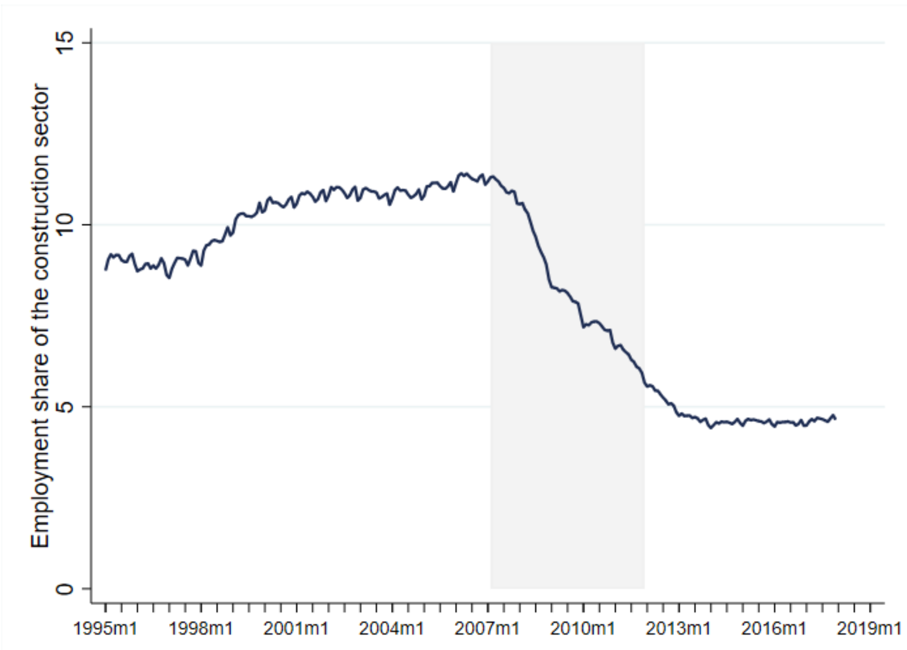
Appendix 1.A Supplementary Figures

Figure 1.11 Employment share of the construction sector, 2000-2017



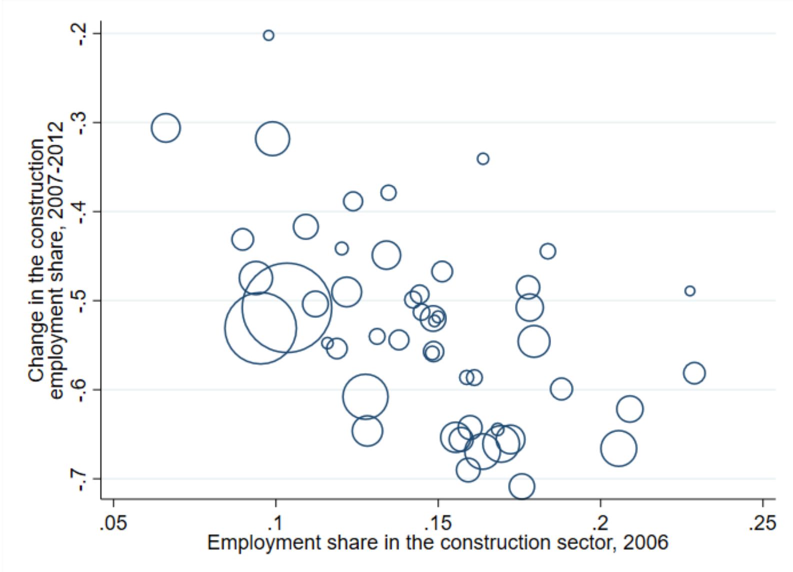
Notes: Men employed in the construction sector as a percentage of all males employed, January 2000 to December 2017. Data was restricted to male workers employed during the referenced period.

Figure 1.12 Employment share of the construction sector, 2000-2017



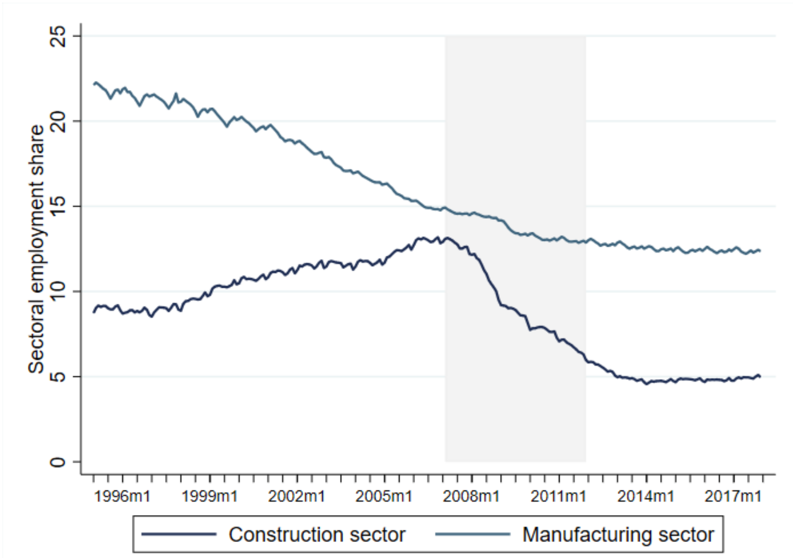
Notes: Native employed in the construction sector as a percentage of all Native employed, January 2000 to December 2017. Data restricts to Native workers employed during the referenced period. The gray area represents the period from January 2007 to December 2012

Figure 1.14 Change in the construction employment share by province, 2007-2012



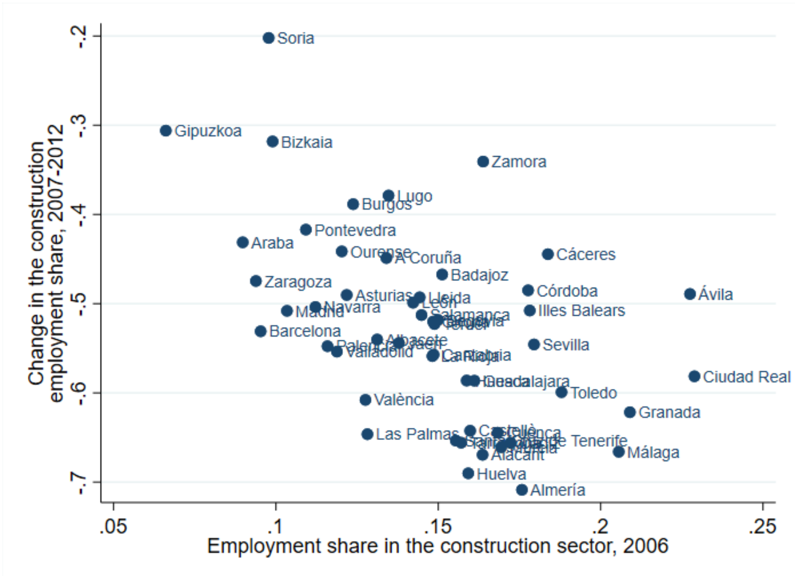
Notes: Change in the employment share of the construction sector by province between 2007 and 2012 against construction employment share in 2006. The sample considers the 50 Spanish provinces. The circles represent 2006 employment for each province.

Figure 1.13 Manufacturing and construction employment shares, 2000-2017



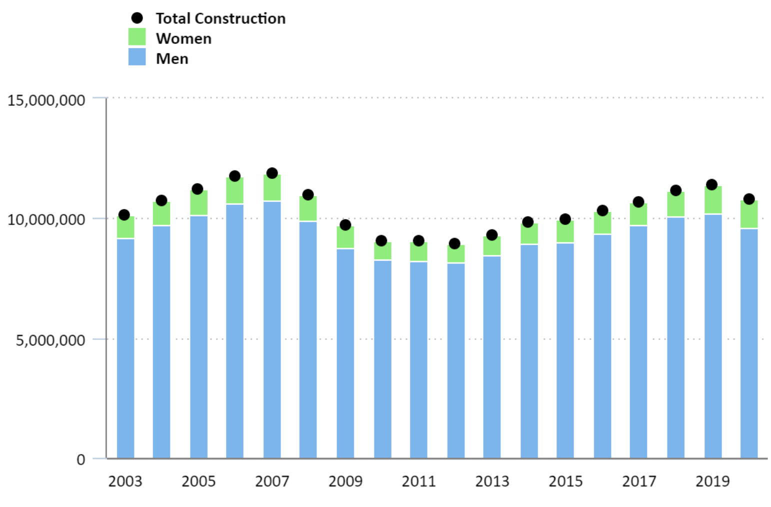
Notes: Employed workers in the construction and manufacturing sector as a percentage of all employed workers, January 2000 to December 2017. Data restricts to workers employed during the referenced period. The gray area represents the period from January 2007 to December 2012

Figure 1.15 Change in the construction employment share by province, 2003-2020



Notes: Change in the employment share of the construction sector by province between 2007 and 2012 against construction employment share in 2006. The sample considers the 50 Spanish provinces.

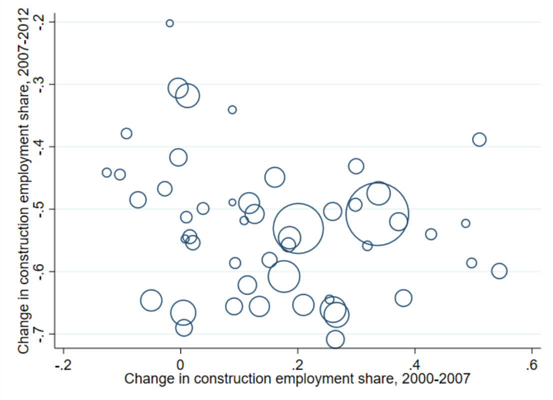
Figure 1.16 Construction sector employment in the US, 2003-2020



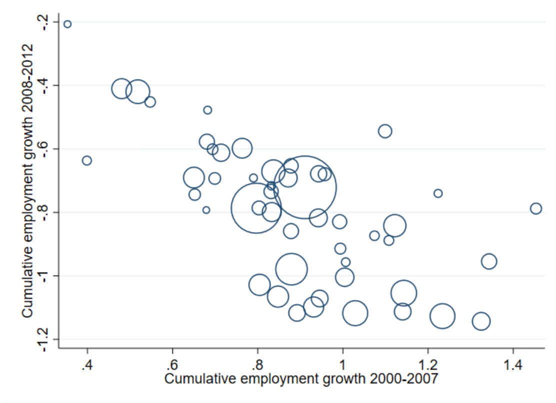
Source: U.S. Bureau of Labor Statistics.

Notes: Construction employment by gender in the US, 2003-2020.
Source: US Bureau of Labor Statistics 2006-2017

Figure 1.17 Employment evolution of the construction sector by province, 2007-2012



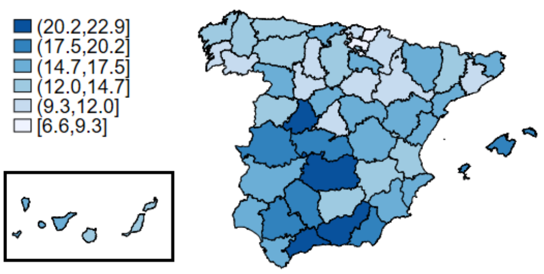
(a) Employment change in the construction sector by province



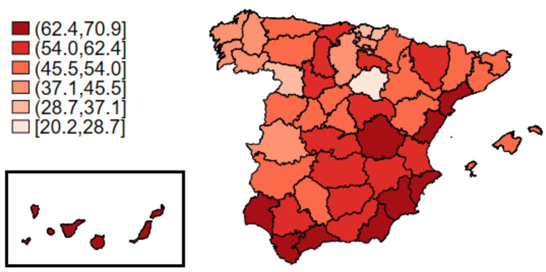
(b) Cumulative employment growth in the construction sector by province

Notes: Panel (a) Change in the employment share of the construction sector between 2000-2007 and 2007-2012. Panel (b) Cumulative employment growth aggregate the yearly employment share growth between 2000-2007 and 2007-2012. The figure considers the 50 Spanish provinces.

Figure 1.18 Employment evolution of the construction sector by province, 2007-2012



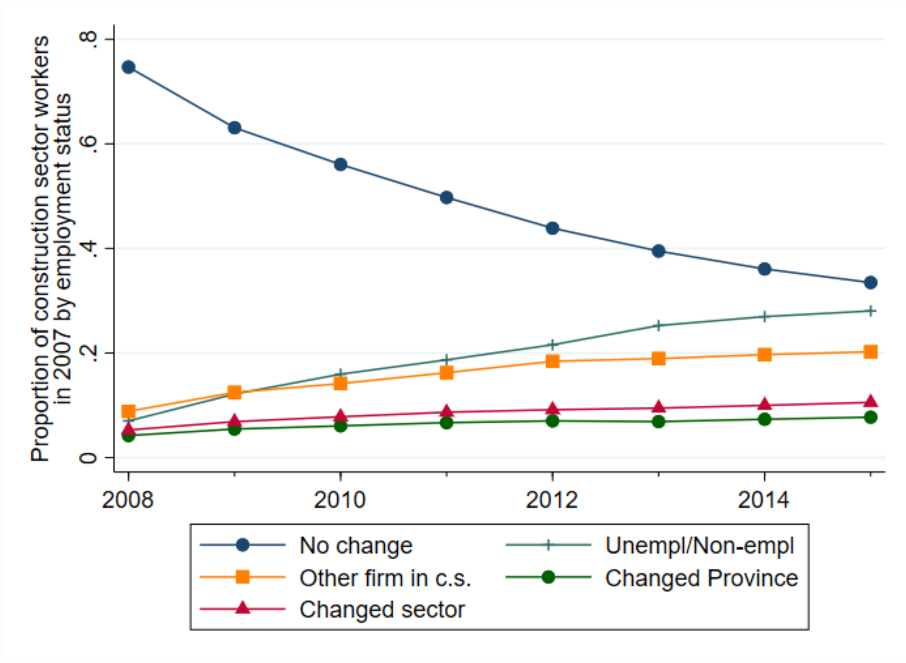
(a) Employment share in the construction sector by province, 2006



(b) Relative decrease in the employment share of the construction sector, 2007-2012

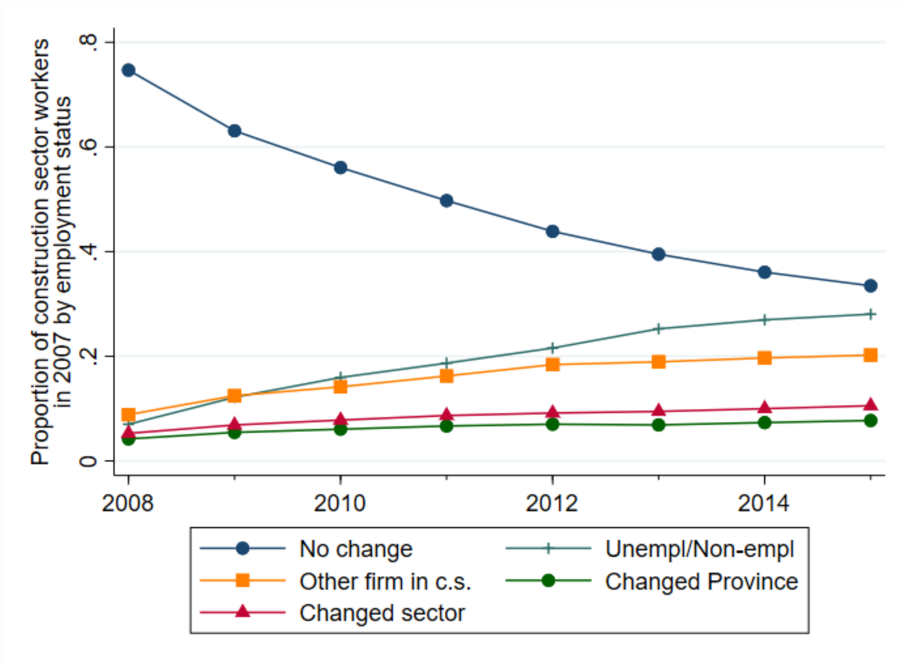
Notes: Panel a) Initial share of workers in the construction sector, shares are based on workers in the complete sample. Panel b) Relative decrease in the share of workers in the construction sector by province between 2007 and 2012. The sample considers 50 Spanish provinces.

Figure 1.19 Working status of individuals employed in the construction sector in 2007



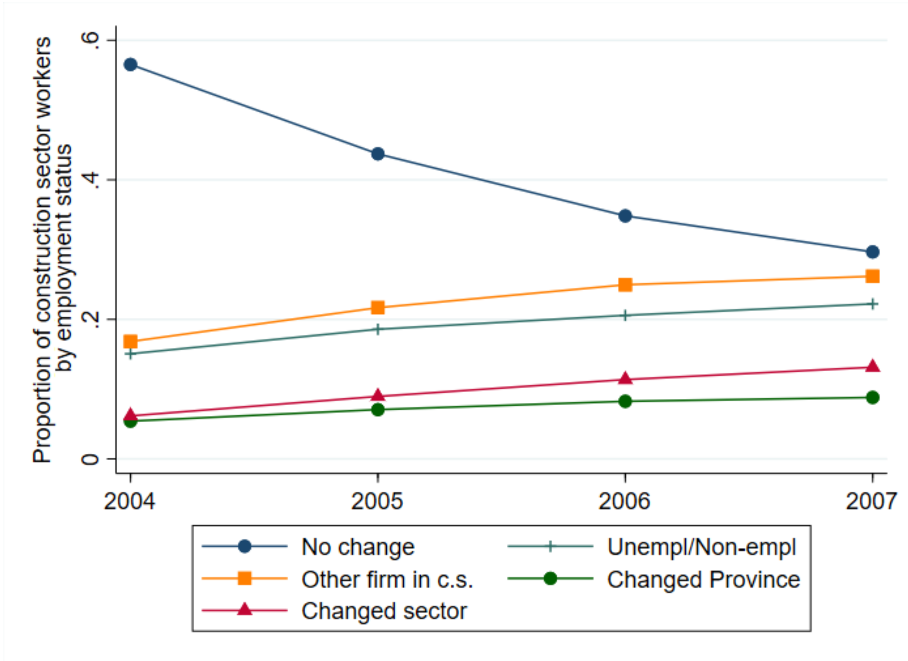
Notes: The shares are computed based on workers in the construction sector in 2007, and every year I tracked their working status up to 2015. The sample includes native and foreign workers

Figure 1.20 Working status of highly skilled individuals in 2007

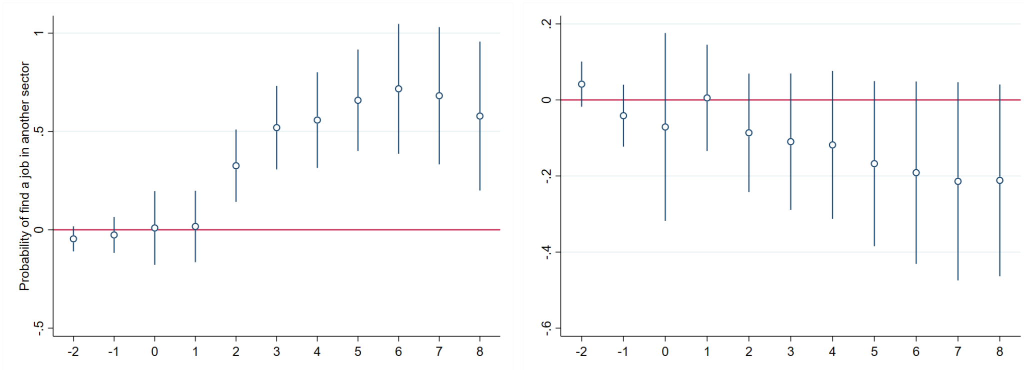


Notes: The shares are computed based on highly skilled workers, and every year I tracked their working status up to 2015.

FIGURE 1.21 Working status of workers in the construction sector in 2003



Notes: The shares are computed based on native workers employed in the construction sector in 2003, and every year I tracked their working status up to 2007.



(a) Shock's impact on the probability of change sector

(b) Shock's impact on the probability of change province

FIGURE 1.22 Impact of contraction of the construction sector employment. Weighted shock

Notes: Sample restricts to workers aged 29-42 and working in the construction sector in 2007. Coefficients of the shock using as an outcome variable the indicator if the worker changed residence province or sector on a rolling basis. a) Out of the construction sector b) In a province different than the residence in 2007. Additional controls by initial share of construction sector employment, Bartik type variable, demographic characteristics, and interactions.

Appendix 1.B Supplementary Tables

Table 1.12 Descriptive evidence of new workers in construction sector

	2004	2007	2012	2017
Age				
24<	0.403	0.347	0.258	0.292
24-35	0.396	0.406	0.352	0.390
35-45	0.156	0.185	0.248	0.189
>45	0.046	0.062	0.142	0.130
Mean age	28.0	29.1	32.7	31.3
Education				
Below secondary	0.695	0.693	0.638	0.646
Secondary	0.184	0.192	0.207	0.211
Tertiary	0.121	0.114	0.155	0.143
Type of contract				
Part-time	0.095	0.091	0.217	0.215
Fixed-term	0.928	0.886	0.872	0.837
Foreign born	0.289	0.424	0.252	0.293
Occupations				
Very-high skilled occupations	0.016	0.019	0.028	0.029
High skilled occupations	0.029	0.029	0.034	0.039
Medium-high skilled occupations	0.039	0.043	0.061	0.053
Medium-low skilled occupations	0.370	0.414	0.421	0.438
Low skilled occupations	0.546	0.495	0.457	0.440

Notes: The table reports the characteristics of new workers in the construction sector per year.

Table 1.13 Descriptive evidence of leavers from the construction sector

	2004	2007	2012	2017
Age				
24<	0.285	0.269	0.167	0.171
24-35	0.432	0.408	0.396	0.344
35-45	0.196	0.221	0.280	0.273
>45	0.088	0.102	0.157	0.212
Mean age	30.6	31.3	34.2	35.3
Education				
Below secondary	0.602	0.611	0.610	0.610
Secondary	0.197	0.191	0.189	0.209
Tertiary	0.201	0.198	0.201	0.181
Type of contract				
Part-time	0.217	0.221	0.286	0.323
Fixed-term	0.846	0.815	0.802	0.820
Foreign born	0.144	0.232	0.208	0.201
Occupations				
Very-high skilled occupations	0.021	0.021	0.030	0.031
High skilled occupations	0.041	0.042	0.057	0.061
Medium-high skilled occupations	0.109	0.114	0.126	0.126
Medium-low skilled occupations	0.450	0.470	0.441	0.425
Low skilled occupations	0.379	0.353	0.346	0.356

Notes: Table reports characteristics of leavers construction sector per year. Leavers are those who do not appear more, or those who leave the construction sector and move to another sector

Table 1.14 Impact of the employment contraction in the construction sector on worker's outcomes. By foreign born status.

	(1) Cumulative wage	(2) Cumulative years	(3) Average yearly wage
		Panel A: Foreign	
shock	-13.87**	-0.743**	-0.170**
	(3.992)	(0.241)	(0.0551)
$ShareCS_{2006}$	-3.804	-1.096**	0.179
	(7.291)	(0.342)	(0.142)
Constant	63.68***	4.292***	1.314***
	(3.725)	(0.253)	(0.0725)
		Panel B: Native	
shock	-27.76***	-1.702***	-0.141**
	(2.504)	(0.147)	(0.0420)
$ShareCS_{2006}$	-10.20	-0.338	-0.115
	(6.880)	(0.392)	(0.117)
Constant	75.13***	5.245***	1.226***
	(1.418)	(0.0783)	(0.0282)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: In each regression, I control for gender, occupation skill level, education, age, and foreign-born status. I restricted workers less than 50 years old in 2007 to avoid workers' early retirement before 2012. Shock measures the relative change in the share of workers in the construction sector by province. Bartik shock measures trends in employment growth in non-construction sectors. Cumulative wage is the sum from 2007 to 2012 of non-zero earnings standardized by the average wage in 2006. Cumulative years are the accumulated days worked from 2007 to 2012 and converted into years. The average yearly wage is the average yearly wage from 2007 to 2012.

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Table 1.15 Impact of the employment contraction in the construction sector on worker's outcomes. By age group.

	(1) Cumulative wage	(2) Cumulative years	(3) Average yearly wage
		Panel: Younger workers (¡25)	
Shock	-34.40***	-1.943***	-0.232***
	(4.457)	(0.239)	(0.0605)
$ShareCS_{2006}$	-32.32**	-1.231*	-0.428*
	(11.39)	(0.585)	(0.178)
Constant	93.67***	5.809***	1.449***
	(5.470)	(0.333)	(0.106)
		Panel: Older workers (¿35)	
Shock	-23.71***	-1.429***	-0.108*
	(3.341)	(0.187)	(0.0526)
$ShareCS_{2006}$	3.081	-0.255	0.0973
	(7.736)	(0.382)	(0.125)
Constant	61.45***	4.395***	1.180***
	(2.104)	(0.124)	(0.0350)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: In each regression, I control for gender, occupation skill level, education, age, and foreign born status. I restrict to workers less than 50 years old in 2007 to avoid workers' early retirement before 2012. Shock measures the relative change of the share of workers in the construction sector by province. Bartik shock measures trends in employment growth in non-construction sectors. Cumulative wage is the sum from 2007 to 2012 of non-zero earnings standardized by the average wage in 2006. Cumulative years is the accumulated days worked from 2007 to 2012 and converted into years. Average yearly wage is the average yearly wage from 2007 to 2012.

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Table 1.16 Impact of the employment contraction on workers' wage and employment trajectories

	(1)	(2)	(3)	(4)
	Cumulative wage			
	Change province		Change sector	
	No	Yes	No	Yes
shock	-29.45***	-17.95**	-33.75***	-18.94***
	(3.368)	(5.313)	(3.430)	(3.678)
Constant	86.73***	75.04***	85.61***	81.64***
	(4.408)	(7.098)	(4.563)	(4.676)
Observations	35592	12531	19118	29005
Controls	Yes	Yes	Yes	Yes
	Cumulative year			
	Change province		Change sector	
	No	Yes	No	Yes
shock	-1.643***	-0.861**	-2.201***	-0.689**
	(0.219)	(0.260)	(0.256)	(0.214)
Constant	5.933***	4.690***	5.986***	5.267***
	(0.330)	(0.288)	(0.402)	(0.321)
Observations	35592	12531	19118	29005
Controls	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The sample is restricted to native workers aged 20-50 years old in 2007, and working in the construction sector cumulative variables are computed between 2007 and 2012. Wage is standardized by the average wage in 2006 for months with non-zero earnings. Every regression controls by: gender, age, education, skill group, foreign status, and interactions between age and education. Bartik is computed without considering the construction sector and predicted values for the outside option are from a first stage **probit model**. The shock is the change in the construction sector employment share between 2007 and 2012

Appendix 1.C Definitions

1.C.1 Bartik

Workers may experience variation in employment opportunities as the construction sector in their initial province of residence is declining, but also as the other sectors experience employment fluctuations. In order to account for such fluctuations, I construct a Bartik-type shock.

$$Bartik_r = \sum_{j=1}^{12} EmplShare^j_{2006,r} \cdot \ln \frac{empl^j_{2012,r}}{empl^j_{2007,r}}$$

Employment growth in each sector is weighted by the local employment share. The employment share is computed without the construction sector.

1.C.2 Reallocation index computation

Sample: Workers not employed in the construction sector from 2000 to 2006. Observations are taken from March each year. I avoid seasonal variation in the compositions of sectors just by considering the employment probabilities in the same month each year.

Controls: Interactions of age categories with educational attainment and age categories with gender, foreign-born status dummy, occupational skill group.

Outcome: Indicator variable is the individual i is employed in sector s at time t

Specification:

$$y^s_i = X_i\beta + \varepsilon_i$$

The estimation is based on the following sectors:

1. Agriculture, livestock, fishing
2. Extractive activities
3. Manufacture
4. Energy, gas, and steam supply
5. Commerce
6. Hospitality
7. Transport and storage, communication
8. Financial and insurance activities
9. Renting
10. Professional, scientific, technical activities
11. P.A. and defense, education, health services
12. Other

Each equation is estimated separately, and the coefficients are used to get the predicted probabilities given the worker's characteristics in my estimation sample. The predicted probabilities of moving to each sector are weighted by the relative size of each sector at the province level without considering workers in the construction sector.

$$
\begin{aligned}
&\sum_{j=1}^{10} P(z=j|x=X_i)\cdot\frac{EmplShare_r^j}{EmplShare^j}\cdot\bar{w}_r\\
=&\sum_{j=1}^{10} \frac{P(z=j|x=X_i)}{EmplShare^j}\cdot EmplShare_r^j\cdot\bar{w}_r\\
=&\sum_{j=1}^{10} \frac{P(z=j|x=X_i)}{P(z=j)}\cdot EmplShare_r^j\cdot\bar{w}_r\\
=&\sum_{j=1}^{10} \frac{P(z=j,x=X_i)}{P(z=j)P(x=X_i)}\cdot EmplShare_r^j\cdot\bar{w}_r
\end{aligned}
$$

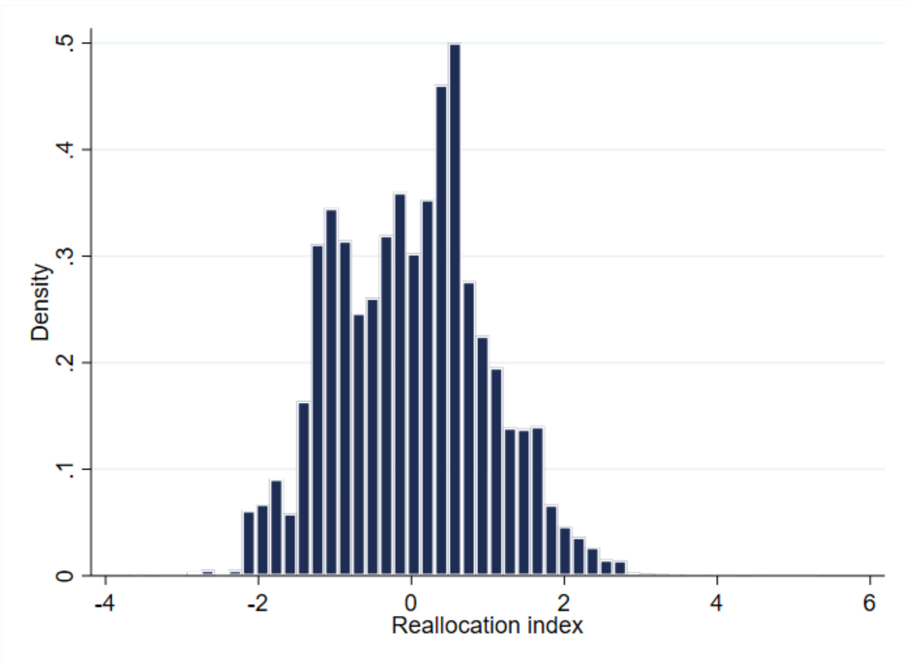


FIGURE 1.23 Histogram of the reallocation probabilities

Notes: Reallocation probabilities of workers employed in the construction sector in 2007.

1.C.3 Description of outcomes

Table 1.17 presents descriptive statistics on cumulative earnings, average earnings, employment, and worker characteristics during the study period for construction workers and non-construction workers as a comparison group. The average non-construction worker earned positive earnings of 4.6 out of a maximum of 6 years and cumulatively 61.56 times their pre-recession average monthly earnings. Workers initially employed in the construction sector had positive earnings 58% of the period between January 2007 to December 2012, about three-fourths the employment of the average non-construction worker. Finally, compared to their counterparts in other sectors, workers in the construction sector have lower educational attainment and are more likely to be male and foreign-born. I only consider native workers in the rest of the paper. During the Great Recession, outcomes of foreign workers were more likely to go unobserved, mainly due to return migration to the home country, which may cause a measurement bias of the effects.

Appendix 1.D Migration

Geographical mobility depends on many factors, including the availability of credit and labor market security, binding conditions during a recession. Then, lower geographical mobility could be expected in comparison to an expansionary period Dix-Carneiro and Kovak (2017), Autor et al. (2014). Since Blanchard et al. (1992) seminal paper, other studies have analyzed the role of labor mobility as an adjustment mechanism finding mixed results. However, recent papers show adjustment from this mechanism is slow Amior and Manning (2018), Dix-Carneiro and Kovak (2017) and depends on worker's characteristics. The least mobile workers are the most vulnerable Gathmann et al. (2020).

Figure 1.24 shows that, on average, 3.25% workers changed job locations between 2000 and 2012. At the highest point, only 4.01% of individuals worked in a different province than the previous year. In comparison, Monras (2018) show that in the United States, the proportion of Americans working in a different metropolitan area compared to the previous year was 5.4 % before the Great Recession and 4.8% after 2007.

If workers move from more exposed to less exposed regions, outflows to other provinces should increase, even if this reaction takes some periods to appear. However, Figure 1.24 shows a decrease during the Great Recession in movers' share. This claim is in line with recent evidence. After a negative shock, exposed regions experience a decrease in inflows and not necessarily a strong response on outflows, Dustmann et al. (2017), Molloy et al. (2011).

However, this aggregate description of worker flows hides compositional changes.

Table 1.17 Descriptive statistics of workers, 2007-2012

	(1) Non-construction	(2) Construction
Labor market outcomes		
Cumulative earnings	61.56	45.80
	(29.07)	(26.37)
Employment	4.55	3.48
	(1.804)	(1.779)
Education		
Below secondary	0.45	0.76
	(0.498)	(0.427)
Secondary	0.26	0.16
	(0.440)	(0.363)
Tertiary	0.29	0.08
	(0.452)	(0.278)
Worker's composition		
Tenure	3.57	2.06
	(4.579)	(3.033)
Average age	33.60	32.54
	(7.924)	(7.843)
Share female workers	0.47	0.08
	(0.499)	(0.273)
Share foreign workers	0.14	0.28
	(0.346)	(0.451)
Obs.	304085	52671

Notes: Workers in the construction and non-construction sectors are classified by their employment sector in 2007. An individual's cumulative earnings are calculated by dividing their non-zero earnings between 2007 and 2012 by their average monthly earnings between 2005 and 2006. Standard deviations are presented in parentheses

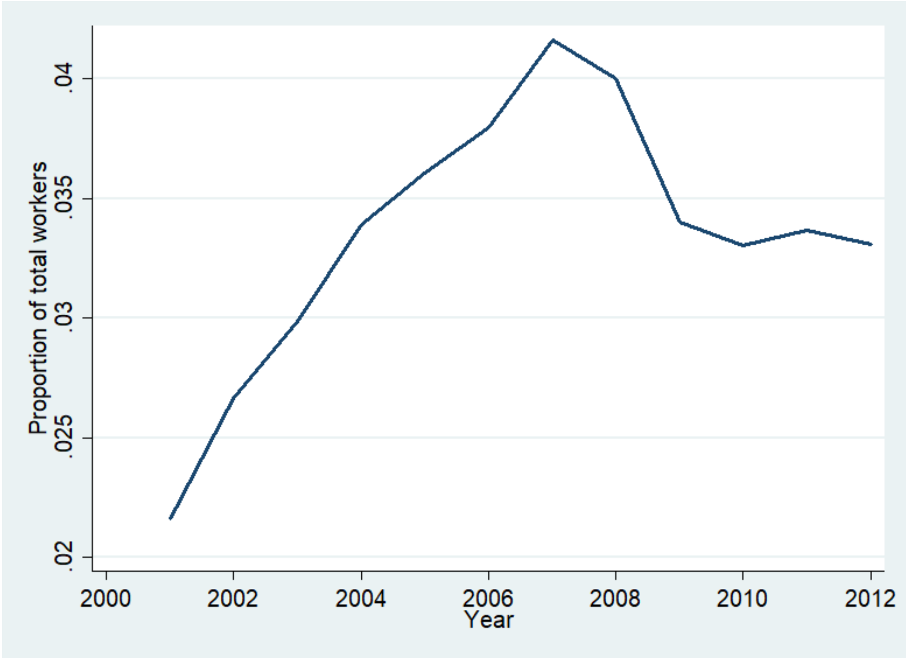


FIGURE 1.24 Share of workers change job's province
Notes: Share of individuals working in a different province with respect to the previous year, 2001-2012. The sample of workers between 2000-2012, based on a sample of workers in MCVL

For instance, on the type of migrants before and after the crisis. So, in order to study this further, the following results change the scope to regional movements. There are two mechanisms through which workers' population in a specific region may change, interregional mobility and movements to and from unemployment or non-employment. This relationship is expressed as:

$$\frac{L_{m,t} - L_{m,t-1}}{L_{m,t-1}} = [\frac{I^r_{m,t}}{L_{m,t-1}} - \frac{O^r_{m,t}}{L_{m,t-1}}] + [\frac{I^u_{m,t}}{L_{m,t-1}} - \frac{O^u_{m,t}}{L_{m,t-1}}]$$

The sub-index m is applied for region, and t for period. The left-hand side represents the relative change in the worker's population between two periods, which is decomposed as inflows minus outflows from each region and inflows minus outflows from a non-working condition[26].

$I^r_{m,t}$ represents the number of workers which moved to region m in period t, and $O^r_{m,t}$ workers that were in region m at $t-1$, but in another region in t. On the other side, $I^u_{m,t}$ accounts for the number of workers that come to region m and previously were in unemployment or non-employment. Finally, $O^u_{m,t}$ shows outflows to unemployment or non-employment.

Given equation 1.D is an exact decomposition, I can decompose the variance as how much of the population growth rate in region m is explained by in-migration

[26]The aim of this section is not on individuals that are not actively working. Then I group unemployed and non-employed workers as individuals in a non-working condition

Table 1.18 Decomposition variance of local population growth

	(1) I_m^r	(2) I_m^u	(3) O_m^r	(4) O_m^u
	Panel A: < 2008			
change	0.0606***	0.695***	-0.0788***	-0.165***
	(0.0143)	(0.0334)	(0.0181)	(0.0428)
Constant	0.0417***	0.0961***	0.0450***	0.0929***
	(0.00202)	(0.00274)	(0.00109)	(0.00391)
Observations	100	100	100	100
	Panel B: > 2008			
change	0.0575***	0.469***	-0.0363***	-0.438***
	(0.00946)	(0.0168)	(0.0102)	(0.0189)
Constant	0.0405***	0.101***	0.0320***	0.110***
	(0.00124)	(0.00201)	(0.00125)	(0.00227)
Observations	450	450	450	450

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Regression of in-migration and out-migration on region m worker's population change. The sample considers the 50 Spanish provinces between 2005 and 2008 in panel A and after 2008 in panel B.

rates and how much by out-migration rates (Dustmann et al. 2017; Monras 2018).[27].

Consider the following regression:

$$y_{tr} = \alpha_0 + \beta change_{tr} + \psi_t + \mu_r + \epsilon_{tr}$$

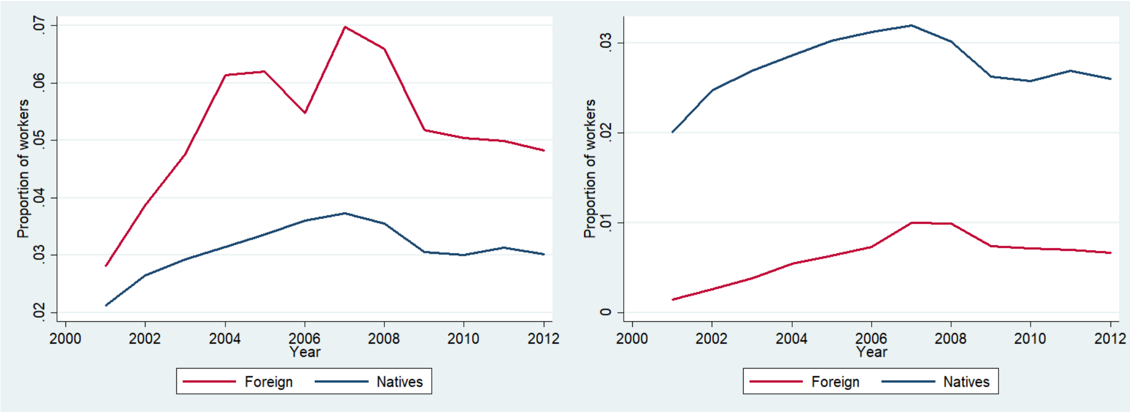
Such that y_{tr} could be inflows or outflows from another region, or from a non-working condition, and $change_{tr}$ the relative change in worker's population of the region m between period t and $t-1$.

Table 1.18 shows worker flows from and to the non-working condition are relatively more important in explaining local population growth. More than 50% of the population growth variation is explained by non-employment flows, with a decrease in inflows' relative importance during the Great Recession, and an increase in outflows to non-employment. This fact is consistent with the drop in employment at the national level. Considering the local growth of workers in the construction sector, an equivalent picture is appreciated. There is a decrease in general with a decrease in outflows to non-employment.

The common idea is that foreign workers are more predisposed to migrate. This includes a more significant propensity to international and interregional migration. I will start by analyzing the proportion of foreign workers in the interregional flows. Figure 1.25 presents the share of movers as a proportion of all workers, divided by

[27]Suppose we have an exact decomposition A=B+C and $\beta_1 = \frac{Cov(A,B)}{Var(A)}$, $\beta_2 = \frac{Cov(A,C)}{Var(A)}$. Then, as A=B+C and properties of covariance $\beta_1 + \beta_2 = 1$, therefore we can interpret β_1 and β_2 as a variance decomposition of A

Figure 1.25 Interregional movements



(a) Movers by group

(b) Movers from total

Notes: Panel (a) Proportion of foreign movers as a share of all foreign workers, and proportion of native movers as a share of all native workers. Panel (b) Proportion of foreign movers as a share of all workers and proportion of native movers as a share of all workers. Movers are computed as workers that one year before had their main job in a different province.

demographic group. Define $G \in \{F, N\}$ as the group-specific identifier, with F for foreign, and N for natives, in panel (a) I present the share $\frac{M_t^G}{P_t^G}$, where M_t^G accounts for the number of individuals in the group G working in a different province than the previous year, and P_t^G the total number of individuals from a group G at time t, while in panel (b) I present $\frac{M_t^G}{P_t^N + P_t^F}$.

Figure 1.25 shows that foreign workers are more likely to change location. Considering the population of foreign workers each year, the proportion of workers who changed location for one year before is higher for foreign than for native workers. However, as presented in panel (a), geographical mobility decreased for both demographic groups during the Great Recession. Also, foreign workers represent a low portion of total movers appreciated in panel (b).

International migration

The data in MCVL does not allow tracking if a worker migrates from Spain, in the case of foreign workers, that would be useful, as an additional mitigating force of a negative shock in the local area is international migration, which in the case of foreign workers is more likely to return to their home country Cadena and Kovak (2016).

Given this constraint, at most, I could be analyzing the probability a worker gets non-employed for a considerable amount of time. In the case of foreign workers, it would suggest they return to their home country.

In native workers, there is a strong familial link and wealth accumulation, which could maintain a long time of non-employment. In foreign workers, this force very

Table 1.19 Probability a worker is non-employed during the Great Recession conditional con observables

	(1)	(2)
	Non-employment	
Foreign	0.253***	0.250***
	(0.00837)	(0.00785)
$ShareCS_{2006}$		-0.309***
		(0.0701)
$\Delta Share$		-0.0682
		(0.0472)
Constant	0.131***	0.136***
	(0.00983)	(0.0222)
Observations	96507	96507

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

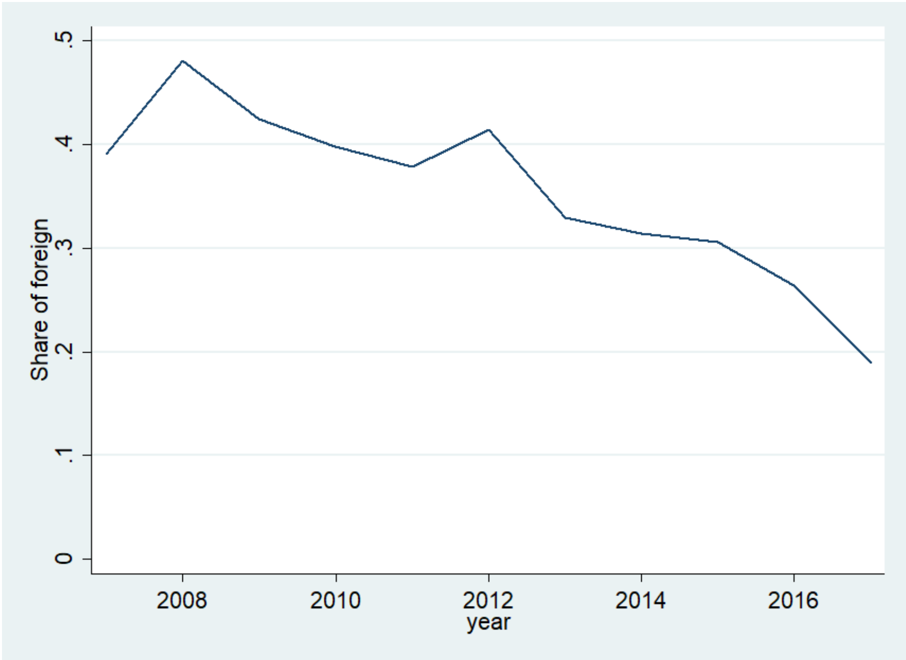
Notes: Probability a worker disappear from my sample between 2007 and 2012 conditional on worker characteristics. The probability is computed from a linear probability model on a dummy that takes value one if workers disappear between 2007 and 2012 controlled by education, age, foreign status, occupational skill group, a decrease of local construction sector share, and initial share of the construction sector. The sample is constrained to individuals in the construction sector in 2007 and is based on a yearly panel with observations from 2005 to 2017.

likely is less critical than if an essential share of foreign workers disappears from the dataset. It is a consistent explanation to argue that they return to their home country.

Table 1.19 shows results from the probability a worker is not seen from some time into the future, as assumed in the previous discussion, among them being a foreign worker implies a higher probability to disappear from the social security records, this proportion is robust on adding controls on the local conditions faced.

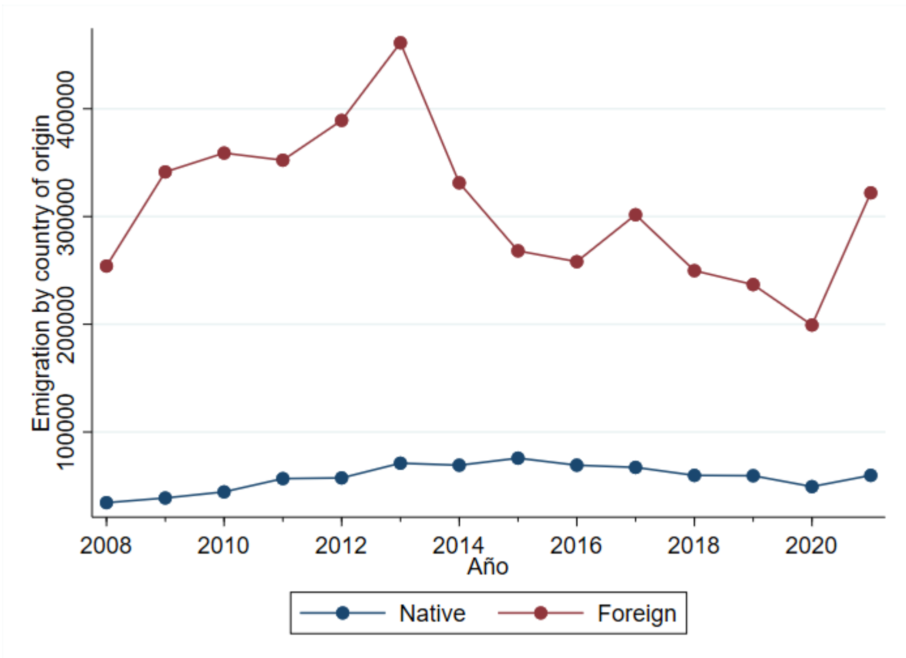
Also, during the first years of the Great Recession, the share of foreign workers that exit the social security records is higher than in years before the Great Recession, and also during the recovery period (Figure 1.27)

Figure 1.26 Share of foreign workers leaving the ss records



Notes: Share of foreign workers by year of exit from social security records of workers in the construction sector during 2007.

Figure 1.27 Emigration by country of birth, 2008-2021



Notes: Total of emigration by country of birth, 2008-2021
Source: INE

Chapter 2

Quasi-random matches: evidence from dual labor markets

A fast-growing literature studies how sorting into particular jobs, firms, or locations affects workers. Following Abowd et al. (1999), there has been much interest in the observation that pay premia vary across firms, the mechanisms that generate such variation (Manning 2021, Card et al. 2018), and its implications (Card et al. 2013). A natural question then is whether jobs also differ in their *dynamic* implications – if workers learn more and enjoy faster earnings growth in some jobs while being "stuck" in others. Indeed, recent studies suggest that earnings growth varies systematically across firms (Arellano-Bover and Saltiel 2021, Pesola 2011), regions (Roca and Puga 2017), and jobs (Kambourov and Manovskii 2009; Gathmann and Schönberg 2010; Garcia-Louzao et al. 2021).

The key challenge when studying such questions is the non-random sorting of workers into jobs. For example, firms paying higher wages might attract better applicants, and workers in urban labor markets might be different from those in rural areas. To address this selection problem, the literature often adopts a fixed effect strategy: by tracking workers across firms, researchers can decompose wages into time-constant differences between individuals (individual fixed effects) and match-specific components (such as firm fixed effects, as in Abowd et al. 1999). While this strategy is ubiquitous, there is an obvious tension: if workers or firms differ in their *level* of pay, they might also differ in wage *growth*, which the fixed effects would not capture.

In this paper, we propose an alternative strategy that exploits the *timing* of worker-firm matching. Specifically, we isolate quasi-random variation in matches by interacting high-frequency information on (i) the duration of contracts on the supply side of the labor market and (ii) transitory fluctuations in job creation on the demand side. We apply this method to address a central question in "dual" labor markets: how do different contract types – fixed-term (FT) or open-ended contracts

(OEC) – affect workers' careers? A common concern is that fixed-term contracts may discourage firms from providing training or other investments to their workers (Cabrales et al. 2017; Albert et al. 2005). While we focus on the consequences for workers, this problem has important aggregate implications, and the prevalence of fixed-term contracts is one suspected reason for low labor productivity in countries characterized by dual labor markets (Cahuc et al. 2016).[1]

Our application focuses on Spain. With the highest rate of temporary employment in Europe of nearly 25% (See Figure 2.10) and as much as 90% of new contracts being fixed-term (until a major reform in 2022), the country provides an interesting context. Moreover, we can exploit rich, matched employer-employee data from Social Security records that track workers over time and contain detailed information on the type and length of individual employment contracts.

We first provide evidence using a standard fixed effects approach, estimating an earnings equation that allows for time-constant differences between individuals and different rates of worker experience gained in fixed-term or open-ended contracts. Consistent with recent evidence by Garcia-Louzao et al. (2021), we find that earnings growth is higher for workers with more experience in open-ended contracts: while earnings grow by 2.7 percent for each year of experience in FTs, they grow by 3.6 percent per year in OECs. These patterns are highly non-linear, and the gap is much greater for experienced than young, inexperienced workers. An intuitive interpretation of these findings is that fixed-term contracts slow skill acquisition and wage growth (i.e., differences in returns to experience). However, they could also be due to workers who secured an OEC early in their career experiencing higher wage growth *irrespectively* of current contract type (i.e., selection).

A key piece of evidence to distinguish between these competing interpretations is an event study graph studying wage growth around contract switches. For example, Card et al. (2013) show that workers who switch from low- to higher-paying firms tend to experience similar wage growth as those that make the reverse switch ("parallel pre-trends"), suggesting that worker-firm matching is sufficiently random in a dynamic sense. However, we show that the parallel trends assumption does not hold in dual labor markets: workers who switch into an open-ended contract as opposed to another fixed-term contract experienced higher wage growth even *before* they entered their new contract. The difference is sizable: while the earnings of workers switching to an open-ended contract grow, on average, by 5% in the year before the switch, earnings growth is negligible for workers who switch to another fixed-term contract instead. This gap remains large when controlling for a detailed set of worker characteristics. This observation suggests that the matching of workers to contract types is not random in a dynamic sense: the differences in wage growth between fixed-term and open-ended contracts primarily reflect heterogeneity between

[1] In addition other relevant outcomes may be affected by labor market duality, such as: fertility (Auer and Danzer 2016; Lopes 2020; Nieto 2022); migration: (Llull and Miller, 2018).

workers rather than differences in returns between contract types.

The selection of workers into contracts is, therefore, a more difficult problem than the selection into firms (Card et al. 2013) or regions (Card et al. 2021). We discuss several reasons why this might be the case. One factor is that the switch to open-ended contracts occurs more often within firms and is therefore based on more information than in the case of workers switching to other firms. Moreover, switching into an OEC within a firm can be a form of promotion; and promotions depend, of course, on the recent performance of the worker. Finally, higher-ability workers are more likely to be matched to better fixed-term contracts, i.e., they might be able to find actual stepping-stones. They would therefore display differential pre-trends even before switching to a permanent position.

Our paper, therefore, adds to two distinct strands of literature. On the methodological side, we relate to recent papers extending the standard two-way fixed effects specification to account for more complicated forms of selection. For example, Roca and Puga (2017) evaluate returns to experience heterogeneity based on city size. Their approach explores both static and dynamic advantages, allowing for heterogeneity of city gains across workers by interacting individual fixed-effects (a measure of unobserved innate ability) with city-size specific experience. Similarly, Arellano-Bover and Saltiel (2021) show that returns to experience vary across firm types. Applying a clustering methodology, they are able to classify firms into *skill-learning* classes which they show are not predicted by firms' observable characteristics.

Compared to these papers, we follow a different strategy: rather than enriching the fixed effects specification to account for specific forms of heterogeneity and dynamic selection, we isolate quasi-random variation in matching workers and firms using an instrumental variable strategy. That is, rather than trying to control for dynamic selection by modeling it explicitly, we aim to circumvent it. Specifically, we interact individual variation in the expiration date of fixed-term contracts with transitory fluctuations in the opening of new open-ended jobs over time to isolate exogenous variation in contract type.

Conceptually, our strategy is similar to studies that analyze the effects of labor market conditions at the entry on worker careers – "graduating in a recession" – (Oreopoulos et al. 2012; Kahn 2010), in particular, recent work by Arellano-Bover (2020) on the selection of workers into different firm types. However, rather than exploiting yearly variation in labor market entry of recent graduates, we exploit high-frequency information on the duration of contracts. Specifically, exploiting the precision of administrative employment records, we are able to match the precise month when the individual's contract is about to end with transitory variation in job openings at the regional level. Our approach faces the usual challenges in establishing instrument relevance and validity. The upside, however, is that we do not have to specify the functional form of individual heterogeneity and dynamic selection.

We first establish the instrument's relevance, showing that the (leave-out) sum of new open-ended contracts is highly predictive for a worker to switch from a fixed-term into an open-ended contract. We then provide evidence to support the instrument independence assumption and exclusion restriction. Instrument independence would imply that facing more open-ended job openings (relative to trend) in the month a contract ends is as-good-as random for the worker. To support this assumption, we show that our instrument is indeed broadly uncorrelated with worker characteristics. However, the exclusion restriction is unlikely to hold without further adjustments. The number of new open-ended contracts (our instrument) does, of course, correlate with general business cycle conditions, so it is not obvious whether a worker enjoys higher wage growth because she started in an open-ended contract or because the economic conditions in this period were generally favorable, affecting wage growth conditional on the contract type. The objective, therefore, becomes to control for general economic trends while exploiting the exact timing of when an individual switched jobs, i.e., we exploit high-frequency variation in the types of contracts that are available while controlling for low(er)-frequency business cycle variation.

To the best of our knowledge, we are the first to exploit this source of exogenous variation to deal with the endogenous sorting of workers into jobs. We argue that it is applicable in many settings. While administrative panel data are not without problems, they offer highly precise (typically, daily) information on the duration of contracts, as this information is directly relevant for the calculation of taxes and social security contributions. Our approach, therefore, exploits a comparative advantage of administrative data (their high frequency), similarly as the fixed effects approach exploits another (their scale).

Apart from this methodological contribution, we also add to the active literature on dual labor markets (Bentolila et al. 2020). The two-tier segmentation that characterizes many European labor markets is the result of a series of reforms that started in the 1980s and intended to tackle high structural unemployment. Fueled by regulations that aimed to introduce more hiring flexibility, fixed-term contracts became widespread. While these low-firing-cost contracts may, in theory, help workers avoid long periods of unemployment, they may also come at the expense of lower human capital accumulation and poor progression toward better jobs. Indeed, previous studies have shown that workers in temporary positions receive less firm-provided training (Cabrales et al. 2017; Bratti et al. 2021). With asymmetric on-the-job learning opportunities and uncertain conversion to permanent positions, long histories of recurrent fixed-term spells can perpetuate workers in low-wage-growth trajectories (Gagliarducci, 2005). While fixed-term contracts may serve as stepping-stones to more stable jobs, the favorable evidence mostly corresponds to countries with low firing costs for fixed and open-ended positions alike (Bentolila et al., 2020). For countries such as Spain and Italy, where not only the share of temporary jobs is higher but also the gaps in employment protection by type contract are large, these contracts more often result in "dead ends" (Güell and Petrongolo 2007; García-Pérez and Muñoz-Bullón 2011; Garcia-Louzao et al. 2021).

The paper is organized as follows: Section 2.1 provides a background of the institutional framework, Section 2.2 introduces the main data source, Section 2.3 provides a characterization of dualism in Spain and preliminary results of a mincerian approach, Sections 2.4 and 2.5 discuss the main sources of endogeneity and our identification strategy, respectively and Section 2.6 analyses the effect of upgrade promotion in workers' career trajectory by evaluating a series of labor market outcomes.

2.1 Institutional framework

In the aftermath of the dictatorship, Spain's institutions underwent major changes, including reforming its labor market legislation. Before 1976, labor laws in Spain were liberal (Toharia, 2002), as most labor contracts required only the acceptance of both employers and employees. The first step toward modernization was Law 16/1976.[2] Under this law, however, all contracts were considered full-time permanent, except where special hiring flexibility was required.

Initiating the dualism of the Spanish labor market, Law 32/1984 established the coexistence of permanent and temporary contracts; the latter was used to promote job creation. With this reform, firms with no seasonal activities could sign temporary contracts with any worker. Therefore, firms may open permanent vacancies with a high severance payment or temporary vacancies with a smaller severance payment. The reform did not alter any of the conditions for permanent contracts, which made temporary contracts more appealing for firms (García-Pérez et al. 2019, Aguirregabiria and Alonso-Borrego 2014).

As a response, a new reform in 1994 restricted temporary contracts to seasonal activities and relaxed dismissal conditions for permanent employees. In practice, however, employers continue hiring temporary workers, not just for seasonal jobs (García-Pérez et al., 2019). This perceived ineffectiveness of the 1994 reform led to additional reforms in 1997 and 2001. The changes created a new permanent contract with a smaller severance payment of 33 days per year worked compared to the 45 in the previous reforms—this new contract was aimed at the young, workers older than 45, and those with disabilities.[3]

It was not until 2012 that hiring costs for permanent employees were significantly

[2] Ley 16/1976 de 8 de Abril de Relaciones Laborales.

[3] The reform of 2001 also included women hired in sectors where they are underrepresented and long-term unemployed.

reduced. The compensation at the termination of the temporary contract was increased, reducing the gap between the dismissal costs of workers with permanent and temporary contracts. In addition, the reform eliminated interim wages in judicial processes. A new open-ended contract was introduced for firms below 50 employees, entailing no severance pay during an extended probationary period of one year. But fixed-term contracts still accounted for more than 20% of all employees.

Various reforms have been implemented in the last 30 years to decrease labor market dualism while preserving hiring flexibility. The proportion of workers in a temporary contract has also decreased during that time. Still, many workers begin their working career on a temporary contract and experience a long sequence of unstable jobs. One major concern is that this lack of job stability has adverse consequences for the accumulation of human capital, fertility, and wages.

2.2 Data

Our main data source combines the 2006-2017 waves of the Continuous Sample of Working Lives (*Muestra Continua de Vidas Laborales* or MCVL). The microdata from the MCVL constitutes a 4% non-stratified random sample of Spain's Social Security administrative records. The sample allows tracking the full working history of individuals back to 1967 and the monthly earnings since 1980. Once an individual with an ongoing relationship with Social Security is included in the sample, it remains in all future waves.[4] Furthermore, every year, those individuals that are no longer affiliated with Social Security are replaced with new workers (along with their whole past labor history). This updating exercise ensures that the sample remains representative.

Several features make this rich dataset optimal for our analysis. A key advantage of the MCVL is its high-frequency records, reporting the exact start and end dates of each contract. This enables us to measure the labor market conditions that workers face at a very detailed (in our baseline analysis, monthly) level. Since we have information on each spell's entry and exit date, we are able to compute the exact days an employee worked. Whenever there is an overlap of spells, we preserve the job characteristics of the main job: i.e., the largest spell of the month. We are then able to build a reliable measure of tenure and work experience with a clear distinction between the experience accumulated in fixed-term and open-ended contracts.

Furthermore, the Social Security records are matched with annual information from the municipal population registry (*Padrón Continuo Municipal*) and income tax records from 2006 onward. The former allows us to expand on workers' demographic characteristics, and the latter on additional worker and firm characteristics.

[4]Employees, self-employed individuals, pensioners, and people receiving unemployment benefits are included in this category.

We observe the date of birth, gender, educational attainment, and country of birth of each worker. While we do not observe occupation directly, we sort workers into five occupational-skill groups that we define based on ten occupational contribution categories that employers must report to Social Security Administration. In principle, these refer to the skill required for a particular job and not necessarily the skills acquired by the worker. Still, they are closely related to the required formal education to execute a particular job.

At the firm level, we observe the province where the firm is located and its size from 2006. Strictly speaking, while a firm can have more than one establishment in different provinces, we treat each establishment as a separate firm. Additionally, for each job, we observe the sector of the economic activity at the two-digit level, the type of contract (permanent or fixed term, full-time or part-time), and whether the worker is self-employed, or a private or public sector employee.

The MCVL contains information on earnings from two distinct sources, social security and tax records. Given that the social security taxable base is bottom and top coded,[5] we compute monthly real earnings from tax records whenever available,[6] which are not subject to censorship. Combining data from several waves allows us to reconstruct the history of tax records which, unlike social security records, do not contain the worker's retrospective history. In earlier years, we used information from social security. Likewise, given that the Autonomous Communities of Navarre and Basque Country collect income taxes independently from the National Government, we only observe social security records for workers of those regions. As we have accurate information on the length of each spell we can compute days worked during each month and daily wages.

2.2.1 Sample restrictions

Our study evaluates the 1998-2017 period. Although we can trace each worker's earnings trajectory back to 1980's, information on the type of contract is reliable only from 1998 onwards. We focus on workers aged 18-49. We restrict the analysis to workers registered in the general social security regime or the special regime for agrarian, sea workers, and mining. This excludes autonomous workers. Since they are not employees and therefore do not hold a contract, they are not part of our study.

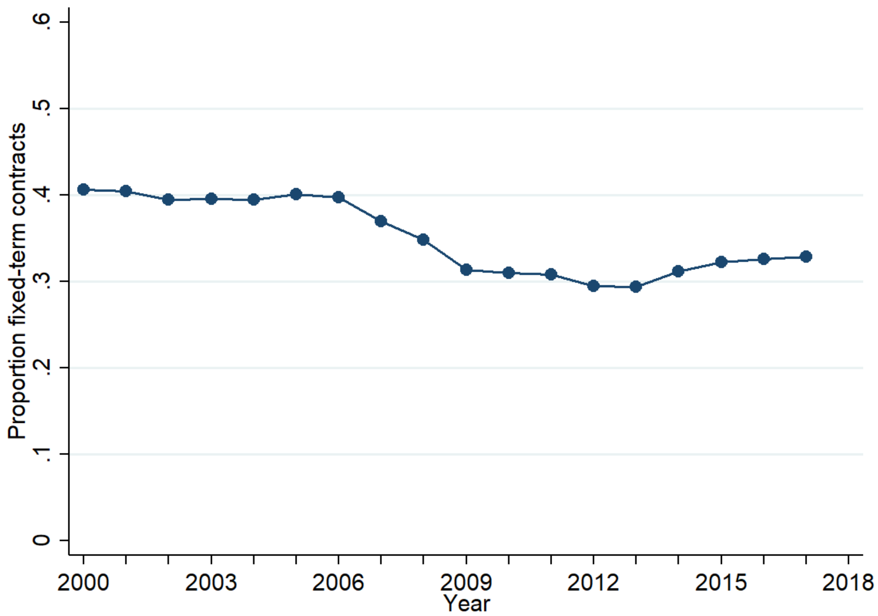
In our main specification, we only consider private sector workers, as the contract duration of public sector employees is highly regulated and centralized, as well as the promotion to permanent positions relies on a special process.[7] However, whenever

[5]The upper and lower bounds are specified by sector and updated every year.

[6]Nominal wages are deflated using the 2009 Consumer Price Index.

[7]Workers in the public sector are usually required to approve specific exams and fulfill special requirements to get a permanent position. This process is quite different from the promotion path

Figure 2.1 Proportion of workers in fixed-term contracts, by year



Notes: Proportion of workers under a fixed-term from 2000 to 2017.

this is the case, our measure of experience does take into account the time that a private employee previously worked in the public sector, either in a fixed or a permanent contract. Regionally, we exclude information from Ceuta and Melilla, for which the sample of workers is very small. Thus, we work with data from 50 provinces.

2.3 Descriptive evidence

One-third of all Spanish employees are employed on a fixed-term basis, on average, over the last few decades. Despite a decline in the share of temporary workers in the aftermath of the Great Recession (Figure 2.1), their share is still very high compared to most European countries.[8] The reduction in the proportion of fixed-term contracts reflects, to a great extent, the decrease in hiring after the financial crisis. The construction sector, which concentrated a large share of temporary workers, was one of the hardest hit. Likewise, young workers' unemployment increased dramatically and remained high for many years, spiking from around 22.3% in 2004 to 44.5% in 2016. This situation also affected the age distribution of temporary workers. As shown in Table 2.1, the share of fixed-term contract workers under 24 years almost halved, from 20.7% in 2004 to 11.2% in 2016.

As discussed previously, the high dualism in the Spanish labor market implies

of private sector workers.

[8]In 2019, more than 25% of Spanish workers were on a temporary contract. See Figure 2.10.

that rather than working as stepping-stones, a large proportion of fixed-term contracts are dead-ends. While this problem is more severe for low-skilled occupations, it cannot be neglected at the top of the distribution. As shown in Table 2.1, the share of high-skilled occupations among temporary contracts has steadily increased. In terms of other workers and job characteristics, these contracts are equally spread among women and men. While most of these contracts correspond to full-time positions, the proportion of part-time jobs under this modality has increased substantially, representing almost one-third of these jobs by 2016.

Table 2.1 Characteristics of workers in fixed-term contracts

	2004	2008	2012	2016
Age group				
<24	0.207	0.174	0.116	0.112
24-35	0.487	0.458	0.433	0.388
36-50	0.262	0.316	0.373	0.400
>50	0.044	0.052	0.079	0.099
Foreign	0.137	0.234	0.205	0.176
Female	0.429	0.457	0.500	0.489
Part-time	0.192	0.198	0.308	0.317
Occupations				
Very high skilled occupations	0.050	0.059	0.083	0.080
High-skilled occupations	0.070	0.081	0.100	0.095
Medium high skilled occupations	0.117	0.126	0.142	0.134
Medium low skilled occupations	0.475	0.479	0.431	0.419
Low-skilled occupations	0.288	0.255	0.244	0.272

Notes: Characteristics of workers employed under fixed-term contracts.

For comparability with previous studies on heterogeneous returns to experience (Roca and Puga, 2017; Garcia-Louzao et al., 2021; Arellano-Bover and Saltiel, 2021), we begin our descriptive analysis by estimating the contribution of contract-specific experience to earnings growth using a classic Mincerian equation. We account for differential returns to experience by explicitly modeling combinations of experience accumulated in fixed-term and open-ended contracts. We estimate the following equation by OLS:

$$\ln w_{irt} = exp_{it}^{FT}(\beta_1 + exp_{it}\beta_2) + exp_{it}^{OEC}(\beta_3 + exp_{it}\beta_4) + X_{it}'\mathbf{\Omega} + \sigma_r + \psi_t + \varepsilon_{irt},$$

where exp_{it}^{FT} and exp_{it}^{OEC} denote the worker's experience accumulated until period t in fixed-term and in open-ended contracts, respectively. The variable exp_{it} is the total experience of individual i up to period t. X_{it} is a vector of time-varying individual and job characteristics, including gender and occupation-skill group interacted with educational attainment, sector fixed-effects, age, age squared, and an interaction of tenure with a fixed-term contract indicator, σ_r is a province fixed effect, ψ_t is a year-month fixed-effect, and ε_{ict} is the error term.

Table 2.2 Wage growth in fixed-term and open-ended contracts

	(1)	(2)	(3)
		ln earnings	
exp	0.051***		
	(0.001)		
$exp^2/1000$	-1.314***		
	(0.032)		
exp_{FT}		0.064***	0.079***
		(0.001)	(0.001)
exp_{OEC}		0.056***	0.071***
		(0.001)	(0.001)
$exp \times exp_{FT}/1000$		-3.373***	-3.312***
		(0.063)	(0.055)
$exp \times exp_{OEC}/1000$		-1.049***	-1.446***
		(0.039)	(0.031)
Obs.	16,266,496	16,266,496	16,255,262
R^2	0.475	0.478	0.754
Controls	Yes	Yes	Yes
Ind. FE	No	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: exp, exp_{FT}, and exp_{OEC} account for experience, experience in fixed-term, and experience in open-ended contracts, respectively. Controls include gender and occupation-skill group interactions on education attainment, sector, region and time fixed-effects, age, age squared, and interactions of tenure with an indicator for a fixed-term contract. Errors are clustered at the worker level.

Instead of the typical quadratic form of homogeneous returns to experience, equation (2.3) considers the product between overall experience and contract-specific experience. This interaction captures that the moment at which workers accumulate experience in each type of contract matters. In other words, the returns to an extra year of lower-quality experience at the beginning of the career may differ from the returns at mid-career.

The estimates are shown in Table 2.2. Disregarding the distinction between fixed-term and open-ended contracts, column (1) shows that one extra year of experience is associated with an increase in individual earnings of 2.5% for workers with ten years of experience. Column (2) breaks down experience by the type of contract where it was accumulated. While the coefficients on linear experience are similar for both contract types, the main differences in workers' trajectories arise from the interaction terms: while the first years of experience in open-ended or fixed-term contracts yield similar wage returns, the growth rate for those in fixed-term contracts is lower in subsequent years. For a worker with ten years of experience, an additional year on a fixed-term contract translates into a 3.0% increase in earnings. In contrast, an additional year in an open-ended contract is associated with a 4.5% surge.

Although this specification acknowledges that the value of accumulated experience in each type of contract might differ, it ignores the potential sorting of workers into each type of contract. For instance, if high-ability workers are over-represented in open-ended positions, the coefficients of Column (2) might reflect that more able workers tend to enjoy higher earnings irrespectively of contract type. Previous work has addressed this concern by including worker fixed-effects, as in Column (3). The worker-fixed effect slightly attenuates the gap between fixed-term and open-ended contract returns, but the overall pattern remains the same. For a worker with ten years of experience, an additional year in a fixed-term position is associated with a wage growth of 4.6% as compared to 5.6% if this experience was accumulated in a permanent contract.[9]

As we show next, these estimates have, however, no causal interpretation, as they reflect that more able workers are (i) more likely to enter an open-ended contract and (ii) enjoy faster earnings growth irrespective of contract type, a form of selection that is not captured by the fixed-effects approach.

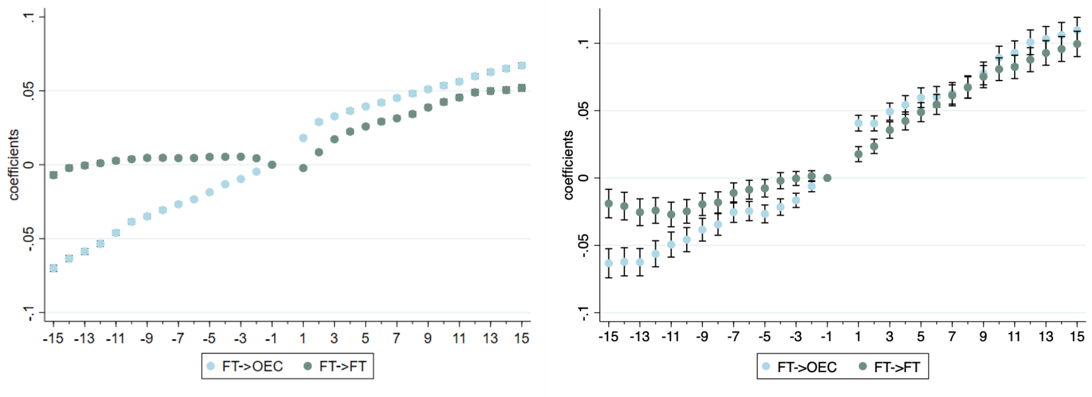
2.4 Selection into permanent positions

These results from the fixed effect model provide suggestive evidence about the differential value of experience that each of these contracts produce: with fewer on-the-job-training opportunities (Cabrales et al., 2017), a temporary contract in a country with high dualism might result in less skill accumulation and slower wage growth. However, a worker fixed-effects specification only captures part of the endogeneity problem arising from contract sorting.

We start examining whether workers with open-ended and fixed-term contracts follow parallel earnings paths before they are promoted using an event-study design. For each worker in the data, we denote the precise month in which the individual ends a temporary contract by $t = 0$, and index future and past months relative to that moment. We use the last complete month in the old contract ($t = -1$) as our base period. After the contract ends, we categorize workers based on their future type of contract, distinguishing workers transitioning from a FT to an open-ended contract (FT→OEC, $T_i = 1$) and workers transitioning to another FT contract (FT→FT, $T_i = 0$). Our baseline specification considers a balanced panel of workers

[9] Based on these results, Figure 2.7 illustrates the earnings trajectory for workers who accumulate experience in a fixed-term, open-ended contract, or a combination of both. While wage growth is almost equal over the first years, the gap in favor of open-ended positions rapidly widens after six years. After ten years, the earnings of a worker employed only in open-ended contracts differ from those who only accumulated fixed-term experience by 21%.

FIGURE 2.2 Earnings consequences from transitioning to OEC or FTC



(a) No controls (b) Additional controls

Notes: The base category is t=-1. Panel (a) Controls for the full set of time and age dummies. Panel (b) includes additional interactions of event time with education and sector FE. Errors are clustered at the worker level. The coefficient from event period 0 is omitted from each graph, given that not all workers worked the whole last month.

whom we observe fifteen periods (months) before and after the event,[10] so the event time t runs from -15 to $+15$. We denote by y_{ist} the log earnings of individual i, in year-month s and at event time t, and estimate the following regression:

$$y_{ist} = \sum_{j \neq -1} \alpha_j^T \cdot \mathbf{I}[j = t] \cdot \mathbf{I}[T_i = 1] + \sum_{j \neq -1} \alpha_j^{NT} \cdot \mathbf{I}[j = t] \cdot \mathbf{I}[T_i = 0]$$
$$+ \sum_k \beta_k \cdot \mathbf{I}\left[k = age_{is}\right] + \sum_p \gamma_p \cdot \mathbf{I}[p = s] + \nu_{ist},$$

where we include a complete set of event time dummies (first term on the right-hand side), age dummies (second term), and year $\times$ month dummies (third term). As we omit the event time dummy at $t = -1$ from the estimation, the event time coefficients measure the impact of moving into a new contract relative to the earnings just before the termination of the previous fixed-term contract.By including a complete set of age dummies, we control non-parametrically for underlying life-cycle trends. We also control non-parametrically for time trends such as business cycle variation, including a full set of time dummies. Including age dummies in the comparison is important because workers in open-ended positions tend to be older than workers who remain in temporary positions.

Results are presented in Figure 2.2. Panel (a) controls for the full set of time and age dummies discussed above. Additionally, Panel (b) also accounts for interactions between event time and worker's education and sector, accounting for earnings growth explained by differences in observable characteristics. The estimates remain unchanged if we include worker fixed effects, as we consider a balanced sample of

[10]Periods may differ from months if workers have a non-employment spell within those fifteen months before or after. Due to sample restrictions, this is ruled out for the pre-period.

workers and the estimates represent the earnings growth of those workers compared to the base period (i.e., worker fixed effects are netted out already).

We would expect that workers face a differential earnings path after event period 0, as temporary contracts may be subject either to earnings penalties or premia (Albanese and Gallo 2020; Kahn 2016), and because returns to experience depend on contract type. However, we observe that earnings evolve very differently even *before* workers start their new contract: those workers who subsequently switch into open-ended contracts enjoy *much* faster earnings growth than those who do not, even while both groups are still in fixed-term contracts. The finding of higher wage returns among workers with more open-ended work experience, therefore partially reflects this difference in worker selection. In fact, the difference in earnings growth between worker types is much more pronounced before any transitions to open-ended contracts take place.

2.5 Identification

In order to deal with the endogeneity of promotions into permanent positions, we propose an instrumental variable strategy. As an exogenous source of variation, we combine individual variation in the expiration date of a fixed-term contract and transitory fluctuations in the opening of new open-ended jobs over time and space. Workers face a positive shock if there is an abnormal increase in permanent openings in the labor market just before their contract expires. This affects promotion probabilities in two ways: in the most direct channel, workers face a tighter labor market with more opportunities of landing a permanent job outside their current firm as their availability is higher. Moreover, other workers might switch to a job in a new firm, creating vacancies that could be filled by promoting fixed-term workers whose contract is about to end.

Exploiting the high frequency of our data, we can precisely match the month when the individual contract is about to end with the job openings at the regional level that precise month. We argue that facing more job openings precisely in the month a contract is about to end is as good as random for the worker.

Specifically, using a leave-one-out approach, we estimate the following first-stage equation:

$$p_{it+1} = \sum_{k=-12}^{12} \alpha_k logOEC_{-i,t+k} + X_{it}\theta + \epsilon_{it},$$

where p_{it+1} indicates whether the worker is promoted to an open-ended contract in $t+1$, the variable $logOEC_{-i,t+k}$ is constructed as the sum of all new open-ended positions in period t in the worker's initial province of residence, leaving out individual i herself. We, therefore, allow for promotions to depend on the total number of new open-ended contracts in period t and leads and lags of this variable, excluding individual's i promotion in the calculation. The first lead, $logOEC_{-i,t+1}$, is our instrumental variable. As we control for a full set of time fixed effects, it captures regional fluctuations in the supply of new open-ended contracts that are as good as random from the perspective of the worker.[11] The instrument independence assumption is therefore plausible. Under our identification assumptions, we would expect the effect of this first lead, captured by coefficient α_1, to be the strongest predictor of an individual's probability to switch into a permanent position. The coefficients on other leads and lags (α_k for $k \neq 1$) should be smaller in magnitude, but might be non-zero, as they capture general business cycle conditions that might not be fully captured by α_1.

Specifically, the inclusion of leads and lags of the instrument serves two purposes. First, to illustrate that transitory fluctuations matter if they hit a worker in exactly the month in which her previous contract runs out, i.e. to show that the first lag has strong predictive power even conditional on a complete set of other leads and lags (instrument relevance). Second, these other leads and lags control for general business cycle conditions, which would violate the instrument exclusion restriction. To further partial-out the effect of the business cycle and seasonal variations in job openings, we add an extensive set of controls, including leads and lags of the total number of new contracts, year, month, province, and sector fixed effects. At the individual level, we also control for gender, overall experience, experience squared, and interactions of age categories with education attainment.

The results from this regression are presented in Figure 2.3.[12] As expected, the effect of the first lead of new permanent positions stands-out strongly. Consistent with our identification strategy, we find that the openings of new open-ended contracts when the worker's contract expires are the strongest predictor of the probability of finding a permanent position immediately after. Moreover, the absence of strong correlations with the rest of the leads and lags indicates that the instrument is capturing the effect of transitory shocks on job market matches, as opposed to general business cycle conditions.

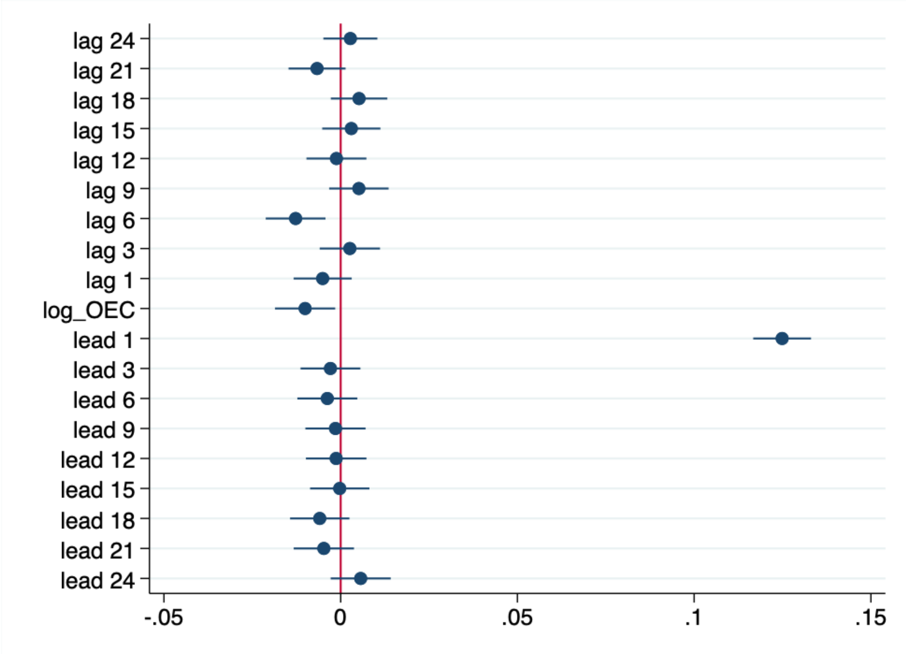
Figure 2.3 depicts the leads and lags in the number of new open positions on the *regional* level. We can apply the same logic to exploit instead new openings of permanent positions at the national and industry level, which might be more consequential for an individual's labor market chances. As shown in Figure 2.4 in the Appendix, we find similar patterns in these alternative specifications.

The instrumental variable identifies the labor market consequences of entering a permanent contract for "compliers", i.e. workers who find a permanent contract

[11] In Figure 2.1 in the Appendix, we provide evidence that $logOEC_{-i,t+1}$ is uncorrelated with worker's characteristics once we account for time and region fixed effects.

[12] The regression estimates for the baseline and alternative specifications are reported in Tables 2.6, 2.7, 2.8, 2.9.

Figure 2.3 The effect of new open-ended contracts on promotion probabilities



Notes: The sample is restricted to workers in the last month of a fixed-term contract of least 0.8 years of tenure but less than 1.2 years of tenure. Coefficients of the probability of being promoted to an open-ended contract in $t+1$ on leads and lags of the log of new open-ended contracts by month. Additional controls: year and month FE, province FE, sector FE, gender, foreign-born status, interactions of age FE and education attainment, experience, experience squared, leads, and lags of new fixed-term contracts.

only if the local labor market conditions are sufficiently favorable. This local average treatment effect (LATE) may differ from the returns to contract type for other type of workers, but is a parameter of high policy relevance – it is precisely those marginal workers who would be affected by policy changes that affect the relative provision of open-ended vs. fixed term contracts on the labor market.

2.6 Results: Reduced-form evidence

Labor market dualism may impact workers' trajectories in several dimensions. Previously, we showed that regional variations in the opening of permanent contracts affect promotion probabilities. In a reduced-form approach, this section examines how the improved upgrade to permanent position opportunities affects workers' labor market outcomes in the short and long-term. Restricting the sample to those workers holding contracts that are about to end, we estimate the following equation:

$$y_{it+h} = \sum_{k=-24}^{24} \alpha_k logOEC_{-i,t+k} + \sum_{k=-24}^{24} \gamma_k logTNC_{-i,t+k} + X_{it}\theta + \epsilon_{it},$$

where y_{it+h} is the worker's i outcome in period $t+h$, with $h = -60, \dots, 60$. Each outcome is studied up to 60 months before and after fixed-term contract expiration, allowing us to explore the long-term effects of contract type and to verify that workers had similar career trajectories in the pre-treatment period. We include 24 leads and lags of the *log* of new open-ended contracts ($logOEC$) relative to the last month of the worker's current fixed-term contract. In order to control for business cycle variation and job creation seasonality, we also include the same number of leads and lags of the *log* total number of new contracts denoted by ($logTNC$).

We can go further and control for business cycle variation more aggressively by additionally controlling for the aggregate leave-one-out average of the outcomes, $\overline{Y}_{-i,t+h}$, as in

$$y_{it+h} = \sum_{k=-24}^{24} \alpha_k logOEC_{-i,t+k} + \sum_{k=-24}^{24} \gamma_k logTNC_{-i,t+k} + \delta\overline{Y}_{-i,t+h} + X_{it}\theta + \epsilon_{it},$$

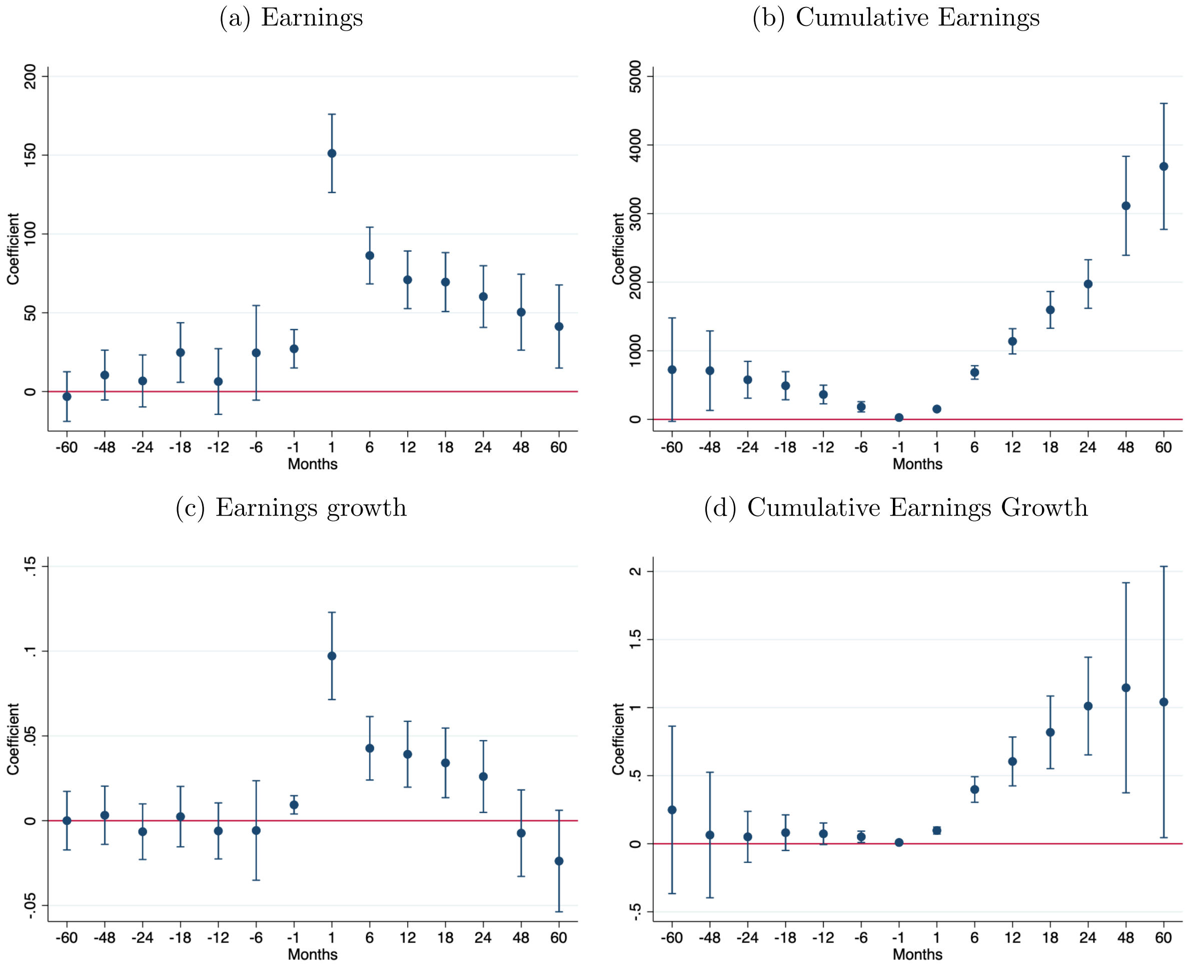
we construct $\overline{Y}_{-i,t}$, based on the full sample of workers, irrespective of the timing of their contract expiration date (i.e., there is no mechanical link between y_{it+h} measured for recently hired workers and $\overline{Y}_{-i,t+h}$ measured for all workers). This should further ensure that we keep economic conditions constant such that our instrument only captures atypical variation in open-ended positions availability, uncorrelated with business-cycle trends. Finally, we add individual and regional controls, including year, month, province, and sector fixed effects, overall experience, experience squared, gender, and interactions of age categories with education attainment.

We consider four earnings-related outcomes. First, we construct earnings by adding up the monthly labor income m for each year. Cumulative earnings are the sum of workers' earnings from the expiration of the fixed-term contract up to period t. Analogously, we construct earnings growth and cumulative earnings growth as the ratio between each variable at t and the monthly earnings at the baseline period 0: i.e., during the last month of the contract before expiring. Thus, the coefficients capture the effect on workers' outcomes compared to their last contract before switching to a new (fixed-term or open-ended) position. In terms of employment we evaluate: employment status, the probability of being employed in an open-ended contract, and cumulative experience in open-ended contracts measured in months. Additionally, we explore mobility responses.

2.6.1 Earnings

Figure 2.4 presents the long-term effects on workers' earnings of the transitory increase in open-ended vacancies *just* at the time of the worker's expiration date. We present the coefficient associated to the first lead of $logOEC_{-i,t+1}$, α_1, which we use as our source of exogenous variation. As shown in panel (a), we find a significant

Figure 2.4 Effect of OEC regional shock on earnings



Notes: The sample is restricted to workers that held a fixed-term position of at least 0.8 but less than 1.2 years of tenure at baseline, who were in the last month of a fixed-term contract between 1998-2012. The coefficients correspond to the effect of the first lead of OEC regional openings on each outcome. All regressions control for the leads and lags of logOEC as well as the log of total new contracts. We also control for the mean of the outcomes at time t, for all workers in the unrestricted sample. Additional controls: year and month FE, province FE, sector FE, gender, foreign-born status, interactions of age FE and education attainment, experience, experience squared, leads, and lags of new fixed-term contracts.

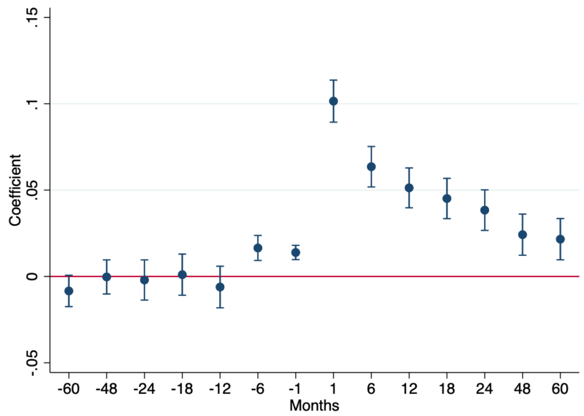
positive effect on workers' earnings, which is more pronounced in the first year after the contract change. While the effect is persistent over time, we observe smaller magnitudes as time goes by. This reduction is mechanic to some extent. A fraction of workers who were *unlucky* at t=0 and remained in a fixed-term contract, will eventually get promoted after a few years such that the gap with respect to those promoted at t=0 becomes smaller, explaining the observed effects. Workers who are more likely to be promoted also experience a significant increase in cumulative earnings (panel b), which captures both higher wages as well as more stable employment trajectories. Moreover, panel c) illustrates a positive effect on earnings growth concentrated over the first years, consistent with the same upgrade dynamics we mentioned before.

2.6.2 Employment and Mobility

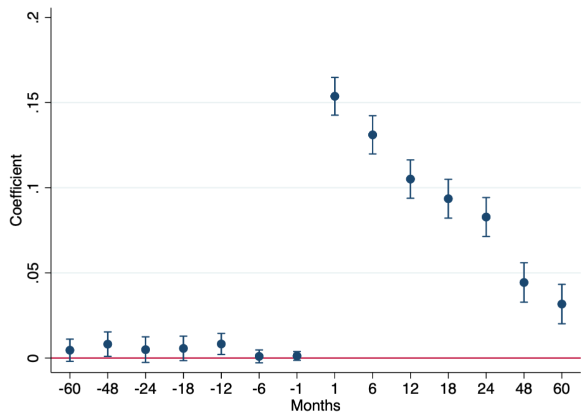
In terms of employment, our results suggest that upgrading to a permanent position places workers on a stable career path. As illustrated in Figure 2.5a, we find that the effect of better opportunities to switch to an open-ended contract translates into a higher employment probability even after 2 years of promotion. As expected, once workers start a job in a permanent contract, they are unlikely to return to a fixed-term position. Moreover, workers seem to be considerably less likely to change sectors and slightly less prone to move to another region, as depicted in Figure 2.6.

FIGURE 2.5 Effect of OEC regional shock on employment

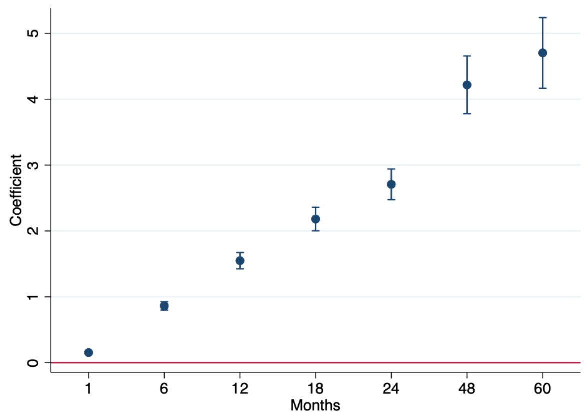
(a) Probability of employment



(b) OEC Status



(c) Cumulative months in OEC

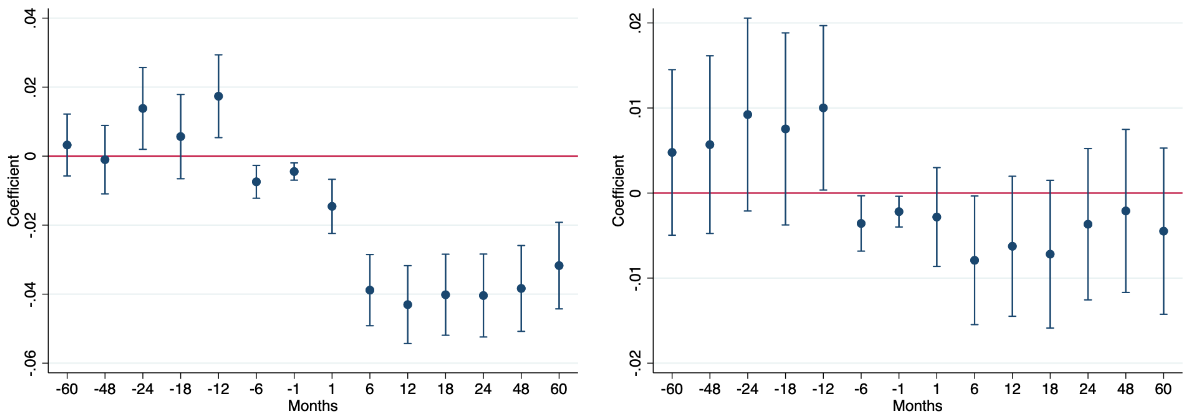


Notes: The sample restricted to workers that held a fixed-term position of at least 0.8 but less than 1.2 years of tenure at baseline, who were in the last month of a fixed-term contract between 1998-2012. The coefficients correspond to the effect of the first lead of OEC regional openings on each outcome. All regressions control for the leads and lags of logOEC as well as the log of total new contracts. We also control for the mean of the outcomes at time t, for all workers in the unrestricted sample. Additional controls: year and month FE, province FE, sector FE, gender, foreign-born status, interactions of age FE and education attainment, experience, experience squared, leads, and lags of new fixed-term contracts.

FIGURE 2.6 Effect of OEC regional shock on workers' mobility

(controlling for total new contracts)

(a) Probability to change sector (b) Probability to change region



Notes: The sample is restricted to workers that held a fixed-term position of at least 0.8 but less than 1.2 years of tenure at baseline and who were in the last month of a fixed-term contract between 1998-2012. The coefficients correspond to the effect of the first lead of OEC regional openings on each outcome. All regressions control for the leads and lags of logOEC as well as the log of total new contracts. We also control for the mean of the outcomes at time t, for all workers in the unrestricted sample. Additional controls: year and month FE, province FE, sector FE, gender, foreign-born status, interactions of age FE and education attainment, experience, experience squared, leads, and lags of new fixed-term contracts.

2.7 Conclusion

The matching of workers to firms, jobs and contract types has important implications both for individual careers and aggregate outcomes. However, it is difficult to provide causal evidence on this question, as workers may sort non-randomly into jobs. The key challenge is to disentangle whether differences in career trajectories are due to unobserved heterogeneity on the supply side or whether they reflect true causal effects from characteristics of the labor market.

By examining the Spanish context as a case study, we investigate how different types of contracts affect workers' careers. Consistent with recent evidence by Garcia-Louzao et al. (2021), workers who spent more time in fixed-term contracts experience lower earnings growth than workers who spent time in open-ended positions. Nevertheless, differences in earnings growth may reflect not only differences in returns between contract types but also heterogeneity among employees.

An event study graph reveals suggestive evidence of the absence of "parallel pretrends", which is crucial to distinguish these explanations. The earnings trajectories of workers who switch from fixed-term to open-ended contracts differ even before the termination of their original contract. The difference is sizable: while the earnings of workers switching to an open-ended contract grow, on average, by 5% in the year before the switch, earnings growth is negligible for workers who switch to another fixed-term contract instead. Next, we provide an alternative to fixed effects methods widely applied in this literature.

We propose a novel identification strategy to address selection bias stemming from the non-random sorting of workers into jobs. Using rich matched employer-employee data, we isolate quasi-random variation in worker-firm matches by interacting high-frequency information on the duration of contracts on the supply side of the labor market and transitory fluctuations in job creation on the demand side.

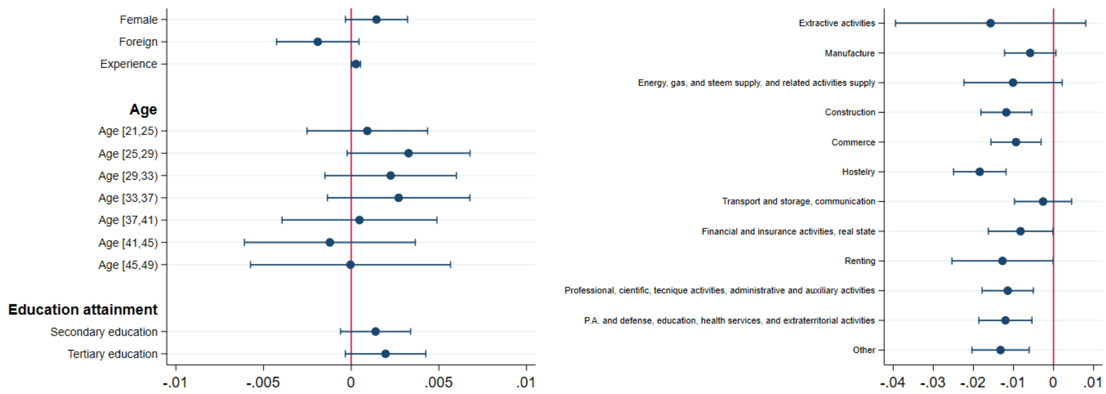
We find that individual promotion probabilities and experience accumulation in permanent positions are highly correlated to transitory variation in the opening of permanent contracts. Moreover, we uncover long-lasting effects on earnings, employment, and workers' mobility from being promoted to a permanent position.

The methodology we use is general, and not restricted to the dual labor market context. The key idea is to exploit two advantages of administrative registers, namely their high frequency, such that we know when exactly a worker's contract ends, and their large size, such that we can measure fluctuations in local labor market conditions. As most administrative registers share those same advantages, our method is widely applicable to address (dynamic) selection in the matching between workers and firms, jobs and contracts on the labor market.

Appendix 2.A Supplementary Figures

2.A.1 IV Results

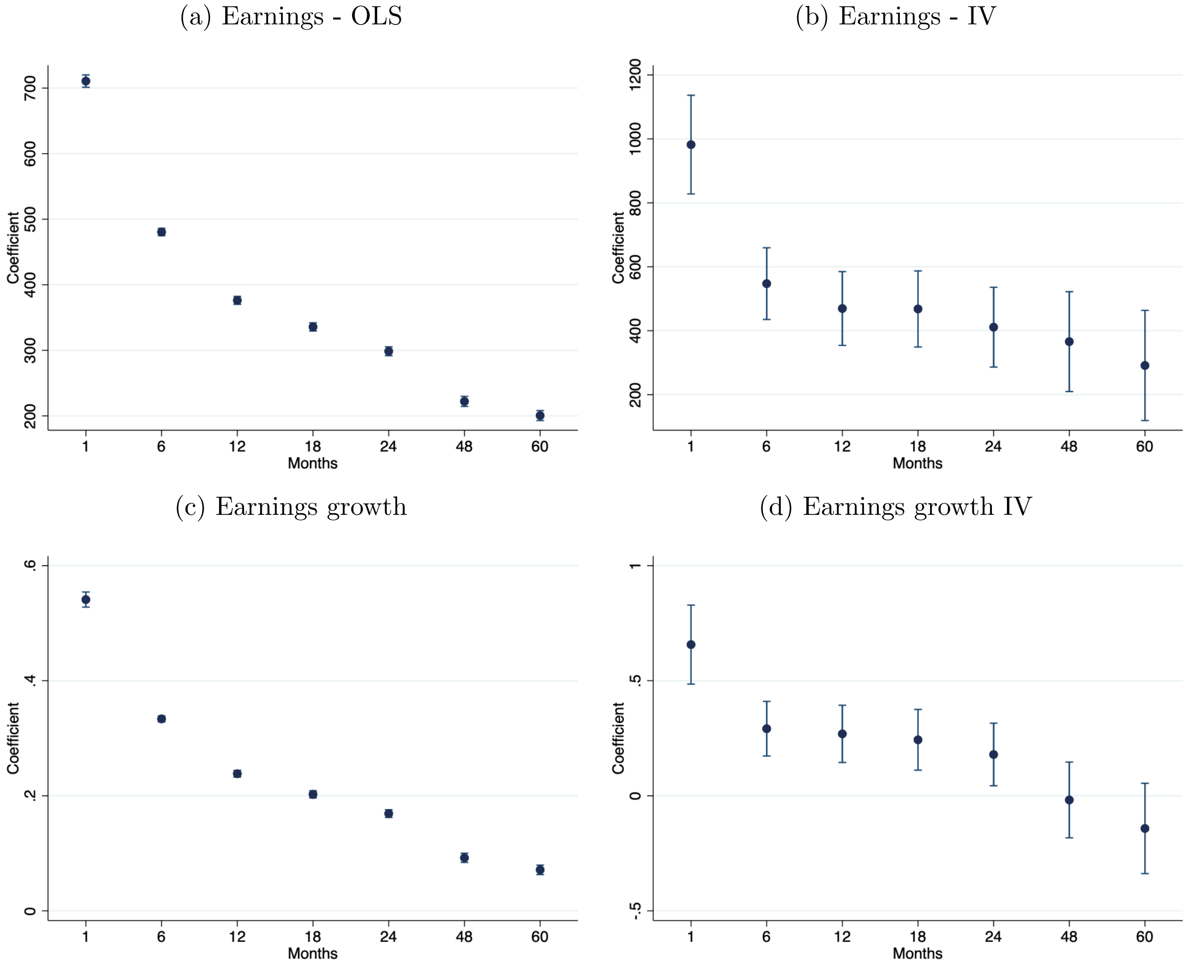
Figure 2.1 Exogeneity: Effect of individual characteristics and sector on $logOEC_{t+1}$



(a) Individual characteristics (b) Sector

Notes: Additionally, we control for leads and lags of logOEC, year, month, and province fixed effects.

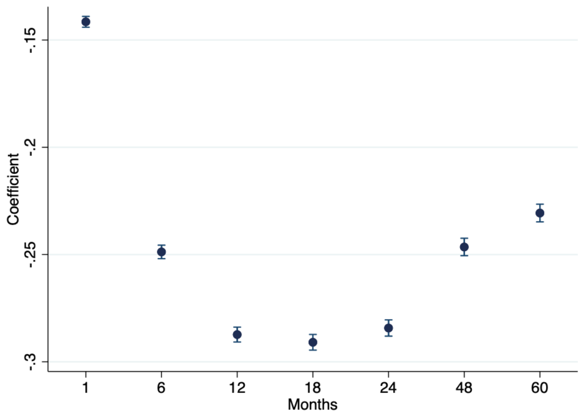
Figure 2.2 Effect of transitioning into an OEC on earnings



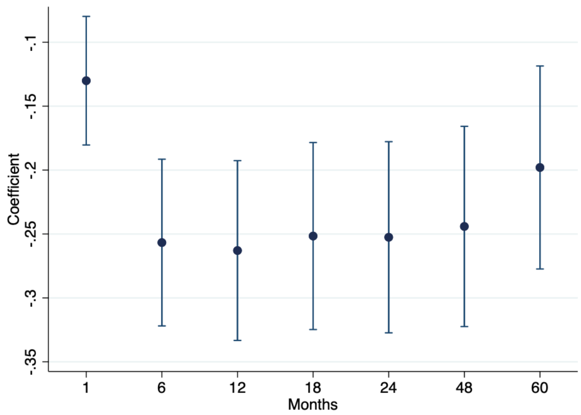
Notes: Sample restricted to workers that held a fixed-term position of at least 0.8 but less than 1.2 years of tenure at baseline, who were in the last month of a fixed-term contract between 1998-2012. The coefficients correspond to the effect of the first lead of OEC regional openings on each outcome. All regressions control for the leads and lags of logOEC as well as log of total new contracts. We also control for the mean of the outcomes at time t, for all workers in the unrestricted sample. Additional controls: year and month FE, province FE, sector FE, gender, foreign born status, interactions of age FE and education attainment, experience, experience squared, leads and lags of new fixed-term contracts.

FIGURE 2.3 Effect of transitioning into an OEC on mobility

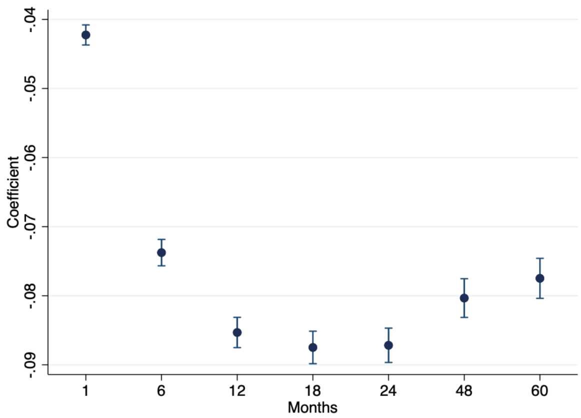
(a) Change Sector - OLS



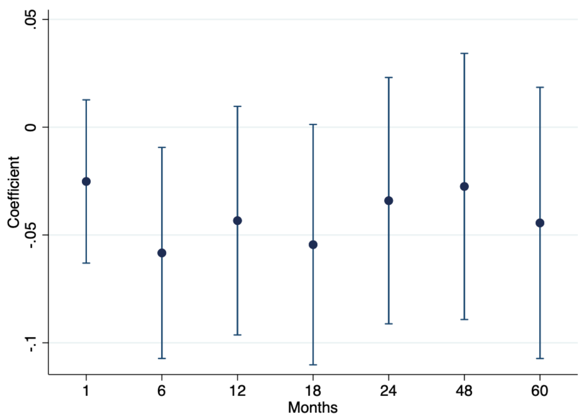
(b) Change Sector - IV



(c) Change Region - OLS

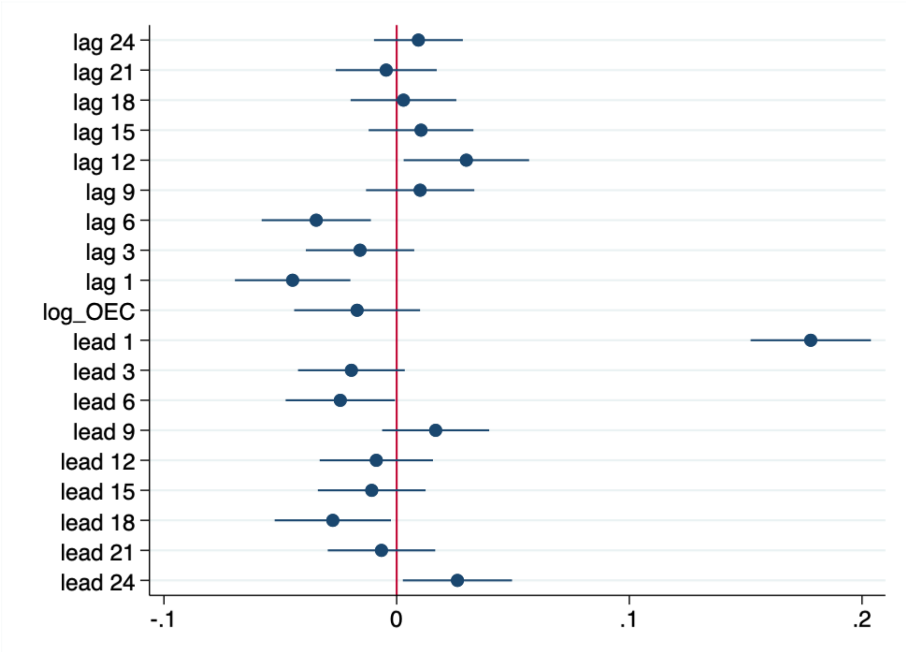


(d) Change Region - IV



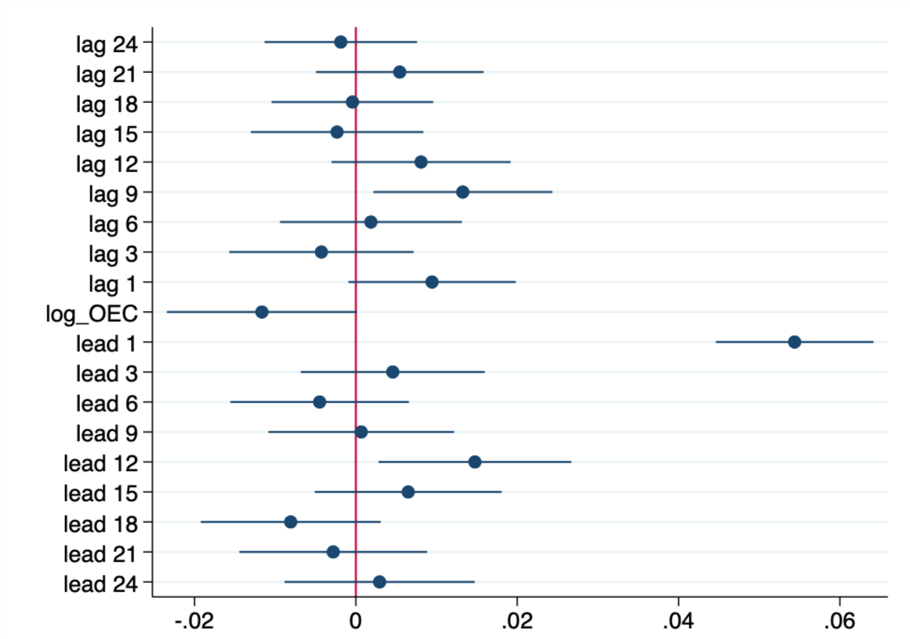
Notes: Sample restricted to workers that held a fixed-term position of at least 0.8 but less than 1.2 years of tenure at baseline, who were in the last month of a fixed-term contract between 1998-2012. The coefficients correspond to the effect of the first lead of OEC regional openings on each outcome. All regressions control for the leads and lags of logOEC as well as log of total new contracts. We also control for the mean of the outcomes at time t, for all workers in the unrestricted sample. Additional controls: year and month FE, province FE, sector FE, gender, foreign born status, interactions of age FE and education attainment, experience, experience squared, leads and lags of new fixed-term contracts.

Figure 2.4 National instrument: Promotion probabilities



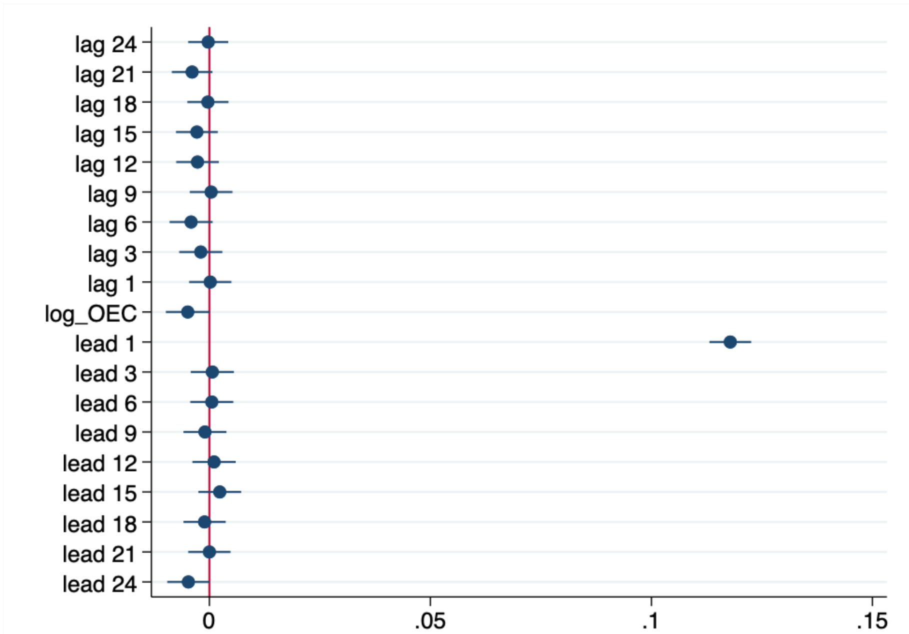
Notes: Sample: Workers in the last month of a fixed-term contract of least 0.8 years of tenure but less than 1.2 years of tenure. Coefficients of the probability of being promoted to a open-ended contract in $t+1$ on leads and lags of the log of new open ended contracts by month. Additional controls: year and month FE, province FE, sector FE, gender, foreign born status, interactions of age FE and education attainment, experience, experience squared, and leads and lags of the opening of new fixed-term contracts.

Figure 2.5 Sectoral instrument: Promotion probabilities



Notes: Sample: Workers in the last month of a fixed-term contract of least 0.8 years of tenure but less than 1.2 years of tenure. Coefficients of the probability of being promoted to an open-ended contract in $t + 1$ on leads and lags of the log of new open-ended contracts by month. Additional controls: year and month FE, province FE, sector FE, gender, foreign-born status, interactions of age FE and education attainment, experience, experience squared, and leads and lags of the opening of new fixed-term contracts.

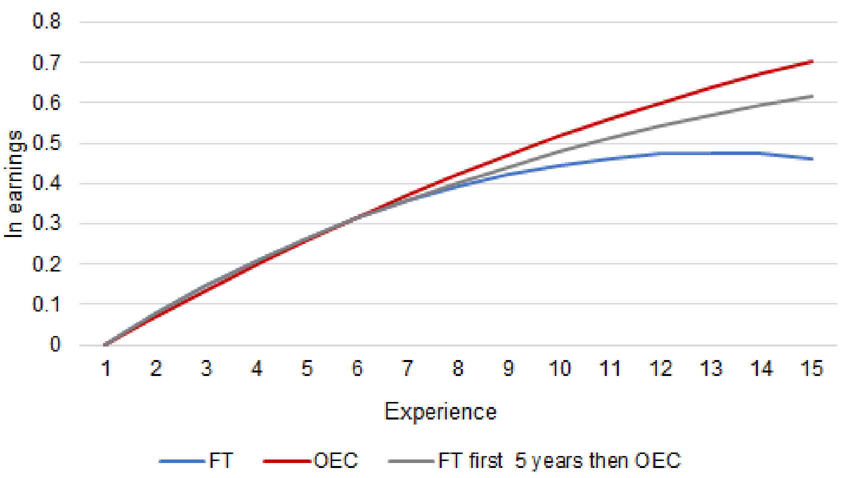
Figure 2.6 Regional and sectoral instrument: Promotion probabilities



Notes: Sample: Workers in the last month of a fixed-term contract of least 0.8 years of tenure but less than 1.2 years of tenure. Coefficients of the probability of being promoted to an open-ended contract in $t+1$ on leads and lags of the log of new open-ended contracts by month. Additional controls: year and month FE, province FE, sector FE, gender, foreign-born status, interactions of age FE and education attainment, experience, experience squared, and leads and lags of the opening of new fixed-term contracts.

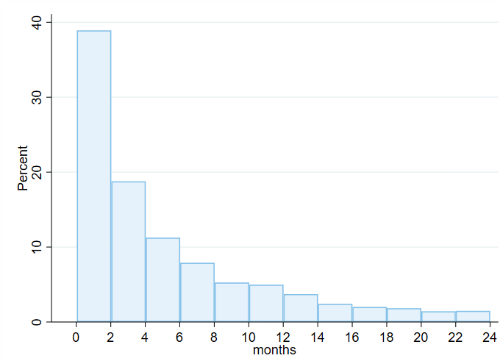
2.A.2 Descriptives

Figure 2.7 Heterogeneous returns to experience by contract type

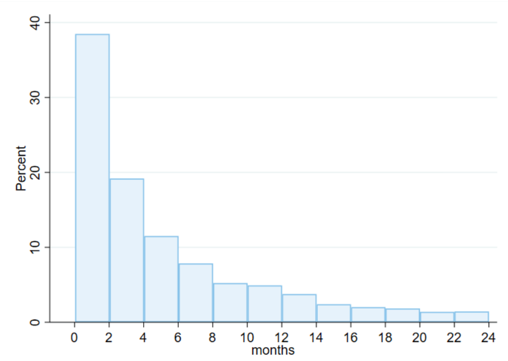


Notes: Fitted values based on experience coefficients from Column (3) in Table 2.2.

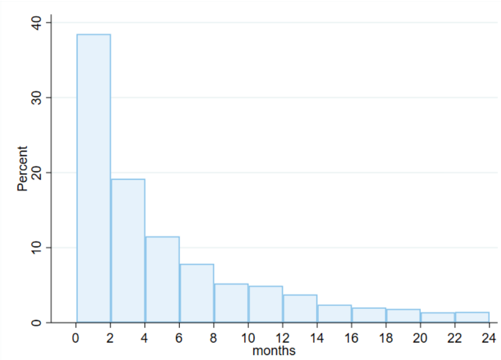
Figure 2.8 Maximum tenure at expiration from FTC: FTC to FTC



(a) 1998-2017



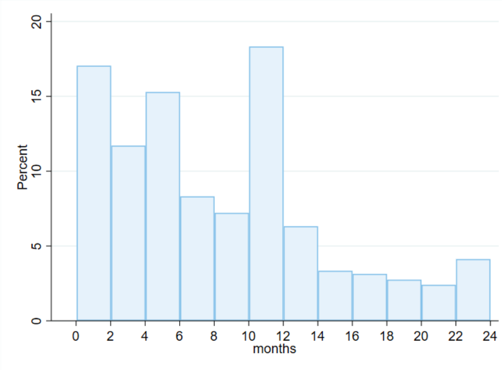
(b) 1998-2017



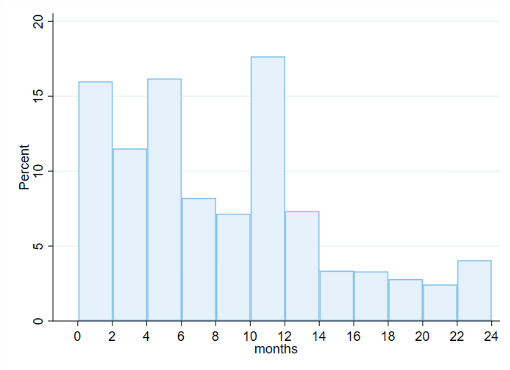
(c) 1998-2017

Notes: Maximum tenure workers that are not promoted

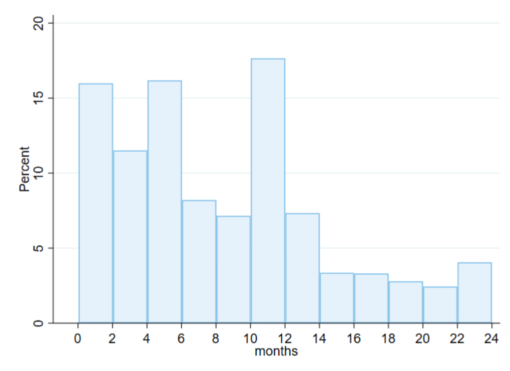
Figure 2.9 Maximum tenure at expiration from FTC: FTC to OEC



(a) 1998-2017



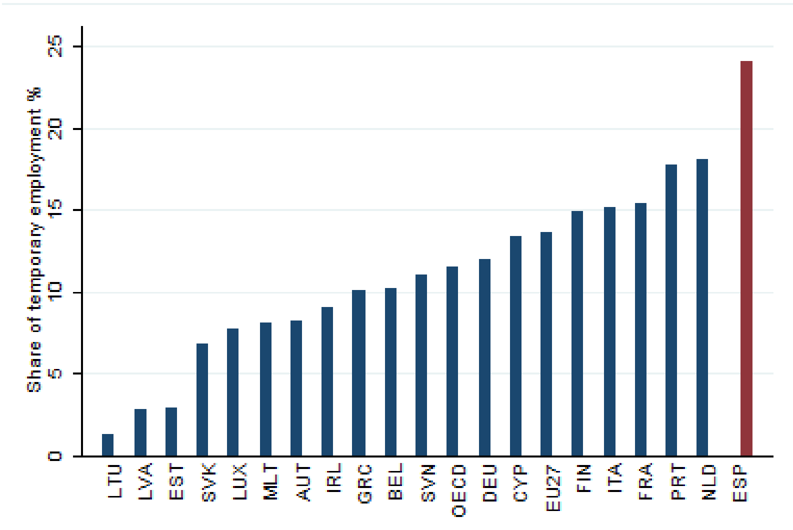
(b) 1998-2017



(c) 1998-2017

Notes: Maximum tenure workers that are promoted

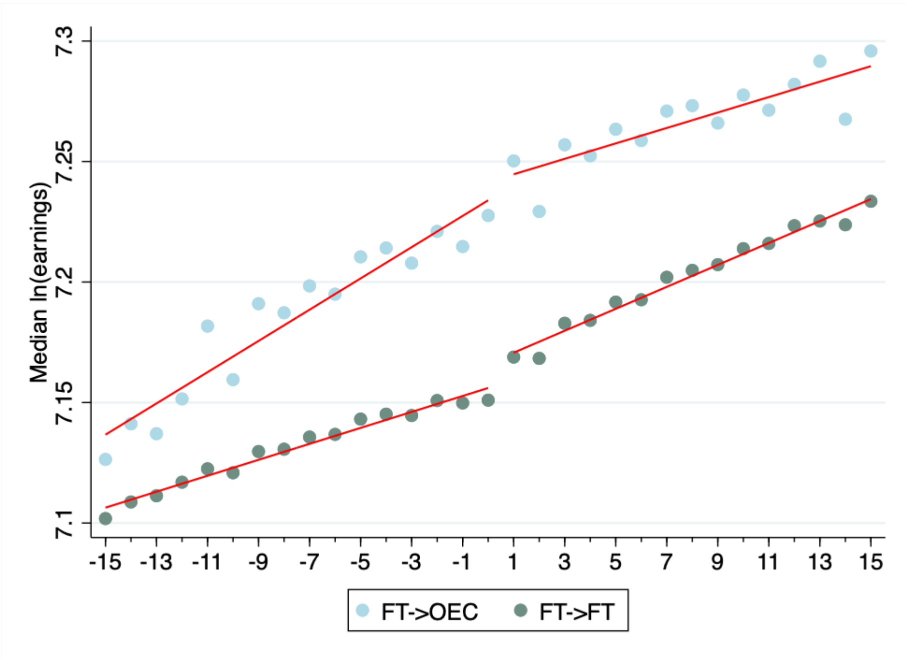
Figure 2.10 Proportion of workers in temporary contracts by country, 2020



Notes: Temporary employment includes wage and salary workers whose job has a predetermined termination date. This indicator is measured as the percentage of dependent employees (i.e. wage and salary workers).
Source: OECD, Labour Market Statistics: Employment by permanency of the job: incidence

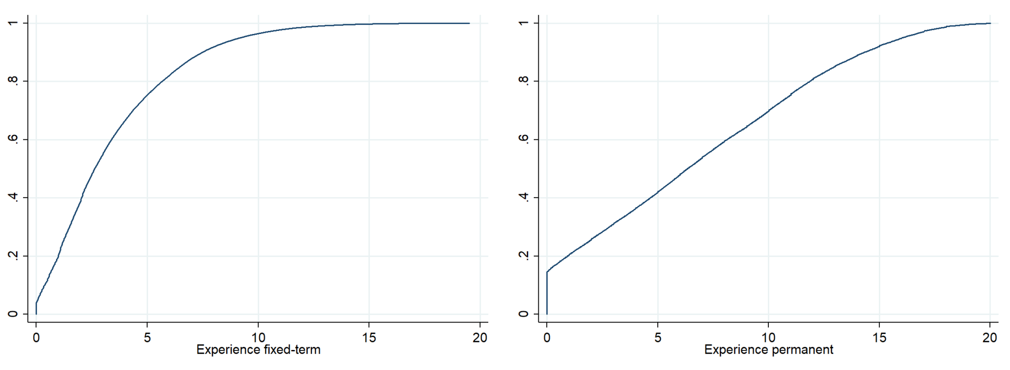
2.A.3 Selection into permanent positions

Figure 2.11 Evolution of earnings: transitioning to a new contract



Notes: Median log earnings of workers 15 months before and after transitioning to a new contract.

Figure 2.12 Cumulative distribution of maximum experience per worker



(a) Fixed-term contracts (b) Open ended contracts

Notes: Maximum experience in the estimation sample by type of contract

Appendix 2.B Supplementary tables

Table 2.3 Heterogeneous returns to experience by contract type

	(1)	(2)	(3)
		ln earnings	
experience	0.0303***		
	(0.000336)		
$experience_{FT}$		0.0247***	0.0266***
		(0.000449)	(0.000726)
$experience_{OEC}$		0.0353***	0.0359***
		(0.000380)	(0.000536)
Obs.	16266496	16266496	16255262
R2	0.474	0.482	0.751

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Sample: Workers who entered the labor market between 1998 and 2003. Workers aged 18-40 years old. Column (1) Baseline specification. Column (2) Considers separately experience in fixed-term and open-ended contracts. Column (3) Additionally includes worker fixed-effects. Additional controls: time and region fixed effects, interactions of gender with educational level, and interactions of occupation skill group and educational level. Regression using shares

Table 2.4 Heterogeneous returns to experience by contract type

	(1)	(2)	(3)	(4)
	ln earnings			
$experience_{FT}$	0.0529***	0.0529***	0.112***	0.112***
	(0.00101)	(0.00101)	(0.00132)	(0.00132)
$experience_{OEC}$	0.0542***	0.0544***	0.0987***	0.0987***
	(0.000698)	(0.000697)	(0.000975)	(0.000973)
$exp * exp_{FT}$	-2.952***	-2.919***	-3.975***	-3.934***
	(0.0821)	(0.0821)	(0.0620)	(0.0619)
$exp * exp_{OEC}$	-0.961***	-0.984***	-1.714***	-1.735***
	(0.0411)	(0.0410)	(0.0298)	(0.0297)
contract fixed-term	-0.0235***	-0.0248***	-0.0348***	-0.0358***
	(0.00155)	(0.00155)	(0.00113)	(0.00113)
tenure	-0.00242***	-0.00233***	-0.00432***	-0.00414***
	(0.000411)	(0.000411)	(0.000246)	(0.000245)
Constant	8.379***	8.060***	7.411***	7.099***
	(0.0140)	(0.0215)	(0.0155)	(0.0208)
Controls	Yes	Yes	Yes	Yes
Individual FE	No	No	Yes	Yes
Sector	share	share	share	share
Tenure	Yes	Yes	Yes	Yes
Skill	FE	FE & Share	FE	FE & Share

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Sample: Workers who entered the labor market between 1998 and 2003. Workers aged 18-40 years old. Every regression controls by worker fixed-effects. Column (1) Baseline specification. Column (2) Sector fixed effects. Column (3) Sector fixed effects and tenure. Column (4) Sector fixed effects, tenure, and type of contract. Standard errors clustered at the individual level. Additional controls: time and region fixed effects, interactions of gender with educational level, and interactions of occupation skill group and educational level. Regression using shares

Table 2.5 Heterogeneous returns to experience by contract type

	(1)	(2)	(3)	(4)	(5)
			ln earnings		
experience	0.0508***				
	(0.000528)				
experience^2	-1.314***				
	(0.0323)				
exp_{FT}		0.0551***	0.0637***	0.0794***	0.0723***
		(0.000788)	(0.000795)	(0.00103)	(0.00105)
exp_{OEC}		0.0539***	0.0558***	0.0706***	0.0670***
		(0.000630)	(0.000613)	(0.000712)	(0.000759)
$exp \times exp_{FT}$		-2.454***	-3.373***	-3.312***	-2.398***
		(0.0636)	(0.0634)	(0.0552)	(0.0554)
$exp \times exp_{OEC}$		-0.975***	-1.049***	-1.446***	-1.298***
		(0.0401)	(0.0389)	(0.0311)	(0.0323)
Obs.	16266496	16266496	16266496	16255262	16255262
R^2	0.475	0.484	0.478	0.754	0.758

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: exp, exp_{FT}, and exp_{OEC} account for experience, experience in fixed-term, and experience in open-ended contracts, respectively. Controls include gender and occupation-skill group interactions on education attainment, sector, region and time fixed-effects, age, age squared, and interactions of tenure with an indicator for a fixed-term contract. Errors are clustered at the worker level. Column (2) and (4) includes interactions of education with age categories

TABLE 2.6 National instrument: Baseline specification

	(1)	(2)	(3)	(4)	(5)
	Promotion to OEC in $t+1$				
$logOEC^{lag}_{12}$	0.0526***	-0.0212**	-0.0228***	-0.0191**	-0.0182**
	(0.00486)	(0.00655)	(0.00650)	(0.00637)	(0.00633)
$logOEC^{lag}_{11}$	0.0570***	0.0799***	0.0801***	0.0705***	0.0712***
	(0.00712)	(0.00822)	(0.00813)	(0.00786)	(0.00783)
$logOEC^{lag}_{10}$	0.0299***	0.0249**	0.0266**	0.0209*	0.0214*
	(0.00824)	(0.00890)	(0.00878)	(0.00852)	(0.00846)
$logOEC^{lag}_{9}$	0.0246**	0.00553	0.00286	-0.000307	-0.000491
	(0.00815)	(0.00874)	(0.00863)	(0.00844)	(0.00838)
$logOEC^{lag}_{8}$	-0.0244**	-0.0130	-0.0127	-0.00972	-0.0103
	(0.00827)	(0.00865)	(0.00855)	(0.00835)	(0.00829)
$logOEC^{lag}_{7}$	-0.0131	0.0445***	0.0448***	0.0399***	0.0398***
	(0.00855)	(0.00910)	(0.00899)	(0.00878)	(0.00871)
$logOEC^{lag}_{6}$	0.0510***	0.0195*	0.0192*	0.0151	0.0136
	(0.00831)	(0.00882)	(0.00871)	(0.00844)	(0.00839)
$logOEC^{lag}_{5}$	-0.0515***	-0.0281**	-0.0282**	-0.0277**	-0.0277**
	(0.00851)	(0.00900)	(0.00889)	(0.00864)	(0.00858)
$logOEC^{lag}_{4}$	-0.0508***	-0.0503***	-0.0487***	-0.0448***	-0.0451***
	(0.00858)	(0.00915)	(0.00904)	(0.00882)	(0.00876)
$logOEC^{lag}_{3}$	0.0265**	0.0122	0.00896	0.00963	0.0127
	(0.00865)	(0.00943)	(0.00932)	(0.00908)	(0.00902)
$logOEC^{lag}_{2}$	-0.0691***	-0.0419***	-0.0419***	-0.0371***	-0.0346***
	(0.00857)	(0.00941)	(0.00930)	(0.00904)	(0.00898)
$logOEC^{lag}_{1}$	-0.0272**	-0.0324***	-0.0288**	-0.0239**	-0.0212*
	(0.00872)	(0.00955)	(0.00944)	(0.00918)	(0.00912)
$logOEC_0$	-0.0479***	-0.0551***	-0.0542***	-0.0444***	-0.0437***
	(0.00905)	(0.0100)	(0.00991)	(0.00964)	(0.00959)
$logOEC^{lead}_{1}$	0.115***	0.267***	0.260***	0.247***	0.242***
	(0.00771)	(0.00944)	(0.00935)	(0.00907)	(0.00902)
$logOEC^{lead}_{2}$	0.0481***	0.0283**	0.0253*	0.0196	0.0168
	(0.00872)	(0.0107)	(0.0106)	(0.0103)	(0.0102)
$logOEC^{lead}_{3}$	-0.00237	-0.0252*	-0.0220*	-0.0188	-0.0188
	(0.00864)	(0.0103)	(0.0102)	(0.00994)	(0.00988)
$logOEC^{lead}_{4}$	0.0346***	0.00872	0.0112	0.00808	0.00931
	(0.00878)	(0.0100)	(0.00995)	(0.00975)	(0.00970)
$logOEC^{lead}_{5}$	-0.0335***	0.00845	0.00958	0.0120	0.0145
	(0.00901)	(0.0104)	(0.0103)	(0.0100)	(0.00999)
$logOEC^{lead}_{6}$	-0.0808***	-0.0431***	-0.0461***	-0.0370***	-0.0346***
	(0.00880)	(0.0101)	(0.0100)	(0.00974)	(0.00969)
$logOEC^{lead}_{7}$	0.0566***	0.0565***	0.0597***	0.0561***	0.0544***
	(0.00892)	(0.0104)	(0.0103)	(0.0100)	(0.00996)
$logOEC^{lead}_{8}$	0.00894	-0.0371***	-0.0366***	-0.0356***	-0.0343***
	(0.00914)	(0.0106)	(0.0105)	(0.0103)	(0.0102)
$logOEC^{lead}_{9}$	-0.0353***	0.00484	0.00220	0.00474	0.00269
	(0.00900)	(0.0108)	(0.0107)	(0.0104)	(0.0103)
$logOEC^{lead}_{10}$	0.0666***	0.00441	0.00680	0.000621	-0.000503
	(0.00917)	(0.0110)	(0.0109)	(0.0106)	(0.0105)
$logOEC^{lead}_{11}$	0.0445***	-0.0332**	-0.0370***	-0.0348**	-0.0372***
	(0.00904)	(0.0112)	(0.0110)	(0.0107)	(0.0107)
$logOEC^{lead}_{12}$	0.0196*	-0.0140	-0.0142	-0.0166	-0.0144
	(0.00837)	(0.0117)	(0.0116)	(0.0113)	(0.0112)
Obs.	331,467	331,467	331,467	331,467	331,467
R2	0.027	0.036	0.061	0.115	0.126
Time FE	No	Yes	Yes	Yes	Yes
Region FE	No	No	Yes	Yes	Yes
Sector FE	No	No	No	Yes	Yes
Individual FE	No	No	No	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Sample: Workers in the last month of a fixed-term contract with tenure of at least 2/3 of a year. Outcome variable if the individual is promoted to OEC in $t+1$ Column (1) controls for leads and lags of new OEC and FTC. Column (2) adds year and month. Column (3) adds province FE. Column (4) adds sector FE. Column (5) adds gender, foreign-born status, the interaction of age FE and education attainment, experience, and experience squared.

Table 2.7 National instrument: Control by new FT contracts

	(1)	(2)	(3)	(4)	(5)
	Promotion to OEC in $t+1$				
$logOEC_{12}^{lag}$	0.0707***	-0.0343***	-0.0333***	-0.0291***	-0.0282***
	(0.00543)	(0.00763)	(0.00756)	(0.00741)	(0.00736)
$logOEC_{11}^{lag}$	0.0844***	0.108***	0.108***	0.0983***	0.100***
	(0.00782)	(0.00993)	(0.00982)	(0.00950)	(0.00946)
$logOEC_{10}^{lag}$	0.00936	0.0106	0.0129	0.00978	0.0106
	(0.00902)	(0.0103)	(0.0102)	(0.00984)	(0.00978)
$logOEC_{9}^{lag}$	0.00405	0.00903	0.00837	0.00552	0.00615
	(0.00867)	(0.00978)	(0.00966)	(0.00944)	(0.00937)
$logOEC_{8}^{lag}$	-0.0245**	-0.00208	-0.00121	0.00119	0.00109
	(0.00879)	(0.00958)	(0.00948)	(0.00925)	(0.00919)
$logOEC_{7}^{lag}$	0.0270**	0.0389***	0.0423***	0.0384***	0.0386***
	(0.00920)	(0.0100)	(0.00993)	(0.00970)	(0.00961)
$logOEC_{6}^{lag}$	0.0378***	0.0252**	0.0244*	0.0185*	0.0170
	(0.00898)	(0.00972)	(0.00961)	(0.00932)	(0.00926)
$logOEC_{5}^{lag}$	-0.0358***	-0.0135	-0.0134	-0.0145	-0.0144
	(0.00909)	(0.0101)	(0.00996)	(0.00968)	(0.00962)
$logOEC_{4}^{lag}$	-0.0270**	-0.0495***	-0.0500***	-0.0485***	-0.0493***
	(0.00924)	(0.00991)	(0.00979)	(0.00955)	(0.00948)
$logOEC_{3}^{lag}$	0.0365***	0.00636	0.00416	0.00506	0.00827
	(0.00931)	(0.0104)	(0.0103)	(0.0100)	(0.00996)
$logOEC_{2}^{lag}$	-0.0373***	-0.0504***	-0.0503***	-0.0454***	-0.0422***
	(0.00905)	(0.0103)	(0.0102)	(0.00987)	(0.00980)
$logOEC_{1}^{lag}$	-0.0370***	-0.0278**	-0.0259*	-0.0230*	-0.0199*
	(0.00917)	(0.0105)	(0.0104)	(0.0101)	(0.0100)
$log_O EC_0$	-0.0592***	-0.0395***	-0.0439***	-0.0382***	-0.0365***
	(0.00954)	(0.0115)	(0.0114)	(0.0111)	(0.0110)
$logOEC_{1}^{lead}$	0.179***	0.264***	0.253***	0.236***	0.231***
	(0.00891)	(0.0112)	(0.0111)	(0.0107)	(0.0107)
$logOEC_{2}^{lead}$	0.0639***	0.0428***	0.0383**	0.0280*	0.0259*
	(0.0103)	(0.0122)	(0.0121)	(0.0117)	(0.0117)
$logOEC_{3}^{lead}$	-0.0595***	-0.0334**	-0.0348**	-0.0341**	-0.0338**
	(0.00981)	(0.0115)	(0.0114)	(0.0111)	(0.0111)
$logOEC_{4}^{lead}$	-0.00244	0.0182	0.0188	0.0108	0.0128
	(0.00993)	(0.0114)	(0.0113)	(0.0111)	(0.0110)
$logOEC_{5}^{lead}$	-0.0371***	0.00316	-0.000223	-0.00246	0.000363
	(0.0102)	(0.0118)	(0.0117)	(0.0114)	(0.0113)
$logOEC_{6}^{lead}$	-0.0348***	-0.00952	-0.0157	-0.0133	-0.0116
	(0.0100)	(0.0114)	(0.0113)	(0.0109)	(0.0109)
$logOEC_{7}^{lead}$	0.0233*	0.0562***	0.0537***	0.0464***	0.0441***
	(0.0102)	(0.0122)	(0.0120)	(0.0117)	(0.0116)
$logOEC_{8}^{lead}$	0.0151	-0.0306**	-0.0333**	-0.0336**	-0.0323**
	(0.0104)	(0.0116)	(0.0115)	(0.0112)	(0.0112)
$logOEC_{9}^{lead}$	-0.0801***	0.0212	0.0151	0.0146	0.0121
	(0.0103)	(0.0123)	(0.0121)	(0.0118)	(0.0118)
$logOEC_{10}^{lead}$	-0.00803	0.00726	0.00753	-0.0000973	-0.00112
	(0.0105)	(0.0119)	(0.0118)	(0.0115)	(0.0114)
$logOEC_{11}^{lead}$	-0.0201	-0.00958	-0.0165	-0.0185	-0.0203
	(0.0103)	(0.0123)	(0.0121)	(0.0118)	(0.0117)
$logOEC_{12}^{lead}$	0.00611	-0.0131	-0.0127	-0.0149	-0.0125
	(0.00992)	(0.0133)	(0.0131)	(0.0127)	(0.0127)
Obs.	331,467	331,467	331,467	331,467	331,467
R2	0.033	0.037	0.062	0.115	0.126
Time FE	No	Yes	Yes	Yes	Yes
Region FE	No	No	Yes	Yes	Yes
Sector FE	No	No	No	Yes	Yes
Individual FE	No	No	No	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Sample: Workers in the last month of a fixed-term contract with tenure of at least 2/3 of a year. Outcome variable if the individual is promoted to OEC in $t+1$ Column (1) controls for leads and lags of new OEC and FTC. Column (2) adds year and month. Column (3) adds province FE. Column (4) adds sector FE. Column (5) adds gender, foreign born status, interaction of age FE and education attainment, experience, and experience squared.

Table 2.8 Regional instrument: Baseline specification

	(1)	(2)	(3)	(4)	(5)
	Promotion to OEC in $t+1$				
$logOEC_{12}^{lag}$	0.00628	-0.00202	-0.00192	0.000687	0.00111
	(0.00321)	(0.00362)	(0.00361)	(0.00351)	(0.00349)
$logOEC_{11}^{lag}$	0.0164***	0.0645***	0.0623***	0.0582***	0.0588***
	(0.00347)	(0.00384)	(0.00381)	(0.00369)	(0.00367)
$logOEC_{10}^{lag}$	0.0246***	0.0107**	0.00910*	0.00690	0.00760*
	(0.00357)	(0.00400)	(0.00397)	(0.00384)	(0.00381)
$logOEC_{9}^{lag}$	-0.00454	-0.00578	-0.00580	-0.00423	-0.00379
	(0.00357)	(0.00395)	(0.00393)	(0.00381)	(0.00379)
$logOEC_{8}^{lag}$	-0.00470	0.00464	0.00345	0.00523	0.00495
	(0.00370)	(0.00406)	(0.00402)	(0.00390)	(0.00387)
$logOEC_{7}^{lag}$	-0.0181***	0.0205***	0.0163***	0.0162***	0.0165***
	(0.00370)	(0.00409)	(0.00406)	(0.00394)	(0.00391)
$logOEC_{6}^{lag}$	-0.00562	0.0171***	0.0160***	0.0124**	0.0128***
	(0.00365)	(0.00405)	(0.00400)	(0.00388)	(0.00385)
$logOEC_{5}^{lag}$	-0.0131***	0.00357	-0.000638	-0.00207	-0.00223
	(0.00372)	(0.00410)	(0.00406)	(0.00394)	(0.00392)
$logOEC_{4}^{lag}$	-0.0252***	-0.000847	-0.00826*	-0.00840*	-0.00868*
	(0.00369)	(0.00410)	(0.00407)	(0.00394)	(0.00391)
$logOEC_{3}^{lag}$	0.00431	0.0301***	0.0262***	0.0256***	0.0261***
	(0.00371)	(0.00415)	(0.00410)	(0.00397)	(0.00395)
$logOEC_{2}^{lag}$	0.00502	0.0115**	0.00326	0.00451	0.00610
	(0.00370)	(0.00415)	(0.00411)	(0.00398)	(0.00396)
$logOEC_{1}^{lag}$	0.0204***	0.0218***	0.0165***	0.0181***	0.0186***
	(0.00372)	(0.00416)	(0.00413)	(0.00400)	(0.00397)
$logOEC_0$	0.0213***	0.00797	0.00601	0.00670	0.00607
	(0.00396)	(0.00422)	(0.00418)	(0.00405)	(0.00403)
$logOEC_{1}^{lead}$	0.114***	0.138***	0.135***	0.127***	0.125***
	(0.00370)	(0.00414)	(0.00409)	(0.00395)	(0.00393)
$logOEC_{2}^{lead}$	0.00571	-0.0437***	-0.0464***	-0.0412***	-0.0413***
	(0.00379)	(0.00433)	(0.00428)	(0.00413)	(0.00411)
$logOEC_{3}^{lead}$	0.000147	-0.0374***	-0.0386***	-0.0333***	-0.0322***
	(0.00376)	(0.00425)	(0.00421)	(0.00407)	(0.00405)
$logOEC_{4}^{lead}$	0.00700	-0.0174***	-0.0216***	-0.0210***	-0.0202***
	(0.00385)	(0.00431)	(0.00426)	(0.00413)	(0.00410)
$logOEC_{5}^{lead}$	-0.0139***	-0.00606	-0.0136**	-0.0146***	-0.0134**
	(0.00384)	(0.00434)	(0.00429)	(0.00415)	(0.00412)
$logOEC_{6}^{lead}$	-0.0148***	-0.0155***	-0.0230***	-0.0232***	-0.0231***
	(0.00380)	(0.00426)	(0.00421)	(0.00408)	(0.00406)
$logOEC_{7}^{lead}$	0.00476	-0.0122**	-0.0176***	-0.0194***	-0.0186***
	(0.00385)	(0.00432)	(0.00427)	(0.00414)	(0.00412)
$logOEC_{8}^{lead}$	-0.0269***	-0.0217***	-0.0277***	-0.0263***	-0.0256***
	(0.00383)	(0.00431)	(0.00426)	(0.00412)	(0.00409)
$logOEC_{9}^{lead}$	-0.0167***	-0.0178***	-0.0258***	-0.0233***	-0.0228***
	(0.00379)	(0.00428)	(0.00425)	(0.00411)	(0.00408)
$logOEC_{1}^{lead}0$	-0.0124**	-0.0353***	-0.0412***	-0.0387***	-0.0389***
	(0.00380)	(0.00433)	(0.00431)	(0.00417)	(0.00414)
$logOEC_{1}^{lead}1$	-0.00580	-0.0319***	-0.0371***	-0.0330***	-0.0320***
	(0.00373)	(0.00429)	(0.00427)	(0.00414)	(0.00411)
$logOEC_{1}^{lead}2$	-0.0286***	-0.0459***	-0.0493***	-0.0439***	-0.0418***
	(0.00373)	(0.00426)	(0.00426)	(0.00412)	(0.00410)
Obs.	331,032	331,032	331,032	331,032	331,032
R2	0.030	0.043	0.060	0.114	0.125
Time FE	No	Yes	Yes	Yes	Yes
Region FE	No	No	Yes	Yes	Yes
Sector FE	No	No	No	Yes	Yes
Individual FE	No	No	No	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Sample: Workers in the last month of a fixed-term contract with tenure of at least 2/3 of a year. Outcome variable if the individual is promoted to OEC in $t+1$ Column (1) controls for leads and lags of new OEC and FTC. Column (2) adds year and month. Column (3) adds province FE. Column (4) adds sector FE. Column (5) adds gender, foreign-born status, interaction of age FE and education attainment, experience, and experience squared.

Table 2.9 Regional instrument: Control by new FT contracts

	(1)	(2)	(3)	(4)	(5)
	Promotion to OEC in $t+1$				
$logOEC_{12}^{lag}$	0.0144***	0.00616	0.00270	0.00466	0.00496
	(0.00336)	(0.00366)	(0.00367)	(0.00357)	(0.00355)
$logOEC_{11}^{lag}$	0.0415***	0.0790***	0.0708***	0.0663***	0.0668***
	(0.00359)	(0.00387)	(0.00386)	(0.00374)	(0.00371)
$logOEC_{10}^{lag}$	0.0218***	0.0175***	0.0125**	0.00999*	0.0107**
	(0.00376)	(0.00404)	(0.00403)	(0.00390)	(0.00387)
$logOEC_{9}^{lag}$	-0.00666	0.000724	-0.00652	-0.00508	-0.00451
	(0.00373)	(0.00399)	(0.00398)	(0.00386)	(0.00383)
$logOEC_{8}^{lag}$	-0.00214	0.0111**	0.00499	0.00652	0.00647
	(0.00385)	(0.00408)	(0.00407)	(0.00395)	(0.00392)
$logOEC_{7}^{lag}$	-0.00266	0.0216***	0.0144***	0.0145***	0.0148***
	(0.00385)	(0.00414)	(0.00412)	(0.00400)	(0.00397)
$logOEC_{6}^{lag}$	0.00964*	0.0190***	0.0155***	0.0123**	0.0126**
	(0.00379)	(0.00408)	(0.00406)	(0.00393)	(0.00391)
$logOEC_{5}^{lag}$	-0.0108**	0.00783	0.000992	0.000277	-0.0000216
	(0.00386)	(0.00413)	(0.00412)	(0.00400)	(0.00397)
$logOEC_{4}^{lag}$	-0.000633	-0.000509	-0.00928*	-0.00898*	-0.00959*
	(0.00386)	(0.00414)	(0.00413)	(0.00400)	(0.00397)
$logOEC_{3}^{lag}$	0.0134***	0.0351***	0.0277***	0.0265***	0.0268***
	(0.00388)	(0.00417)	(0.00415)	(0.00403)	(0.00400)
$logOEC_{2}^{lag}$	0.0133***	0.0185***	0.00550	0.00620	0.00757
	(0.00386)	(0.00418)	(0.00418)	(0.00405)	(0.00402)
$logOEC_{1}^{lag}$	0.0199***	0.0278***	0.0181***	0.0187***	0.0191***
	(0.00388)	(0.00419)	(0.00418)	(0.00405)	(0.00402)
$logOEC_{0}$	0.0258***	0.0140***	0.00698	0.00682	0.00628
	(0.00405)	(0.00424)	(0.00423)	(0.00409)	(0.00407)
$logOEC_{1}^{lead}$	0.135***	0.144***	0.133***	0.125***	0.122***
	(0.00385)	(0.00417)	(0.00415)	(0.00401)	(0.00399)
$logOEC_{2}^{lead}$	-0.00344	-0.0405***	-0.0504***	-0.0457***	-0.0457***
	(0.00400)	(0.00436)	(0.00435)	(0.00421)	(0.00418)
$logOEC_{3}^{lead}$	-0.0138***	-0.0355***	-0.0474***	-0.0422***	-0.0409***
	(0.00396)	(0.00428)	(0.00428)	(0.00414)	(0.00412)
$logOEC_{4}^{lead}$	-0.00377	-0.0156***	-0.0281***	-0.0276***	-0.0265***
	(0.00403)	(0.00433)	(0.00433)	(0.00419)	(0.00416)
$logOEC_{5}^{lead}$	-0.0111**	-0.00878*	-0.0228***	-0.0236***	-0.0223***
	(0.00405)	(0.00437)	(0.00435)	(0.00421)	(0.00418)
$logOEC_{6}^{lead}$	-0.00389	-0.0163***	-0.0298***	-0.0295***	-0.0293***
	(0.00400)	(0.00430)	(0.00429)	(0.00415)	(0.00413)
$logOEC_{7}^{lead}$	-0.00202	-0.00971*	-0.0238***	-0.0249***	-0.0242***
	(0.00407)	(0.00435)	(0.00434)	(0.00421)	(0.00419)
$logOEC_{8}^{lead}$	-0.00665	-0.0176***	-0.0308***	-0.0291***	-0.0287***
	(0.00403)	(0.00433)	(0.00433)	(0.00418)	(0.00416)
$logOEC_{9}^{lead}$	-0.0153***	-0.0125**	-0.0279***	-0.0262***	-0.0258***
	(0.00402)	(0.00431)	(0.00432)	(0.00417)	(0.00414)
$logOEC_{10}^{lead}$	-0.0129**	-0.0240***	-0.0404***	-0.0385***	-0.0389***
	(0.00407)	(0.00436)	(0.00438)	(0.00424)	(0.00421)
$logOEC_{11}^{lead}$	-0.00684	-0.0191***	-0.0344***	-0.0315***	-0.0304***
	(0.00399)	(0.00433)	(0.00435)	(0.00421)	(0.00419)
$logOEC_{12}^{lead}$	-0.0199***	-0.0319***	-0.0467***	-0.0423***	-0.0402***
	(0.00395)	(0.00431)	(0.00434)	(0.00420)	(0.00417)
Obs.	331,032	331,032	331,032	331,032	331,032
R2	0.042	0.052	0.061	0.114	0.125
Time FE	No	Yes	Yes	Yes	Yes
Region FE	No	No	Yes	Yes	Yes
Sector FE	No	No	No	Yes	Yes
Individual FE	No	No	No	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Sample: Workers in the last month of a fixed-term contract with tenure of at least 2/3 of a year. Outcome variable if the individual is promoted to OEC in $t+1$ Column (1) controls for leads and lags of new OEC and FTC. Column (2) adds year and month. Column (3) adds province FE. Column (4) adds sector FE. Column (5) adds gender, foreign-born status, the interaction of age FE and education attainment, experience, and experience squared.

Appendix 2.C Additional robustness and discussion

2.C.1 Inequality

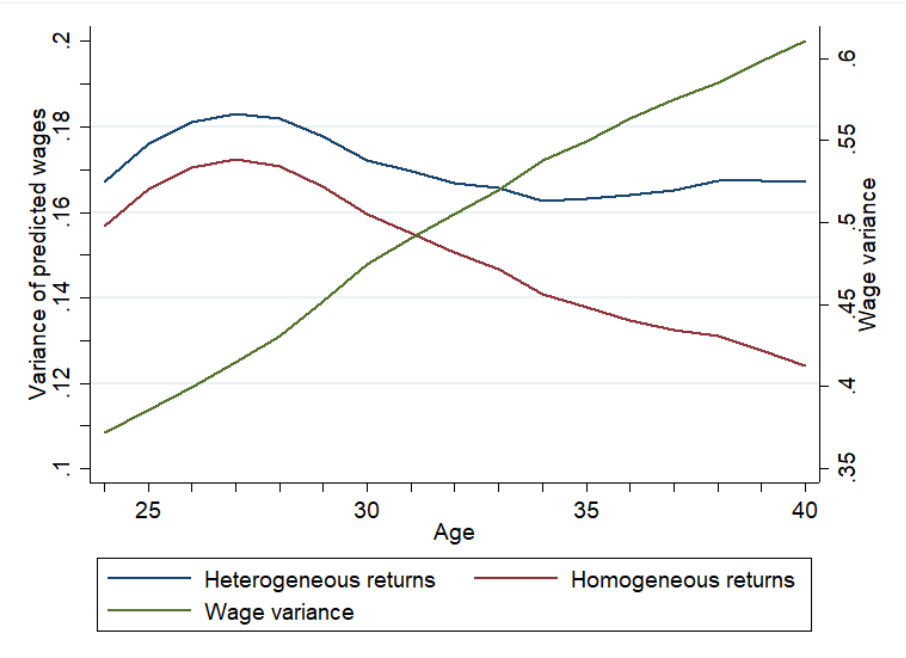
The dualism between permanent and fixed-term contracts creates persistent inequalities in the workers' earnings trajectories. The prior evidence establishes that one year of experience can generally have different returns depending on the type of contract where such experience was acquired. There is a significant share of workers who spend many years on temporary contracts, which has persistent effects on wage distribution.

We study how much of the heterogeneous long-term wage growth can be related to a different cumulative experience in fixed-term and permanent contracts. If experiences in permanent and fixed-term contracts were similarly distributed across young workers, the returns to experiences would not account for much of the variance in realized earnings. However, suppose many workers spend most of their careers on fixed-term contracts while others are just a tiny part. In that case, the returns to experiences could account for a substantial fraction of the variance in realized earnings. By using the sample of workers studied previously, the exercise tracked the variance of earnings and the part of the variance explained by differences in the accumulation of work experience. This exercise follows the approach by Arellano-Bover and Saltiel (2021) and computes:

$$\rho_a = \frac{\operatorname{Var}\left(\sum_{FT,OEC} \hat{\gamma}_m \cdot \operatorname{Exp}(m)_{\mathrm{it}} \;\mid age_{\mathrm{it}} \;= a\right)}{\operatorname{Var}\left(\ln y_{it} \mid \mathrm{age}_{it} = a\right)} \text{ and } \rho_a^H = \frac{\operatorname{Var}\left(\hat{\gamma} \cdot \operatorname{Exp}_{i\mathrm{it}} \mid \mathrm{age}_{\mathrm{it}} = a\right)}{\operatorname{Var}\left(\ln y_{it} \mid \mathrm{age}_{\mathrm{it}} = a\right)}$$

Figure 2.13 shows the fraction of the variance of wages explained by the returns to experience. The share of earnings variance accounted for experience decrease in the mid-30s, reaching 16.1% and 13.7% for heterogeneous and homogeneous returns to experience, respectively. After that, the proportion of explained volatility remains stable once the experience quality is considered, assuming homogenous returns to experience. The explained part continues decreasing. At age 40, the gap in explained earnings volatility is close to 5 p.p. Thus, the conventional approach of assuming all experience to be homogeneous substantially underestimates the fraction of earnings variance accounted for by varying experience profiles across workers.

Figure 2.13 Variance of returns-to-experiences component over variance of log earnings



Notes: The returns to experience are calculated from a Mincerian equation on experience and interaction of education and gender, education and occupational skill group, age, age squared, sector, province, time fixed effects, and contract type. The homogeneous returns assume the returns to experience are the same regardless of the type of contract— the heterogeneous returns to experience control by the experience in fixed-term contracts and permanent contracts.

Chapter 3

Internal migration and job stability

3.1 Introduction

Internal migration plays a crucial role in regional development by acting as an insurance mechanism against local economic shocks and progressively narrowing regional disparities. However, despite this crucial role, the long-lasting impact of economic shocks on worker outcomes and the prevailing regional disparities in many countries raises the question of why there is limited geographic mobility.[1] According to economic theory, migratory decisions are impacted by a number of factors that, in equilibrium, may rationalize some geographical differences. These variables include:

1. comparative wage levels, actual and expected;
2. comparative unemployment rates and benefits;
3. the availability of housing; and
4. migration costs: travel, information, and the psychic cost of leaving one's culture, friends, and relations.

It is important to note that certain determinants, which significantly impact migration decisions, may not be directly observable, posing challenges to their study and analysis. Expanding on the previous limitation, the work by Amior and Manning (2018) points out that employment rates can serve as an alternative measure of local well-being compared to the more commonly used real consumption wage. However, it is important to recognize that current employment or unemployment rates may not

[1] Bilal (2021) argues regional disparities in France are explained by the sorting of firms and workers across the country. Amior and Manning (2018) examine the role of economic shocks in explaining US regional disparities.

necessarily reflect future employment prospects, particularly in regions characterized by high job instability.

In many European countries, workers often experience significant job insecurity due to the coexistence of stable (open-ended contracts) and unstable jobs (fixed-term contracts). The likelihood of continuing in the same job for those employed under fixed-term contracts depends on the possibility of being promoted to a permanent position. Consequently, the current unemployment rate loses some of its explanatory power due to the presence of substantial heterogeneity in job quality.[2]

Keeping in mind the discussion above, it is important to understand how temporary employment influences internal migration and interacts with other local conditions, an interaction that remains to be explored. On the positive side, evidence suggests that regions with a high share of fixed-term workers tend to have a high turnover rate (Cahuc and Postel-Vinay 2002; Blanchard and Landier 2002), attracting workers into more dynamic regions. Alternatively, in the regions where long-term jobs are scarce, migration may be discouraged as workers suffer from intermittent unemployment periods and neglect migration benefits from higher average earnings in a region.[3]

This paper analyzes the link between job instability and internal migration among Spanish workers. I utilize Social Security and tax records' high-frequency data to investigate the spatial distribution of fixed-term contracts across Spanish provinces. The main goal is to assess how Spain's labor market duality affects workers' migration decisions and influences migration patterns across provinces. To achieve this, I first provide an overview of recent trends in internal mobility in Spain. Subsequently, I present empirical evidence on the impact of a high proportion of fixed-term contracts on migration flows and individual migration choices.

This research adds to the expanding body of literature examining factors influencing internal migration.[4] While income disparities have been widely recognized as important motivators for migration, the impact of wage uncertainty on migration decisions has received limited attention. In this study, I leverage variations in job stability across Spanish provinces to provide evidence of the influence of employment uncertainty on internal migration.

My research also contributes to the literature on internal mobility in Spain (Antolin and Bover 1997; Bentolila 1997; Maza and Villaverde 2004). In the past, studies have relied on survey data. Because of data availability, most of those stud-

[2]According to some studies in Spain, unemployment rate differentials lack explanatory power to explain internal mobility among Spaniards.

[3]Bentolila (1997) "Some of this turnover may have spilled into migration. Although some informal, supportive evidence for this idea, for example, that young workers - disproportionately hired under fixed-term labor contracts - have increased their share in total migration, some econometric evidence suggests that fixed-term contracts reduce migration".

[4]For a recent comprehensive review of the literature on internal migration, refer to Jia et al. (2023).

ies lack periodicity and suffer from the typical limitations of those using survey data. Exploiting high-frequency information in Spanish administrative records, I tracked workers who moved multiple times a year, allowing me to study short- and long-term migration.

An initial descriptive analysis reveals that permanent and temporary contracts in the Spanish labor market influence two types of migration: short-term and long-term. Short-term movers are workers who frequently relocate, specifically those who stay in the destination province for less than six months. On the other hand, long-term movers are individuals who settle in the destination region for at least two years. Among short-term movers, 90.7% had previous experience with fixed-term contracts, compared to 69.7% among long-term migrants. Additionally, the sector of destination strongly influences the duration of workers' stays. Specifically, within the group of short-term movers, 16.9% transitioned to the agriculture sector, while 18.13% moved into construction. These sectors are characterized by a significant presence of temporary employment opportunities. Conversely, only 5.44% of workers in agriculture and 14.61% in construction remained in the destination province for at least two years.

The findings emphasize the significant influence of the "push" factor, where regions with a higher proportion of fixed-term contracts experience reduced inflows, despite the potential for higher turnover rates to attract workers. Specifically, a one percent increase in fixed-term workers corresponds to a 0.6% decrease in inflows to that region. Additionally, migrants are less inclined to settle in areas with a higher prevalence of fixed-term contracts. On average, a 10 percent increase in the share of fixed-term contracts results in a 1.98-month shorter duration of worker stays. Furthermore, I examine the effect of the 2012 labor market reform on the transition to permanent contracts and its impact on internal migration patterns. By analyzing the changes in promotion probabilities towards permanent contracts before and after the reform, I aim to understand the relationship between job stability and workers' migration decisions. Specifically, I investigate whether workers in regions with higher job instability before the reform exhibit a lower likelihood of migration than similar workers after the policy change. This analysis highlights the importance of reducing job uncertainty in influencing internal migration behavior.

3.2 Motivation

The Employment Protection Legislation (EPL) in many European countries makes dismissing employees difficult. Several countries have adopted fixed-term contracts with lower firing costs to address this, aiming to enhance hiring flexibility. These contracts were initially seen as beneficial for low-skilled and young workers, aiming to improve labor market outcomes. However, they have introduced new complexities to labor market stability and dynamics. An unforeseen consequence is the limited promotion opportunities during the early years of employment, resulting in diminished job security (Blanchard and Landier, 2002) and adversely affecting the salaries of young workers (García-Pérez et al., 2019).

Temporary employment schemes have a well-documented impact on employees' career development and aggregate outcomes in a number of European countries. Evidence from other regions also shows that comparable employment rules have unanticipated effects on employment and job stability. For example, in the US, David and Houseman (2010) find that temporary-help job placements do not improve and may diminish subsequent earnings and employment for workers in those programs. Evidence from a randomized control trial in Jordan by Groh et al. (2016) finds that an equivalent policy, using vouchers, does not work as a stepping stone to higher quality jobs, a typical result for fixed-term contracts. However, there are some studies using European data that show that temporary jobs can act as a stepping stone to higher-quality jobs (Ichino et al., 2008).[5] According to those studies, whether temporary positions are helpful or bad depends on how broadly they are employed and how they interact with labor market institutions. The probability of being promoted to a permanent job increases with the duration of the contract but decreases with repeated temporary jobs and especially with interruptions (Gagliarducci, 2005). Therefore, it would appear that temporary employment itself is not detrimental to employment prospects but rather the intermittent nature of it (Güell and Petrongolo, 2007).

Even if fixed-term contracts can help workers secure permanent jobs, the long-term effects of easily available fixed-term contracts remain uncertain. Indeed, when workers lose a permanent job, they may be back on a fixed-term contract, and their return to stable employment may be delayed. Such continuous interruptions may have consequences not only on the earnings trajectories of workers but also on other outcomes like fertility decisions (Nieto, 2022), the accumulation of experience (Garcia-Louzao et al., 2021), and migration decisions (Llull and Miller, 2018).

Fixed-term contracts are often used to hire young workers who find promotion to a permanent contract critical in their careers. There is evidence that workers who enter the labor market during a recession suffer long-term losses (Fernández-Kranz and Rodríguez-Planas 2018; Oreopoulos et al. 2012), and those who start in a better learning environment have greater cumulative earnings compared to those who start in smaller firms (Arellano-Bover, 2020). As a result, it is puzzling why young workers, who have the greatest potential benefits, do not relocate to regions that match their skills and job expectations.[6]

The uncertainty surrounding future employment opportunities can deter geo-

[5] For additional references see Filomena and Picchio (2021).

[6] In the United States, evidence suggests they are more mobile than other groups (Molloy et al., 2011).

Figure 3.1 Share of workers in temporary contracts, 2005 and 2015

Notes: Share of workers in temporary contracts in 2005 and 2015 by province. Each marker was weighted by the employment size of each province in 2005.

graphical mobility, particularly for young workers. In this regard, the duality of the labor market represents a significant obstacle. Figure 3.1 demonstrates the remarkable stability in the ranking of Spanish provinces based on the proportion of fixed-term jobs from 2005 to 2015, despite the severe impact of the Great Recession on the Spanish economy. It is crucial, therefore, to examine how this enduring job instability across Spanish provinces can influence workers' motivations for migration.

3.3 Data

I use data from the Continuous Sample of Working Lives (MCVL, hereafter). This random sample drawn from Spanish Social Security records contains 4% of all workers whose status is affiliated with Spain's Social Security.

An observation in the MCVL is any update in the individual's labor market status or any variation in their job characteristics (including firm or contract updates within the same firm). The data record all changes since the date of first employment or since 1980 for earlier entrants. Using this data, I constructed a monthly panel tracking the working lives of sampled individuals. On each date, I know the individual's labor market status and, if working, the occupation and type of contract, the establishment's sector at the NACE three-digit level, and its location.

The Continuous Sample of Working Lives (MCVL hereafter) possesses a critical feature that allows for the tracking of workers based on their workplace locations.

As Social Security Administration requires, employers maintain separate codes for each province where they operate, facilitating the monitoring of workers' geographic mobility. Moreover, the MCVL includes precise dates indicating the start and end of contracts, enabling the examination of workers' movements even within a month. Unlike studies that rely on yearly movements, which may not accurately reflect workers' mobility, the MCVL permits the study of short-term movements and allows for a more nuanced analysis of the relationship between temporary contracts and migration.

One limitation of this data is that it does not capture the characteristics of workers during periods of unemployment or non-employment. For instance, if a person migrates to a new region after losing their job and finds employment months later, the migration episode would be recorded as a job-to-job transition. The MCVL provides individual characteristics from social security records, such as age and gender, as well as information from Spain's Continuous Census of Population (Padrón Continuo), including country of birth, nationality, and education attainment.

3.4 Internal mobility in Spain

3.4.1 Migration patterns

Research on internal mobility has proliferated in recent years, as evidenced by the number of articles in top journals on this subject.[7] Advances in this area help understand migration patterns (Hunt et al. 2008; Foster 2017) and the role of regional mobility in mitigating the impact of negative shocks on workers' outcomes (Hornbeck and Moretti 2022; Blanchard et al. 1992; Bartik and Rinz 2018; Bartik et al. 2019; Notowidigdo 2011; Yagan 2014). There has been a specific emphasis on the causes and consequences of the reduction in internal mobility in the United States (Molloy et al., 2011). This raises the question of whether such drops are the consequence of favorable factors that reduce the need for workers to relocate or labor market frictions that prevent people from relocating (Jia et al., 2023). Because evidence from other countries is scarce, I begin this section by comparing recent mobility patterns in Spain to those in the United States.

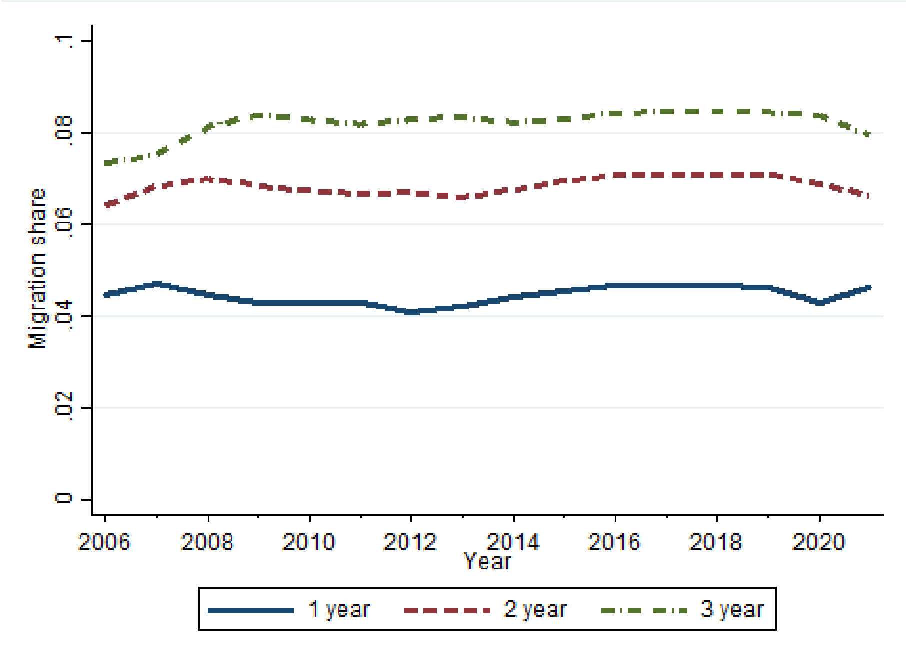
Figure 3.2 displays the percentage of workers who have migrated in recent years.[8] From 2006 to 2021, a notable observation is that the percentage of workers relocating within a year does not exhibit significant fluctuations, in contrast to evidence from the US.[9] On average, it remains around 4.5% of all employed workers. This

[7]See footnote 1 in Jia et al. (2022).

[8]The yearly province of residence is defined as the mode of the province in which the worker is employed throughout the year. In years of no availability due to unemployment or non-employment, the worker is assumed to remain in the same province until another employment spell is recorded.

[9]A similar figure is presented in the appendix, Figure 3.9, based on data from the Spanish Labor

FIGURE 3.2 Migrant workers' share, 2006-2021



Notes: Each line represents the percentage of workers who have migrated in the recent one, two, or three years. The province of residence is defined as the location where the worker spends the majority of the year.

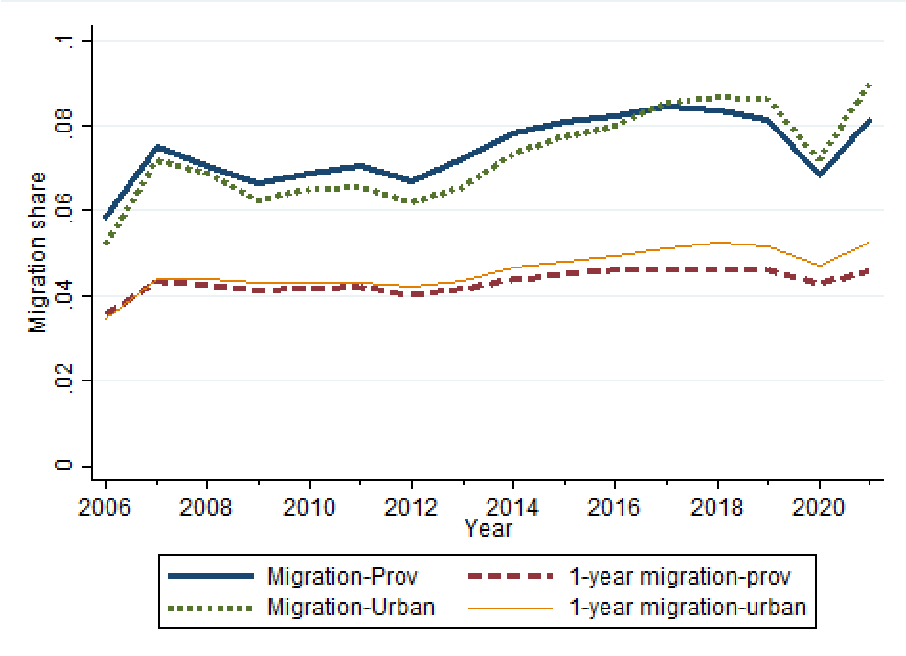
period encompasses economic booms, crises, and recovery, which may contribute to explaining some of the observed cyclical fluctuations. Additionally, Figure 3.2 illustrates that the proportion of workers who migrated within the last two or three years follows similar patterns, with a slightly higher proportion of migrated workers. On average, around 8% of the total employed workforce migrated within the last three years.

3.4.2 Comparative analysis of internal migration definitions in Spain

When studying internal migration, an important decision arises, as noted by Molloy et al. (2011). These decisions involve choosing the appropriate geographic unit to define potential origins and destinations and determining the time period during which individuals must make their moves. Comparing evidence from different countries adds to the difficulties due to differences in size and the number of prospective regions from which workers can choose, which varies substantially across countries. For example, in the United States, a common approach involves the use of metropolitan areas—regions encompassing densely populated urban agglomerations and their surrounding territories, characterized by shared industries, commercial areas, transport networks, infrastructure, and housing. Nonetheless, this geographic unit has two main drawbacks. Firstly, it fails to cover the entire territory of the United

Force Survey (EPA).

Figure 3.3 Comparative of migration shares, 2006-2021



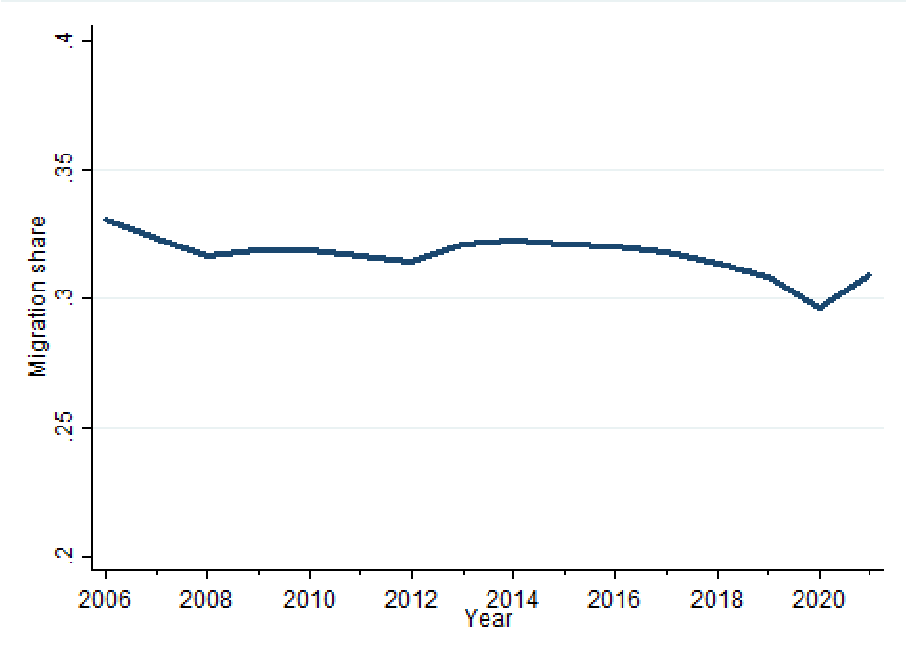
Notes: The plot shows the proportion of workers who relocated to a different province or urban area each year. The solid and dashed lines represent provinces as the geographic unit, while the dotted and thin line represents urban areas. Additionally, two definitions of migration are considered: one where the worker moved at any time during the year and another where the worker changed their location for at least one year, known as 1-year migration.

States, thereby neglecting migration flows from rural regions. Secondly, metropolitan boundaries are revised every few years, posing challenges for consistent measurement of migration over time. When examining migration in Spain, urban areas serve as the nearest approximation to metropolitan areas. The Ministry of Housing in Spain established these urban areas in 2008, and they have remained unaltered ever since. Similar to metropolitan areas, these regions encounter the same limitations. They encompass 85 urban areas, accounting for 68% of Spain's population and covering 10% of its land area (Roca and Puga, 2017).

Because urban areas do not cover the entire country, I will also show the migration rate between Spain's 50 provinces and compare both geographic units. In addition, this study uses longitudinal data, allowing for the evaluation of different periods and migration measures, as I can track workers on a monthly basis. In this section, I focus on two possible measures. The first compares the province of the main job, while the second accounts for internal migrants who changed province during the year. This latter metric allows me to examine workers who migrated but later returned to their home province, which is impossible to do with survey data.

Figure 3.3 offers a comparative analysis of migration patterns, taking into account various migration measures and geographic units as reference points. The dashed line represents the migration share depicted in Figure 3.2. The analysis does not provide evidence of a declining migration share, except for a slight decrease

Figure 3.4 Migrant workers' share based on birth province, 2006-2021

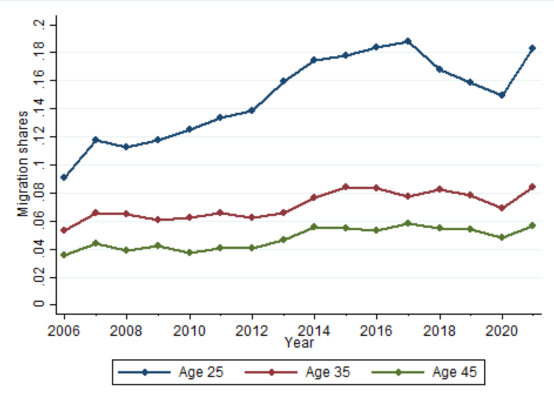


Notes: Migration share here is defined as the proportion of workers not employed in their birth province.

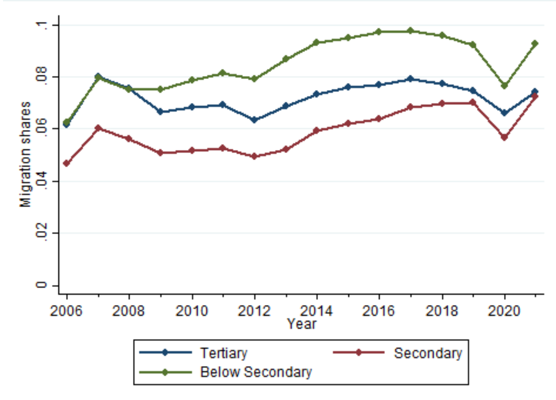
during the Great Recession and the initial phase of the COVID-19 pandemic. However, in both cases, the migration share subsequently recovered. On the other hand, when accounting for any potential migration throughout the year, a stronger cyclical fluctuation is observed during the period. For example, the solid blue line indicates that 8% of workers shifted provinces of residence in 2007. This figure began to fall during the Great Recession, reaching 7%, but recovered in 2013, with a modest drop in 2019 and 2020. The most notable observation from this comparison is the higher migration share in this alternative migration measure. This indicates that a significant portion of workers in Spain engaged in internal migration movements throughout the year. This type of internal mobility is often not captured using labor force surveys or similar datasets. Finally, the graph reveals comparable patterns with similar migration shares when examining mobility between urban areas instead of provinces. This decreases the concern about an arbitrary definition of geographic regions when analyzing internal mobility patterns in Spain.

A commonly used measure for migration is to identify workers as migrants when they reside outside their birth state, region, or province. Figure 3.4 provides additional supporting evidence on internal migration rates by illustrating the proportion of workers who do not work in their province of birth. It is important to note that this measure excludes foreign workers from the comparison, as foreign workers' place of residence naturally differs from their province of birth. However, despite this limitation, the evidence presented in this plot reveals a stable share of internal migrants, displaying similar fluctuations observed in previous plots that can be attributed to the impact of the Great Recession and the COVID-19 pandemic.

Figure 3.5 Migrant workers' share by individual characteristics, 2006-2021



(a) Age group



(b) Education attainment

Notes: The age-based distribution of migration shares focuses on those aged 25, 35, and 45; the education attainment considers workers with tertiary education, secondary education, and less than secondary education. Shares are calculated using the employed workforce of their respective age group. A worker is considered a migrant if she changes their province of residence at any time during the year.

It is worth mentioning that since 2014, there appears to be a downward trend in the proportion of internal migrants using this measure, which may be influenced by various factors such as economic conditions or demographic shifts. This trend will be further investigated in the following section, which examines migration shares for different cohorts, education levels, and foreign-born workers.

3.4.3 Internal Mobility Rates Across Demographic Groups

While the overall migration shares have been stable over the past two decades, notable shifts could appear in the composition of migrants. These changes are not readily apparent when examining migration shares at the national level. Therefore, this section examines migration shares based on age, education attainment, and foreign-born status.

An important consideration is the potential impact of cohort effects, wherein workers may alter their propensity to migrate. To investigate this further, Figure 3.5a presents the migration shares of workers aged 25, 35, and 45 as proportions of their respective populations.

The initial observation reveals contrasting migration patterns between younger and older workers. In 2006, approximately 9% of young workers relocated to a different province, a share that is slightly lower for older workers. However, this figure steadily increased for younger individuals, reaching nearly 19% for workers aged 25 in 2017. Conversely, there has been a more stable migration share among older workers.

This pattern may be attributed to the concurrent rise in college attainment during the same period. Figure 3.5b examines migration shares based on education attainment to investigate this hypothesis. This partially explains the observed trend, as the increase is primarily among individuals with a college education. However, following the Great Recession, the increase in migration shares can be observed across all education levels. Hence, it suggests a cohort effect that cannot be entirely accounted for by the increase in educational attainment.

Several factors may have influenced the small growth in the internal mobility rate before the Great Recession. One of these factors is the expansion of the construction sector, which experienced a surge due to the housing bubble. The correlation between the growth in the construction sector and the internal migration rate can be attributed to the prevalence of temporary contracts within this sector. These contracts often necessitate relocation once they expire. Moreover, the construction sector employs a large proportion of foreign-born workers who are typically more geographically mobile, a well-established observation in the literature (Cadena and Kovak, 2016). The combination of temporary contracts and the mobility tendencies of foreign-born workers creates a continuous cycle of relocation and employment, potentially contributing to the observed trend.

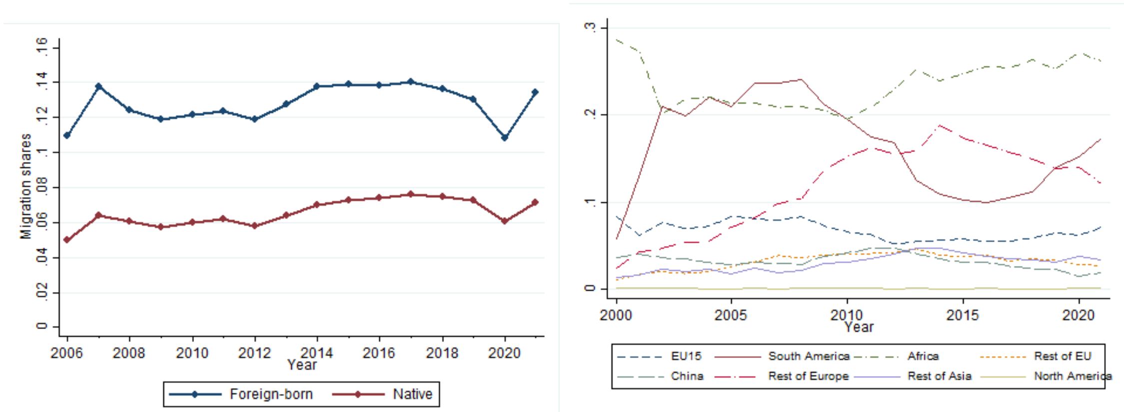
Two notable events during the expansion were the large increase in foreign-born workers. Since 2000, there has been a large influx of foreign migrants, and a regularization episode in Spain in 2005 (Moraga et al., 2019), explaining the remarkable growth of foreign employment since 2000. A comparison between foreign workers and natives is relevant during this period.

Figure 3.6a examines internal migration rates separately for native-born and foreign-born workers as shares of each population. The graph shows that foreign-born workers migrate much more often compared to native workers. In 2007, the share of native workers who changed provinces of residence peaked at around 6%, but this number is much higher for foreign workers at 14%. Foreign employment has also experienced a greater decline in movers than native employment during the Great Recession. In addition, there are no signs of a falling migration trend during this time, which contrasts with what is observed in the US.

Empirical evidence from the United States suggests that Mexican workers are more responsive to economic shocks compared to other foreign employees (Cadena and Kovak, 2016). Acknowledging this variation, I divided the share of foreign workers who migrate between provinces by nationality. I analyzed eight distinct groups: EU15, the rest of the EU, Europe, South and Central America, North America, Africa, China, and the rest of Asia. Figure 3.6b illustrates the results of this analysis.

While the overall proportion of foreign workers migrating within Spanish provinces has remained stable since 1995 (Figure 3.2), the composition of these migration flows has undergone significant changes. Since 2000, there has been a notable increase

Figure 3.6 Migrant workers' share by individual characteristics, 2006-2021



(a) Migration shares by foreign-born status

(b) Composition of foreign-born internal migrants

Notes: It is defined as migrant individuals who live in a different province than they did one month before and aggregated by year. Panel b) shows the percentage of foreign-born internal migrants by region.

in the proportion of Latin American employees, particularly those from Ecuador and Colombia. However, with the onset of the Great Recession, there was a decline in this percentage as other European nations, particularly Romania, witnessed an increase in the number of migrants.

One factor that potentially contributes to the differing mobility patterns between native-born and foreign-born workers is their employment sectors. Foreign-born workers are overrepresented in low-skilled occupations but also in sectors that require a certain degree of geographic mobility, such as agriculture and construction. Table 3.1 provides supporting evidence for this observation by comparing the destination sectors of native-born and foreign-born migrants before and after the Great Recession. The first two columns highlight that, prior to the Great Recession, a significant proportion of movements by both native-born and foreign-born workers were toward jobs in agriculture, construction, and hospitality. However, this share is even higher among foreign-born workers, with 15.6% and 31.1% of them moving to jobs in agriculture and construction, respectively. In comparison, native workers exhibited a lower share of mobility in the construction sector, with only 19.2% transitioning to construction and 6.7% to agriculture, following a change in their province of residence. Interestingly, 14.2% of Spaniards relocated to work in public administration, education, and health, whereas this proportion was significantly lower at 3.4% for foreign-born workers.

The Great Recession has also changed the sector's destination for internal migrants. A significant decrease in the share of workers moving to construction in 2014 is partially offset by an increase in workers moving to agriculture and professional, scientific, and technical activities. For native workers, however, the recomposition is less pronounced, with an increase in workers shifting to the hospitality and public sectors.

Table 3.1 Destination sector for migrants, by foreign-born status

	2004		2014	
	Native	Foreign	Native	Foreign
Agriculture, livestock, fishing	6.69%	15.56%	7.53%	30.28%
Extractive activities	0.23%	0.13%	0.12%	0.07%
Manufacture	7.62%	6.70%	6.49%	3.46%
Energy, gas, and steam	0.50%	0.27%	0.54%	0.12%
Construction	19.15%	31.11%	8.51%	9.25%
Commerce	11.87%	7.91%	12.73%	8.90%
Hospitality	8.17%	13.17%	10.88%	14.76%
Transport	4.71%	4.13%	4.12%	4.08%
Financial and insurance	2.72%	1.27%	2.18%	0.88%
Renting	0.46%	0.33%	0.29%	0.25%
Professional, scientific, technique activities	19.06%	13.83%	21.35%	19.50%
P.A. and defense, education, health	14.26%	3.38%	19.09%	5.32%
Other	4.55%	2.21%	6.18%	3.15%

Notes: Sample is restricted to workers who changed their province of residence during the year and categorized workers by the sector of destination.

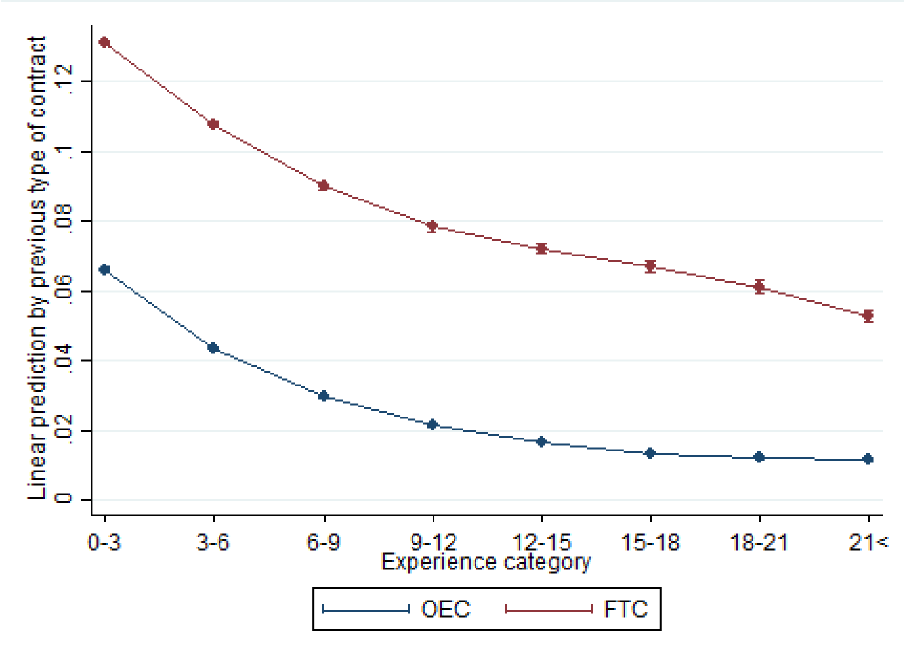
A worker's contract can influence internal mobility in Spain. Labor market institutions have a substantial impact on employees' wage trajectories; data suggests that this dualism is closely linked to a variety of outcomes, ranging from fertility to human capital accumulation. Addressing migration may be of particular interest; young employees are more geographically mobile and more likely to be employed on a temporary contract. As a result, they are more mobile and are influenced by the uncertainty of a temporary contract in their employment. Additionally, this channel was suggested previously, including Bentolila (1997), Antolin and Bover (1997), and Gil and Jimeno (1993).

Figure 3.7 illustrates the differential probability of migration conditional on the type of contract before the province change. The patterns shown in Figure 3.7 are based on a linear probability model controlled by a large set of individual characteristics. The figure shows that across all experience levels, workers in a fixed-term contract are more likely to migrate than workers in an open-ended contract. Additionally, open-ended contract workers have a lower probability of migrating with experience, a sign of stability once workers get a permanent position.

For most experience levels, workers on fixed-term contracts are more likely to migrate than those on open-ended contracts. As a worker gains experience, this gap reduces, but it remains noteworthy. A worker with more than 21 years of experience is 3.3 percentage points more likely to migrate if she is on a fixed-term contract than a similar worker employed in a permanent position.

Fixed-term contracts exhibit a distinct pattern across sectors as hiring instruments. Specifically, the construction sector predominantly relies on temporary employment, whereas other sectors generally exhibit lower rates of temporary work.

Figure 3.7 Migration probability by type of contract and experience



Notes: LPM of migration dummy on experience categories, additional controls: age categories, year, province, sector FE. Interaction of education and gender, and occupational skill group.

Moreover, the duration of contracts varies significantly between fixed-term and open-ended contracts, indicating a level of instability that may discourage workers from undertaking long-distance moves.

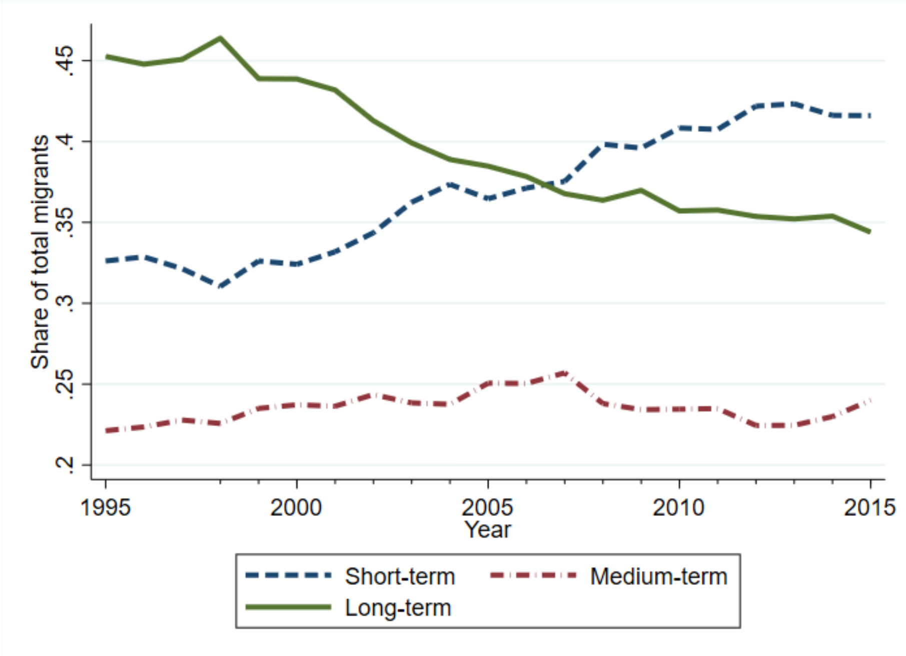
There are two types of movements associated with fixed-term contracts. Firstly, workers may relocate for seasonal jobs, with the intention of staying in a particular province only for the duration of their contract before returning to their previous province. Secondly, the prospect of securing a temporary job may discourage workers from pursuing long-distance relocations, as the lack of income stability reduces the perceived value of earnings in the destination province.

These factors collectively shape the relationship between fixed-term contracts and geographical mobility, highlighting the nuanced dynamics at play when considering the influence of temporary employment on workers' migration decisions.

3.4.4 Short-term vs. Long-term Migrants

Interregional migration can be classified into two categories: long-term migrants, who permanently settle in a different region, and short-term migrants, who move between regions without establishing permanent residency. To illustrate, workers in the construction sector often need to mobilize to regions with ongoing construction projects, which may involve multiple relocations within a relatively short period. On the other hand, consider a textile worker whose factory has been relocated to

Figure 3.8 Long-term vs. short-term migrants by year



Notes: Migration shares are calculated based on workers' time in the destination province. Short-term migrants stay in the destination province for less than six months, while medium-term migrants stay for six months to two years. Finally, long-term migrants are those who stay for at least two years.

another region; in this case, they would need to move and establish their residence in the new region.

Figure 3.8 illustrates a variation in the share of short-term and long-term migrants by year. Based on future information, workers are classified based on their time spent in the destination province. Short-term migrants are those who stay less than six months, medium-term migrants are those who remain more than six months but less than two years, and long-term migrants are those who stay more than two years. According to the results, fewer people are settling in the destination region, with a growing fraction staying for a few months.

Table 3.2 provides descriptive statistics about short-term, mid-term, and long-term migrants. Averages are based on migrants between 1995 and 2019. In subsequent years, it was impossible to check whether migrants stayed longer than two years in the destination province. Short-term migrants tend to be younger and have lower educational attainment than long-term migrants. Among migrants, 60.3% had less than secondary education, and 47.1% had more than tertiary education. A noteworthy characteristic of short-term migrants is that they are more likely to be employed on fixed-term contracts, with 90.6 percent of workers on temporary contracts.

The occupational skill level and destination sector show similar patterns. Short-term migrants are, on average, in less skilled occupations and overrepresented in certain sectors. In agriculture, livestock, and fishing, 16.9% of workers are short-term migrants, compared to 5.44% who are long-term migrants. Those who work in the public sector, such as those in public administration, defense, education, and health care, are more likely to have been long-term migrants, with 16.38% staying at least two years and 10.7% staying less than six months in the destination sector.

The descriptive analysis of migrants shows some relationships between fixed-term contracts and the incentives workers have to migrate. I will formally describe this relationship and show how the stability of job relationships may affect workers' migration incentives.

3.5 Employment Instability and Internal Migration

In the standard random utility framework, potential migrants evaluate the costs and benefits of migrating to each destination. They choose the one that produces the highest net expected return. Thus, economic opportunities are made up of two components: the expected wage rate and the probability of receiving it (Treyz et al., 1993), where the local unemployment rate usually approximates the latter. Nevertheless, in an environment of significant labor market instability, such as a dual labor market with permanent and temporary contracts, workers internalize the prospect of being promoted in origin and destination regions in their migration decision.

A starting point to study the previous is examining flows between provinces and considering how they change with the share of fixed-term contracts at the local level. The following specification also controls for the local unemployment rate at the destination province and by origin fixed effects, exploiting how variation in the share of fixed-term contracts as a proxy for the employment stability affects the flows between Spanish provinces. In this specification, I consider how worker inflows into province k from province j change with the share of fixed-term contracts in the origin and destination province. To do this, I estimate the following equation:

$$logInflows_{jkt} = \beta_0 + \beta_1 ShareFTC_{jt} + \beta_2 ShareFTC_{kt} + X_{jkt}\beta + \varepsilon_{jkt},$$

where $logInflows_{jkt}$ is the log inflows rate from province j into province k in period t, including both short-term and long-term migration flows, $ShareFTC_{jt}$ is the employment share in fixed-term contracts in year t and province j. Finally, X_{jkt} is a vector of regional controls, including the local unemployment in the origin and destination province, and employment share by sector, and ε_{jk} the idiosyncratic error term.

Table 3.2 Characteristics short-term and long-term migrants

	Short-term migrants	Medium-term migrants	Long-term migrants
Age			
<22	10.71%	7.53%	8.13%
25-25	14.74%	13.01%	13.58%
25-30	23.47%	25.34%	27.22%
30-35	17.64%	19.64%	20.74%
35-40	13.41%	14.15%	13.61%
40-45	9.50%	9.53%	8.46%
45<	10.53%	10.80%	8.26%
Education			
Below secondary	60.30%	52.78%	47.14%
Secondary	18.03%	19.80%	21.39%
Tertiary	21.67%	27.42%	31.47%
Fixed term contract	90.66%	78.19%	69.09%
Foreign born	26.62%	21.63%	16.24%
Occupational skill group			
Very-high-skilled	3.29%	7.49%	8.82%
High-skilled	5.57%	9.75%	10.28%
Medium-High-skilled	10.60%	13.95%	16.24%
Medium-low-skilled	45.17%	44.47%	42.23%
Low-skilled	35.37%	24.34%	22.43%
Destination sector			
Agriculture, livestock, fishing	16.90%	8.06%	5.44%
Extractive activities	0.10%	0.18%	0.23%
Manufacture	4.84%	6.90%	8.48%
Energy, gas, and steem supply	0.28%	0.40%	0.69%
Construction	18.13%	18.55%	14.61%
Commerce	7.97%	11.17%	14.32%
Hospitality	9.26%	9.65%	9.22%
Transport and storage, communication	3.51%	4.88%	4.94%
Financial and insurance activities	1.09%	2.13%	3.16%
Renting	0.33%	0.38%	0.41%
Professional, cientific, tecnical activities	21.44%	17.29%	17.73%
P.A. and defense, education, health services	10.70%	15.75%	16.38%
Other	5.46%	4.65%	4.39%

Notes: This table only includes migration events from 1998 to 2015. There may be more than one migration event during the period, so workers may appear more than once.

TABLE 3.3 Flows among provinces and job instability

	(1)	(2)	(3)
	Dependent variable: log Inflow Rate		
$Share^{FTC}_{destination}$	-4.415***	-4.478***	-1.255**
	(0.333)	(0.272)	(0.428)
$Share^{FTC}_{origin}$	1.507***	1.788***	1.802***
	(0.333)	(0.272)	(0.259)
Observations	7283	6145	6145
R^2	.066	.483	.530
Controls	Yes	Yes	Yes
GeographicDistance	No	Yes	Yes
SectorShares	No	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Inflows are calculated as the number of workers who moved from one province to another during a given year. Each year, there are no duplicates. The controls are all constructed for the last year of the interval, therefore 2007, 2013 and 2021.

Table 3.3 presents the results of estimating the previous equation using inflows data for the 50 Spanish provinces between 1998 and 2021. Flows data is aggregated into three periods as some provinces have few movements. The periods comprise 1998-2007, 2007-2013, and 2013-2021. Column (1) shows the baseline specification in which the only controls are the local unemployment rate at the destination and origin province. As shown in the other columns, the coefficient's sign is robust even when additional controls are included. Column (3) shows that provinces with a higher share of fixed-term contracts receive fewer inflows and experience more worker outflows. An increase of 10% in the share of fixed-term contracts in a region is related to a decrease in 0.1 log points in inflows and an increase of inflows from regions with a higher share of fixed-term contracts. Which in net shows that workers reallocate into regions with more job stability.

Section 3.4.1 highlights that workers have the option to migrate to a region either as short-term or long-term migrants. Furthermore, the motivation to migrate as a short-term migrant is intensified when entering a region with a higher prevalence of unstable employment opportunities. To explore this connection, I will exploit the rich individual-level data from the MCVL, and not only the information at the regional level, enabling the inclusion of more precise individual and regional factors to investigate how an unstable local labor market influences the duration of workers' stay. Specifically, I examine the impact of job insecurity on the length of time workers remain in their destination regions. Consequently, the following equation is employed to investigate this relationship:

$$MonthsOut_{irt} = \alpha_0 + \alpha_1 ShareFTC_{rt} + X_{it}\beta + \psi_t + \mu_r + \varepsilon_{rt},$$

where $MonthsOut_{irt}$ is the number of months individual i was in province r entering at time t, $ShareFTC$ is my variable of interest which accounts for the share of workers in fixed-term contracts in province r, and time t. X_{it} is a vector of individual characteristics that measure individual characteristics at entry into province r, including destination sector fixed-effects, experience, interactions of six age categories with education attainment, gender, occupational skill group, and foreign-born status. Additionally, ψ_t is a set of year fixed effects and μ_r province fixed effects.

Table 3.4 Local employment share of temporary employment and migration duration

	(1)	(2)	(3)
	Dependent variable: Months Out		
$ShareFTC$	-19.89***	-8.914*	-9.355*
	(4.054)	(3.996)	(3.981)
Constant	73.74***	62.20***	64.81***
	(1.533)	(1.509)	(1.556)
Obs.	743,784	743,784	743,784
R^2	0.125	0.146	0.157
SectorFE	No	Yes	Yes
Individual controls	No	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Sample is restricted to workers who changed their province of residence. The dependent variable measures the number of months a worker stayed at the destination province. Additional controls include province, year, and sector fixed effects, foreign-born status, experience, gender, and interactions of age categories and education attainment. Standard errors are clustered at the worker level.

Table 3.4 confirms that regions with a large share of unstable employment keep fewer migrants. Based on Column (1), there is a negative and statistically significant relationship between the share of fixed-term contracts in a province and the number of months migrants stay there. An increase of 10% in the share of fixed-term contracts implies workers stay on average 1.98 months less in the destination province. As shown in Column (2), the sectoral composition can explain much of the effect since when I control for sector fixed effects, the coefficient decreases by 55%. Lastly, Column (3) controls for many individual characteristics, but the coefficient remains almost the same, indicating that differences in the composition of local workers cannot explain the result.

3.6 The 2012 labor market reform

In my final analysis, I examine the impact of the 2012 labor market reform, which was implemented in response to the economic challenges faced by the Spanish economy following the 2008 financial crisis. This reform aimed to address widespread job losses during that period, particularly focusing on improving conditions for young workers and individuals employed under temporary contracts. Specifically, I explore a policy introduced as part of this reform that offers financial incentives to firms for hiring and retaining individuals under 30.

I aim to study the impact of labor market reform on the migration patterns of young workers in regions with high job instability. I expect that after the reform was implemented in February 2012, young workers in these volatile areas would exhibit reduced relocation rates compared to their counterparts before the reform.

It is worth noting that although the 2012 labor market reform brought significant changes to firing costs, including a reduction in the severance payment gap between fixed-term and open-ended contracts, there was limited observed change in the share of fixed-term contracts during the years leading up to the reform (Figure 3.10). Therefore, in my analysis, I exploit the fluctuations in job stability while keeping the overall percentage of fixed-term contracts relatively constant.

In the initial analysis, I examine the influence of these incentives on the likelihood of securing an open-ended contract within specific time frames (1, 3, 6, 12, and 18 months) for a sample of individuals who experienced job loss, I restrict to workers aged 18 to 35. The treatment group comprises workers under 30. To facilitate a comparison of outcomes for young workers prior to the labor market reform, the estimation sample includes observations from 2010 to 2014.

To evaluate the impact of the labor market reform on promotion probabilities, I analyze the likelihood of young and older workers obtaining open-ended contracts before and after the reform, which was implemented in February 2012. I estimate the following model using a sample of workers whose contracts are set to expire:

$$p_{it} = \alpha D_i \times T_t + D_i + T_t + X_{it}\beta + \varepsilon_{it}$$

where the indicator variable D_i identifies whether a worker is younger than 30 years old, and the indicator variable T_t identifies if the event occurred after February 2012. X_{it} represents a comprehensive set of individual controls to ensure comparability. These controls include interactions between gender and education attainment, foreign-born status, age group, occupation skill group, and year-fixed effects.

The estimation results are presented in Table 3.5, demonstrating the expected effect on the probability of obtaining an open-ended contract following the reform. This effect becomes more pronounced over the first year, with the highest coefficient for the outcome three months after the event. The analysis reveals that following the 2012 labor reform, young workers experienced an increased probability of being promoted to open-ended contracts and securing more stable employment.

Implementing this policy reduces job uncertainty among young workers, which in turn lowers the likelihood of migration. To explore this effect and gather further

Table 3.5 Treatment impact on the probability of being in an open-ended contract

	(1) 1 month	(2) 3 months	(3) 6 months	(4) 12 months	(5) 18 months
Treatment	0.071***	0.109***	0.078***	0.028***	0.034***
	(0.009)	(0.009)	(0.008)	(0.007)	(0.007)
Obs.	114,168	114,168	114,168	114,168	114,168
R^2	.032	.030	.036	.055	.056
Controls	Yes	Yes	Yes	Yes	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The treatment's impact on the likelihood of obtaining an open-ended contract at 1, 3, 6, 12, and 18 months. The sample is constrained to workers under 35 years old who experienced job loss between 2010 and 2014. The treatment group consists of individuals younger than 30. Additional controls include gender and education attainment interactions, age group, foreign-born status, occupation skill group, and fixed effects for year and province.

evidence regarding the impact of job instability on internal migration, I employ the following specification:

$$y_{it} = \alpha ShareFTC_{rt} \times D_i \times T_t + \psi_0 ShareFTC_{rt} + D_i + T_t + X_{it}\beta + \varepsilon_{it},$$

the variable y_{it} represents an indicator for worker i migrating during year t, while the key coefficient of interest, denoted as α, captures the effect of having increased job stability opportunities following the reform. The interaction $D_i \times T_t$, represented as $Treatment_{it}$, captures whether worker i is part of the treatment group in period t. As additional controls, I include year fixed-effects and individual controls, including gender, foreign-born status, education attainment, age group, occupational skill group, and sector of economic activity. I leverage the treatment differences between young and older workers in this subsample of workers in the final month of their contracts, including permanent and fixed-term ones.

The findings, as shown in Table 3.6, support the previous hypothesis, with a negative coefficient indicating the influence of labor market reform on employees' migratory incentives. One result of the reform was a reduction in uncertainty about future possibilities for young workers who previously faced restricted opportunities for permanent job openings. As a result, their desire to remain in their particular regions grew. This conclusion is consistent with prior findings on the effects of the Spanish labor market's dual character. Furthermore, when I include sector fixed effects in Column (2), the coefficient is slightly attenuated, indicating that a portion of this effect is related to the sector in which workers are employed.[10]

[10] In the appendix, Tables 3.9 and 3.10 provide further evidence of the robustness of the findings. When the sample is limited to native workers, the effect size slightly increases, aligning with the notion that labor market instability may have a stronger impact on native workers who have stronger ties to a particular region.

Table 3.6 The impact of the 2012 labor reform on internal mobility

	(1)	(2)
	y_{it}: Internal migrant	
$Treatment_{it} \times shareFTC_{rt}$	-0.044**	-0.035*
	(0.016)	(0.014)
Obs.	173,973	173,973
R^2	.008	.015
Controls	Yes	Yes
Sector FE	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The sample is limited to workers who experienced job loss between 2010 and 2014. The variable y_it indicates whether worker i changed their province of residence during the year. Additional controls consist of year fixed-effects and individual characteristics, including gender, foreign-born status, education attainment, occupational skill group, and sector of economic activity. The first column displays the baseline specification, while column (2) further incorporates sector-fixed effects.

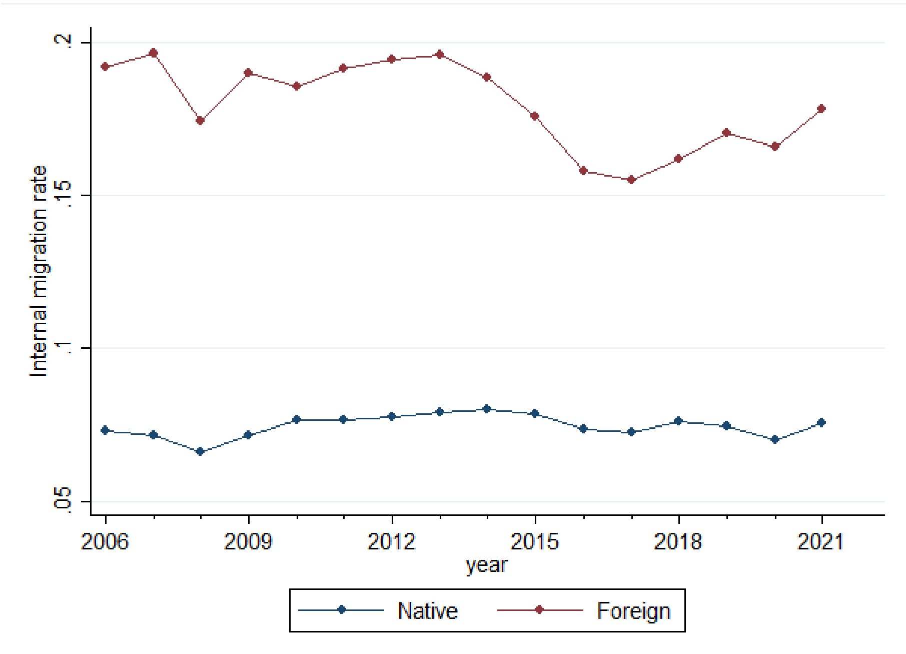
3.7 Conclusion

The topic of internal migration has received the attention of researchers for numerous years due to its potential implications for regional economies, social dynamics, and demographic trends. In Spain, a notable concern arises from the substantial proportion of fixed-term contracts in relation to total employment. This study seeks to analyze how labor market dualism may contribute to low internal migration rates.

This paper focuses on examining the relationship between temporary contracts and internal migration within Spain. The findings indicate that provinces with a higher prevalence of temporary contracts tend to experience lower worker inflows. Furthermore, it is observed that individuals who migrate to regions characterized by significant job instability tend to have shorter durations of stay compared to those who migrate to more stable regions. To conduct this analysis, data from the Spanish Labor Force Survey (EPA) and the Continues Sample of Working Lives (MCVL) are utilized to explore internal migration trends and patterns alongside temporary employment dynamics across various regions of Spain. In contrast to findings from the United States, there is no evidence of a downward tendency in internal mobility, but it has been rather stable over the last 20 years.

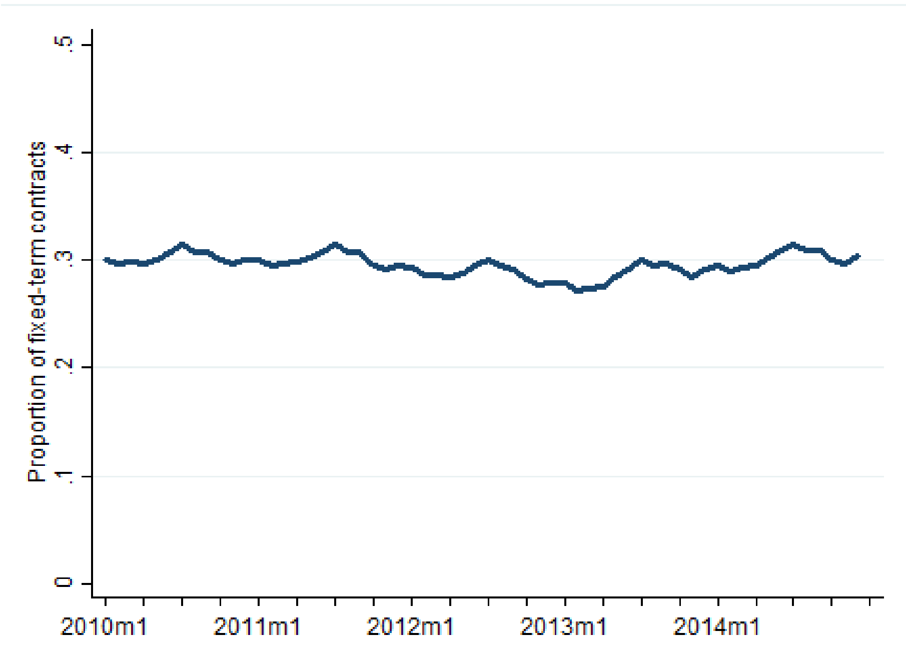
Appendix 3.A Supplementary Figures

FIGURE 3.9 Internal migration share, 1998-2021



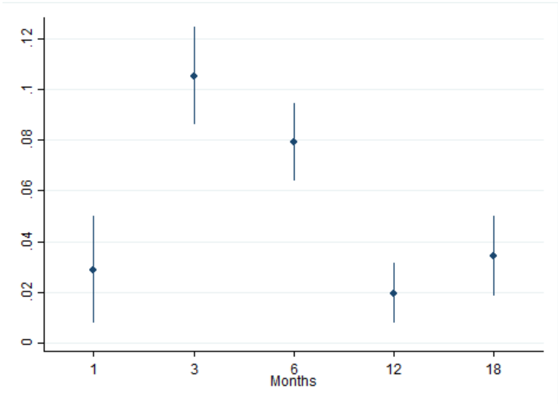
Notes: Internal migration share in Spain. Migrants are computed as those who, in the reference period, changed their municipality of residence. Categories are based on the nationality of the worker. *Source:* EPA

FIGURE 3.10 Share of employees with fixed-term contracts, 2010-2014

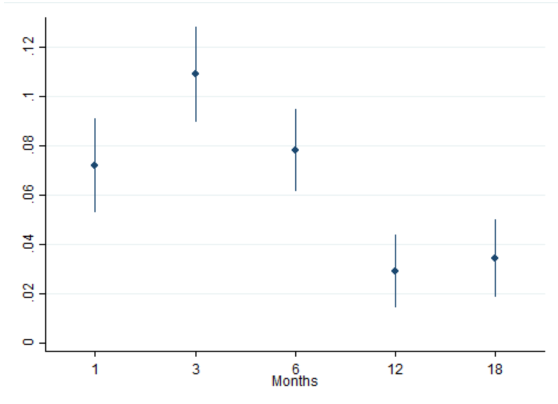


Notes: Share of workers in fixed-term contracts on a monthly basis from January 2010 to December 2014:

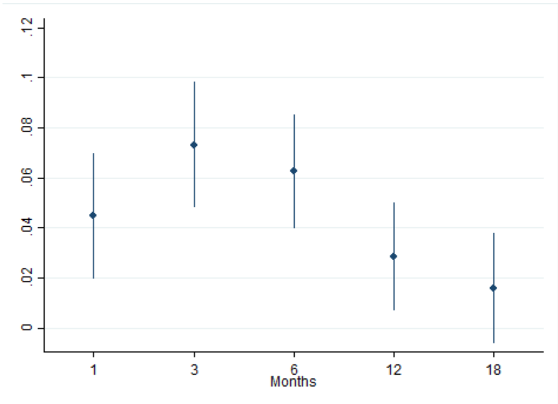
Figure 3.11 Treatment impact on the probability of being in an open-ended contract



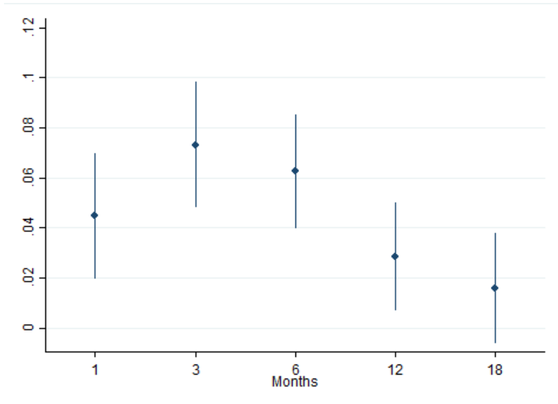
(a) Model 1



(b) Model 2



(c) Model 3



(d) Model 4

Notes: The treatment's impact on the likelihood of obtaining an open-ended contract at 1, 3, 6, 12, and 18 months. The sample is constrained to workers under 35 years old who experienced job loss between 2010 and 2014. The treatment group consists of individuals younger than 30 for observations after February 2012. Additional controls include gender and education attainment interactions, foreign-born status, occupation skill group, and fixed effects for year and province. Model 1 is the baseline specification. Model 2 adds the age group as a control. Model 3 further narrows down the analysis to workers aged 26 to 34. Lastly, Model 4 restricts the baseline specification to observations from 2011 to 2013.

Appendix 3.B Supplementary Tables

Table 3.7 Robustness: The impact of the 2012 labor reform on internal mobility of workers

	(1)	(2)
	y_{it} : Internal migrants	
$Treatment \times shareFTC_{rt}$	-0.020	-0.018
	(0.015)	(0.014)
Obs.	114,168	114,168
R^2	.013	.022
Controls	Yes	Yes
Sector FE	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The sample is limited to workers who experienced job loss between 2010 and 2014. The variable y_it indicates whether worker i changed their province of residence during the year. Additional controls consist of year fixed-effects and individual characteristics, including gender, foreign-born status, education attainment, occupational skill group, sector of economic activity, and province fixed-effects. Column (1) shows the baseline specification. Column (2) additionally include sector fixed effects.

Table 3.8 Robustness: The impact of the 2012 labor reform on internal mobility of native workers

	(1)	(2)
	y_{it} : Internal migrants	
$Treatment \times shareFTC_{rt}$	-0.035**	-0.034**
	(0.012)	(0.011)
N	90,249	90,249
R^2	.014	.023
Controls	Yes	Yes
Sector FE	No	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The sample is limited to workers who experienced job loss between 2010 and 2014. The variable y_it indicates whether worker i changed their province of residence during the year. Additional controls consist of year fixed-effects and individual characteristics, including gender, foreign-born status, education attainment, occupational skill group, sector of economic activity, and province fixed-effects. Column (1) shows the baseline specification. Column (2) additionally include sector fixed effects.

Table 3.9 The impact of the 2012 labor reform on internal mobility of native workers

	(1)	(2)
	y_{it}: Internal migrants	
$Treatment \times shareFTC_{rt}$	-0.057***	-0.053***
	(0.012)	(0.012)
Obs.	90,249	90,249
R^2	.011	.019
Controls	Yes	Yes
Sector FE	No	Yes

Standard errors clustered by province in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The sample is limited to workers who experienced job loss between 2010 and 2014. The variable y_it indicates whether worker i changed their province of residence during the year. Additional controls consist of year fixed-effects and individual characteristics, including gender, foreign-born status, education attainment, occupational skill group, and sector of economic activity. Column (1) shows the baseline specification restricted to native workers. Column (2) additionally include sector fixed effects.

Table 3.10 The impact of the 2012 labor reform on internal mobility of workers

	(1)	(2)	(3)
	y_{it}: Internal migrant		
$Treatment \times shareFTC_{rt}$	-0.041**	0.011	-0.046*
	(0.014)	(0.086)	(0.039)
Obs.	114,168	52,816	106,133
R^2	.008	.015	.018
Controls	Yes	Yes	Yes

Standard errors clustered by province in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The sample is limited to workers who experienced job loss between 2010 and 2014. The variable y_it indicates whether worker i changed their province of residence during the year. Additional controls consist of year fixed-effects and individual characteristics, including gender, foreign-born status, education attainment, occupational skill group, and sector of economic activity. Column (1) presents the baseline specification. Column (2) additionally restricts workers aged 26-32 years. Column (3) restricts observations between 2011 and 2013.

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