From bricklayers to waiters: Reallocation in a deep recession

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Abstract

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 into 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 level of sectoral concentration.

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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. In order 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), 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. In other contexts, however, sectoral mobility may be a relevant adjustment mechanism. Additionally, I study both 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 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 a 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.

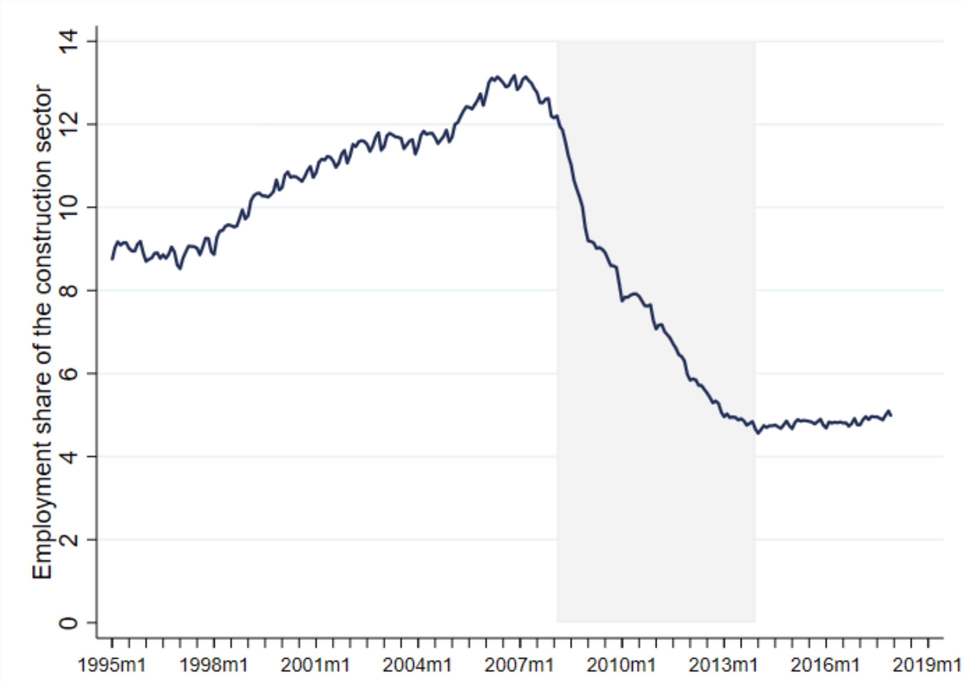
Through this paper, I contribute further evidence on the impact of economic shocks on workers' labor market outcomes (Autor et al. 2014; Dix-Carneiro and Kovak 2017) and the long-term consequences of job loss (Jacobson et al. 1993; Gulyas et al. 2019). I also examine the dynamics of the shock's impact on workers' earnings and employment, providing additional evidence on workers' reactions. Similar to Autor et al. (2014), I

[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 worker's earnings and employment trajectories, respectively.

Figure 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 years old and employed during the referenced period. The shaded area comprises the years of the Great Recession in Spain, between 2008 and 2014.
Source: MCVL 2006-2017

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 both 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 into 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, therefore 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 which 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

[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.

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 workers' 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 which 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.

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 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

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

definition of the worker's relevant labor market. By defining this as a region or a particular occupation within one, the set of possible jobs would be overestimated or underestimated if they did not take into account the possibility of changing occupations. Therefore, I consider that workers receive random offers that depend on the likelihood that the worker may be matched in equilibrium with a firm in that sector, which is captured by the probability that a worker with characteristics X_i is matched to a firm in each sector.

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 captured 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 $V_t(X_i, r)$:

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

$$\tilde{V}_{t+1}(X_i, r) = \sigma^r_{cs} V_{t+1}(X_i, r) + (1 - \sigma^r_{cs})\mathbb{P}(X_i, r), \tag{2}$$

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 how likely are workers with characteristics X_i 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.

[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 on 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.

Combining expression (1) and (2):

$$V_t(X_i,r) = \underbrace{w(X_i) + V_{t+1}(X_i,r)}_{\text{Utility in absense of shock}} \underbrace{-\mu_r(1-\sigma^r_{cs})V_{t+1}(X_i,r)}_{\text{Impact of the shock}} + \underbrace{\mu_r(1-\sigma^r_{cs})\mathbb{P}(X_i,r)}_{\text{Attenuation of the shock}}. \tag{3}$$

Equation (3) 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 (3) 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 expression 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 adjustment 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 conditional on the initial earnings. This equation is the starting point in the empirical exploration of the impact of the decline of 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 the 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 size of the sector 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:

$$p_{j,i} = \frac{P(X = X_i, J = j)}{P(X = X_i)P(J = j)} \tag{4}$$

Equation (4) 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. 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:

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

$$= \sum_j P(J = j | X = X_i) \frac{Share_j^r}{Share_j} \tag{5}$$

[12] In Section 7, I apply another measure that exploits the transition probabilities conditional on the worker's characteristics.

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.

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

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, which are 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 the analysis focuses primarily on 2007-2013 earnings. For this reason, I rely on earnings from tax records when available. An example 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 also includes 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 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.

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 the lack of reliable 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 20 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 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 business cycle.

[13] Bonhomme & Hospido (2017) shows a comparison of 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, which makes both sources of earnings comparable.

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 each worker's suitability for jobs within each sector based on their observable characteristics. This utilizes equation (6), as explained in Section 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.[14]

$$Reallocation(X_i, r) = \sum_{j=1}^{J} \mathbb{P}(J_f = j|X_i) \frac{EmplShare_j^r}{EmplShare_j} \tag{6}$$

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.[15] I regress an indicator variable of the individual's job 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. 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. As a final step and to simplify the interpretation, the reallocation index

[14] In Section 7.3, the likelihood that each worker will migrate to another province is also taken into account. However, the main results remain largely unchanged.

[15] The results are not significantly different when I use different time windows.

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, there is a significant impact heterogeneity 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.

4 Description of the Construction Sector

Table 1 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 to decrease the unemployment rate. However, the decline in employment shares during the Great Recession shows how vulnerable such workers are to economic fluctuations.

Additionally, Table 1 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 A1) as well as leavers (Table A2). 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.

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

Table 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
Mean 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.
Source: MCVL, 2006-2017

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.

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, unemployment, 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:

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

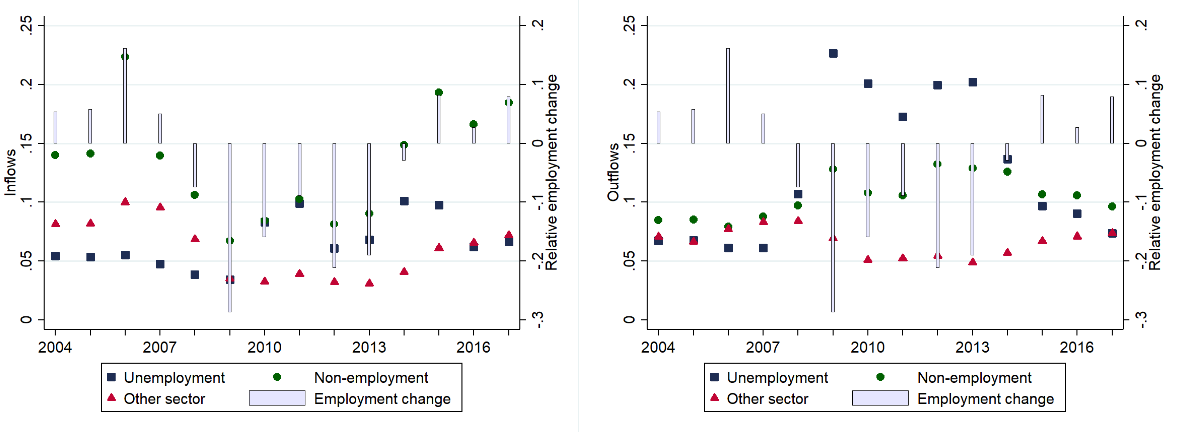
I show the results of this decomposition in Figure 2. Panels (a) and (b) present inflows and outflows, respectively. The blue bars in both figures represent the relative changes in construction employment.

According to Panel (a), inflows from unemployment, non-employment, and other sectors had a similar evolution. During this period, inflows from non-employment accounted for most of the employment growth, which is 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 large legalization 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 1 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 2, 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.

Figure 2: Aggregate flows from/to the construction sector



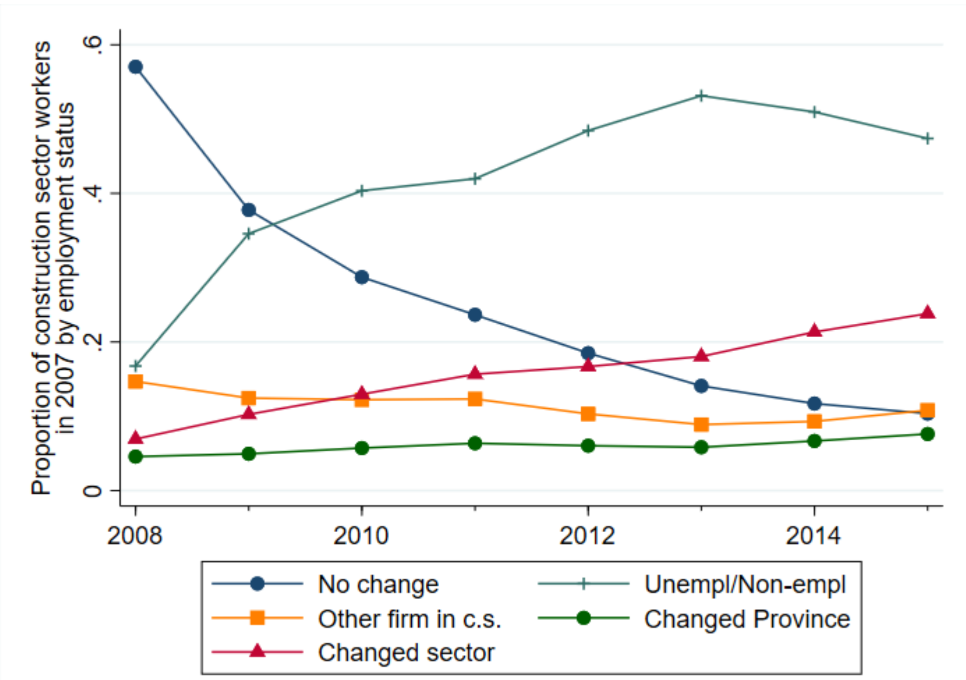
(a) Inflows to construction sector

(b) Outflows to construction sector

Notes: Panel (a) Outflows to construction sector that one year before were in another sector, non-employment or unemployment for the population in $t-1$ Panel (b) Inflows to construction sector that one year before were in another sector, non-employment or unemployment for workers in $t-1$. The sample is restricted to yearly observations between 2003 and 2017 of workers aged 20-60.

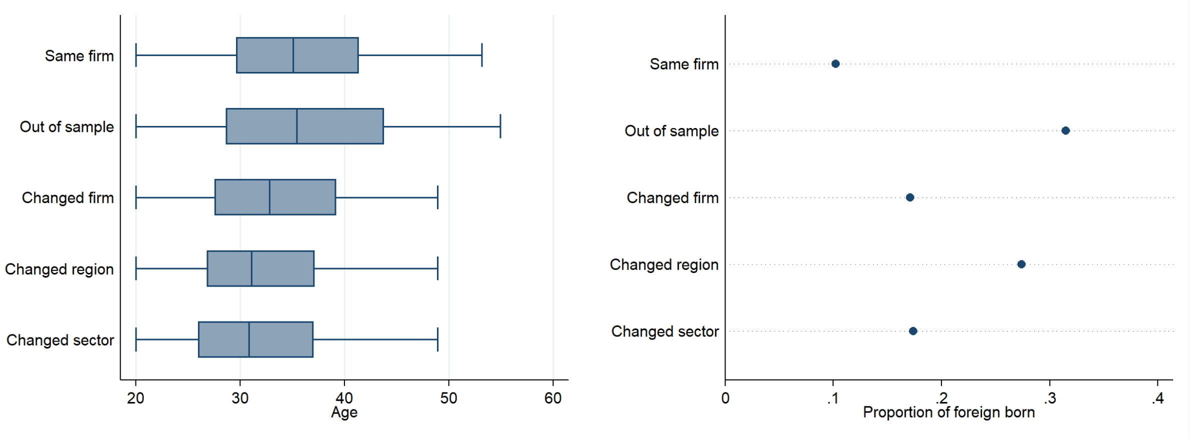
Source: MCVL 2006-2017

Figure 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.
Source: MCVL 2006-2017

Figure 4: Working status of workers in the construction sector in 2007



(a) Mean 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. Sample is restricted to workers in the construction sector in 2007 and aged 20-55 years old

Source: MCVL 2006-2017

The results are presented in Figure 3, in which I emphasize three main points.[17] [18] 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 during the same period.

Different factors are responsible for the employment decline in the construction sector. However, this analysis does not provide information about the 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

[17] I present in appendix A10 the same graph for high-skill workers as a comparison group largely unaffected by the shock. Additionally, I present in appendix A11 the same graph for a sample of workers in the construction sector in 2003, which compares changes in the working status before the Recession.

[18] The share of non-employed workers seems exceptionally high. To study this Figure, **??** tracks workers using a more restrictive sample; the sample considers native workers aged 20 to 45 years old and employed in the construction sector in 2007. Using this sample, the qualitative results are maintained

ask which workers are most likely to be found in each employment status after the housing bust.

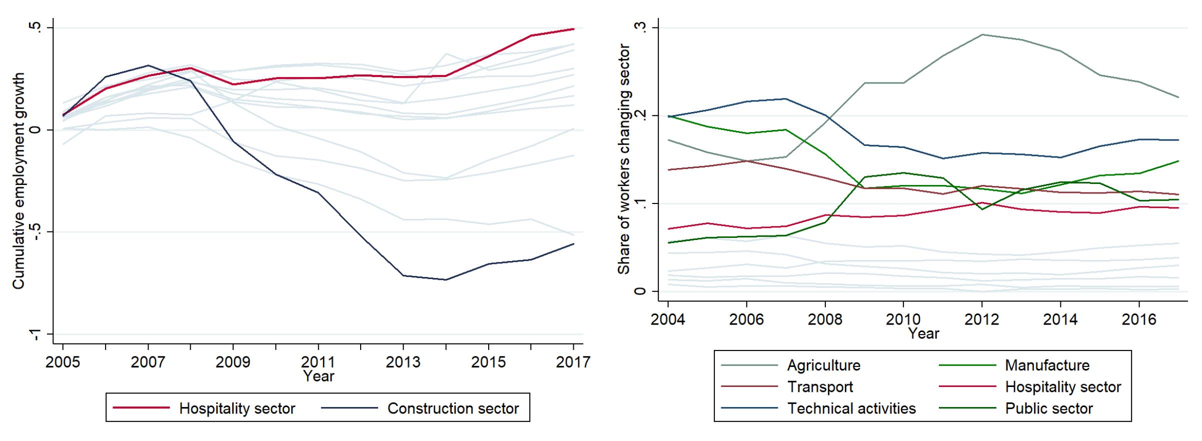
The Figure 4 shows the average age and the proportion of foreign-born workers in the different categories of working status in 2013. As above, these results are based on the sample of workers employed in the construction sector in 2007. According to the results, workers who changed regions or sectors are younger than those who stayed in the construction sector or stayed unemployed. Over the past decade, a large fraction of workers has 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 the appendix D.0.1 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.

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 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 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 indi-

Figure 5: Cumulative employment growth and sector of change from the construction sector



(a) Cumulative employment growth

(b) Movers by 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.
Source: MCVL 2006-2017

vidual workers switching sectors. In addition, it is dependent on their skill set's relative demand. As an exploratory exercise, panel b) of Figure 5 shows how workers initially in the construction sector moved to very different sectors.

4.2 Province level impact

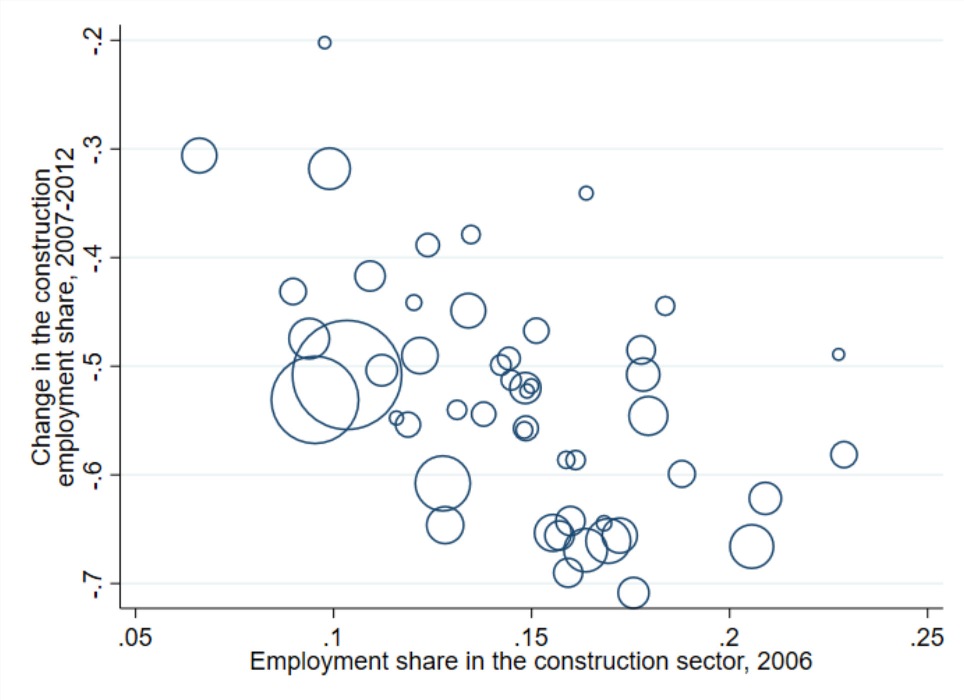
The initial employment share and the employment contraction of the construction sector during the Great Recession differed among the Spanish provinces.[19] My empirical analysis exploits the asymmetric regional decline in job opportunities based on these exposure differences.

The initial employment share of the construction sector by province ranges from 6.8 to 24.14 percent (Figure 6), such that the employment share is higher in the southern provinces.[20] 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 the employment in 2007.

[19] 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

[20] The same graph using labels for each province is in the appendix (Figure **??**) and maps (Figure **??**)

Figure 6: Change in share of workers in the c.s. during the GR by province



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 uses 50 Spanish provinces and all workers employed in April of each year.
Source: MCVL 2006-2017

5 Worker level impact

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 3. 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:

$$y_i = Shock_i^r \beta_0 + \mathbf{X}_i' \Delta + \epsilon_i, \tag{7}$$

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

Table 2: Cumulative earnings and 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.
Source: MCVL 2006-2017

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.[21]

X_i represents individual worker and regional characteristics. The full set of controls include 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,[22] 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 2, I provide baseline estimates of equation (7). Column (1) includes the

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

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

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 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.

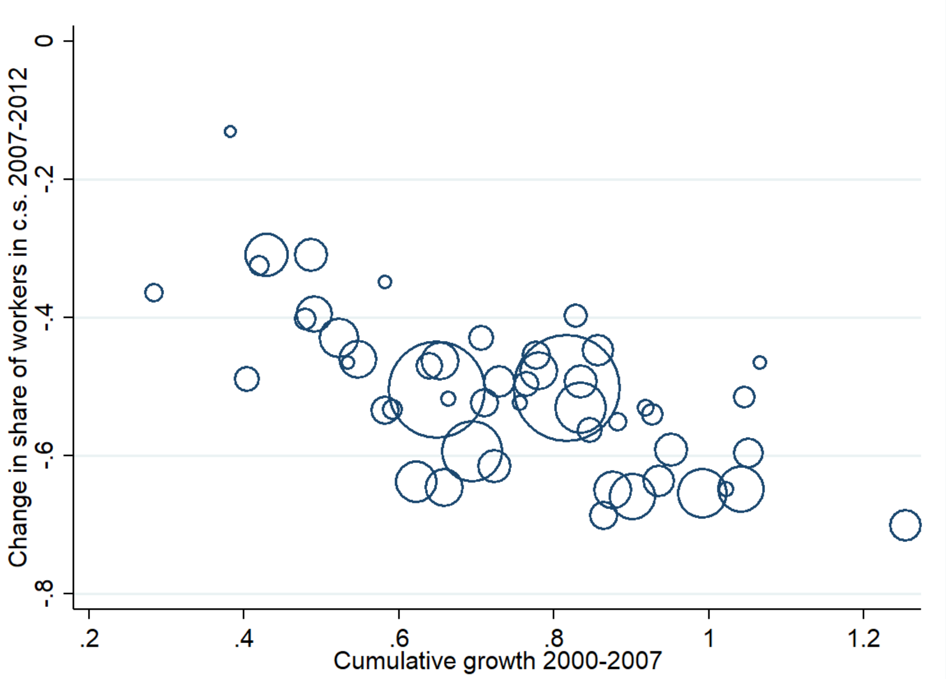
To interpret the coefficient estimates of this specification, consider two workers residing in provinces in the 75th and 25th percentile of exposure, respectively: Valencia, where the employment decline in the construction sector was 59.34%, and Badajoz, where it was 45.53%. On average, workers experienced 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.[23] 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.

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

[23]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 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.
Source: MCVL 2006-2017

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 2007 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 3. All the specifications account for the same set of controls as Column (3) of Table 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 for a sample of workers not employed in the construction sector.

Table 3: Labor market impact of the bust in the construction sector

	(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.

Source: MCVL 2006-2017

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.

5.1 Dynamic analysis

In this subsection, I examine the evolution of workers' impact on employment and earnings over time. Figure 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 (7) on the estimation sample:

$$y_{it} = Shock_i^r \beta_0 + \mathbf{X}_i' \Delta + \epsilon_{it} \tag{8}$$

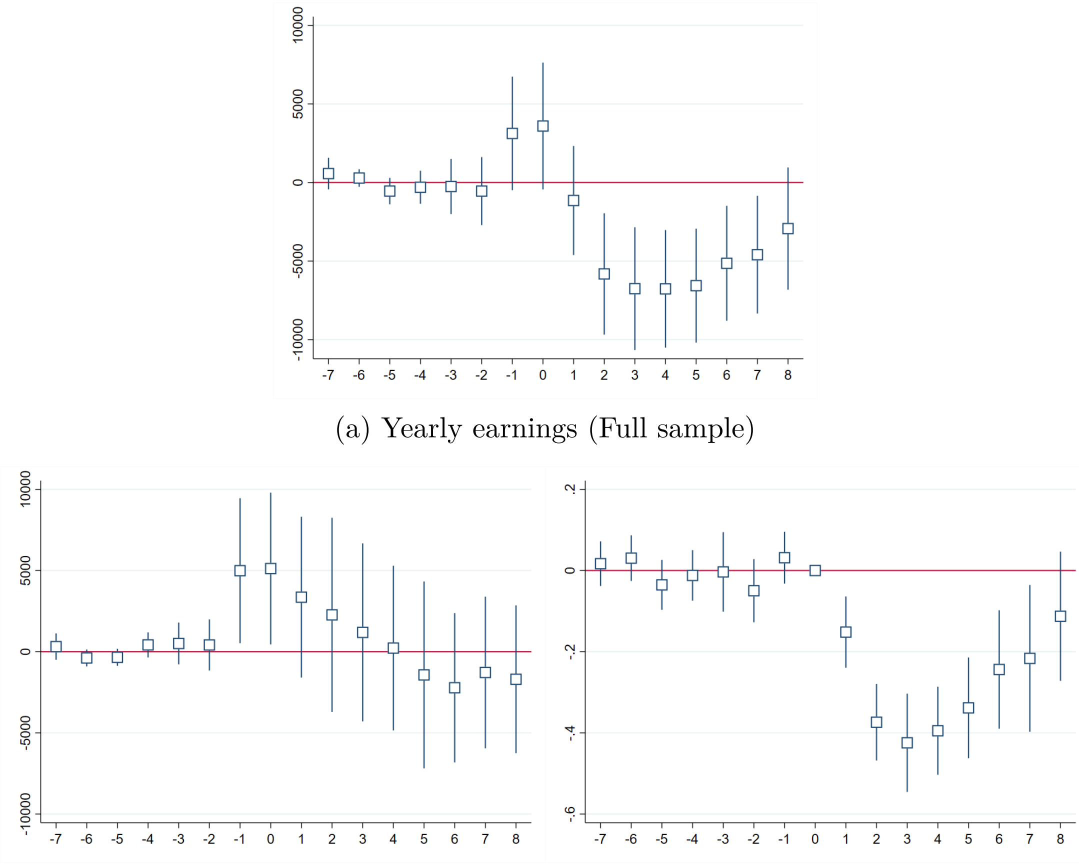
y_{it} is i's labor market outcome: the binary employment status of year t and the yearly earnings at year t. $Shock_i^r$ denotes the local shock to the individual's i initial province of residence. $\mathbf{X}_i$ is a vector of individuals' observable characteristics measured in 2007 and regional characteristics 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 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 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

Figure 8: Impact of the constraction in the construction sector employment



(a) Yearly earnings (Full sample)

(b) Yearly earnings (Only employed)

(c) Binary employment status

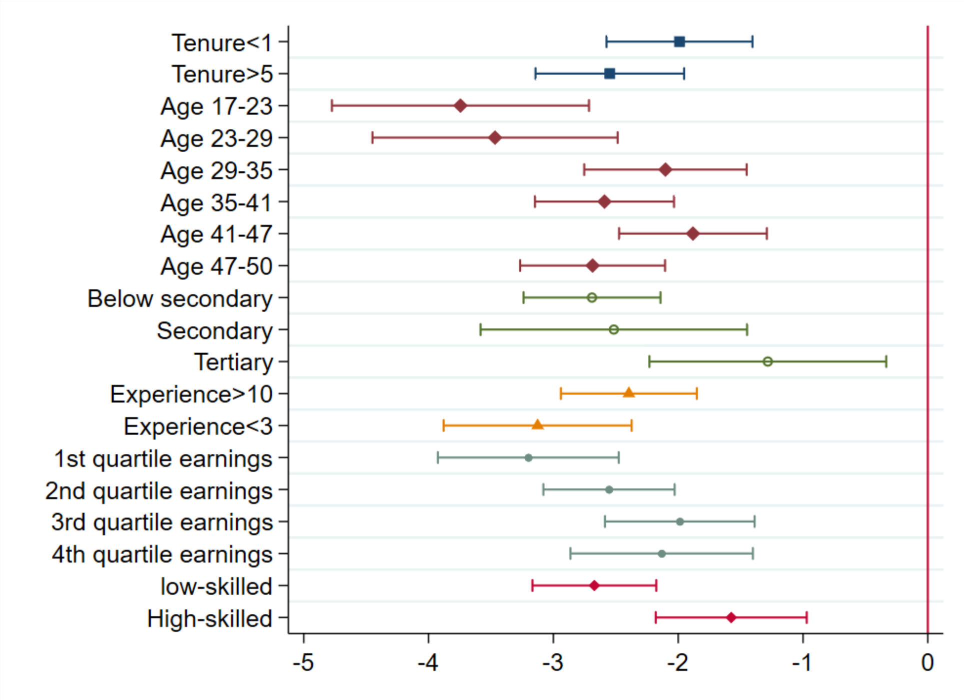
Notes: Sample is restricted to workers aged 29-42 and working in the construction sector in 2007. Coefficients of the shock using an outcome variable indicate whether the worker has a valid employment spell each year. (1: the worker appears in the year, 0: the worker is not in the sample). The average earnings are calculated over the non-zero earnings of each year. Additional controls are initial share of construction sector employment, Bartik type variable, and demographic characteristics.
Source: CSWL 2006-2017

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.

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 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

Figure 9: Cumulative earnings and local employment decline in the construction sector



Notes: 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 of months with non-zero earnings. Every regression controls by: gender, age, education, skill group, and 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. Source: MCVL, 2006-2017

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 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 control by all the worker and regional characteristics used in the previous section.

Results are presented in Table 6. A test of equality for the four coefficients 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 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.

5.3 Worker's labor market adjustment

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.

Table 4: Heterogeneity of the shock's impact on employment and earnings

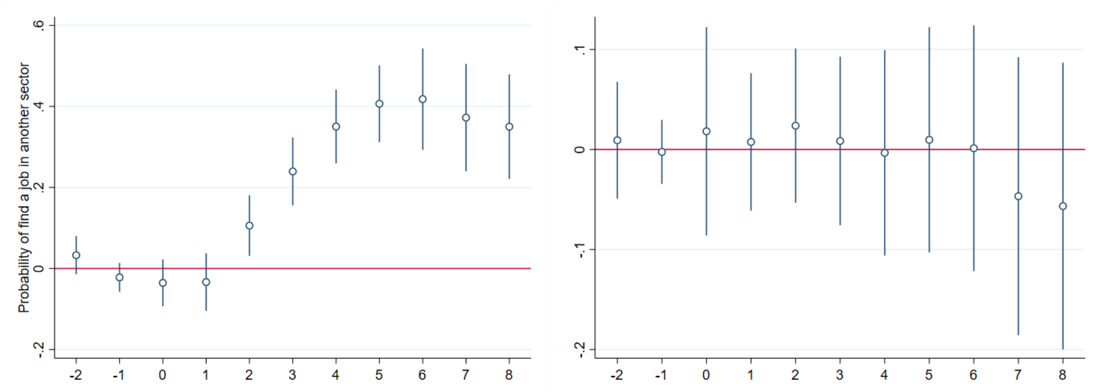
	(1) Cumulative earnings	(2) Employment	(3) Average earnings
$Q_1^{earnings} \cdot Shock$	-2.659***	-2.111***	-0.0116**
	(0.267)	(0.186)	(0.00391)
$Q_2^{earnings} \cdot Shock$	-2.271***	-1.798***	-0.00723
	(0.262)	(0.181)	(0.00391)
$Q_3^{earnings} \cdot Shock$	-2.093***	-1.677***	-0.00531
	(0.267)	(0.183)	(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 at 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.
Source: MCVL 2006-2017

Figure 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 initial share of construction sector employment, Bartik type variable, demographic characteristics, and interactions.
Source: MCVL 2006-2017

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 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 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 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 (9). $Shock_m$ 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' 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.

$$Shock_r^{adj} = Shock_r - \sum_{k \neq r} \mu_{r \to k} Shock_k \tag{9}$$

Table 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.

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.

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,

Table 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.

Source: MCVL 2006-2017

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 jobs options available to a given worker within their labor market. In most empirical studies, a local labor market refers to a defined geographic region.[24] Alternatively, they can be defined by exploiting worker flows within a region (Nimczik (2020)). Nevertheless, any binary labor 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 2. I get similar results when constructing the reallocation index using transition probabilities between sectors instead of worker similarity.

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

Table 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 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.
Source: MCVL 2006-2017

6.1 Sectoral composition and the contraction of the construction sector

This subsection expands equation (7) 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 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 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[25]. This effect is statistically significant, though the economic magnitude is small.

6.1.1 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

[25] 0.0857*0.6463*1596; the average monthly real earnings are 1596 real Euros.

Table 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	-2.445***		-1.897***		-0.00810*	
	(0.245)		(0.177)		(0.00343)	
$Q_1 \cdot Shock$		-2.892***		-2.336***		-0.0123*
		(0.377)		(0.293)		(0.00580)
$Q_2 \cdot Shock$		-2.479***		-1.875***		-0.00738
		(0.409)		(0.273)		(0.00509)
$Q_3 \cdot Shock$		-2.641***		-1.882***		-0.0115*
		(0.248)		(0.180)		(0.00443)
$Q_4 \cdot Shock$		-1.840***		-1.569***		-0.00166
		(0.235)		(0.228)		(0.00487)
Constant	6.654***	6.367***	5.029***	4.868***	0.116***	0.113***
	(0.153)	(0.146)	(0.123)	(0.138)	(0.00264)	(0.00288)
Observations	46392	46392	46392	46392	46392	46392
R^2	.2338	.2341	.3231	.3233	.0315	.0316
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 at 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.
Source: CSWL 2006-2017

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 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.

6.2 The composition of sectors and the switching between sectors

This section assesses whether sectoral composition influences workers' willingness to change sector. The adaptation to economic shocks may occur by relocating to a less affected region or by changing sectors. In Section 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 sector, 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 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 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.

6.3 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

Table 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 probit model of indicator variables if worker 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, 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 .

Source: MCVL 2006-2017

Table 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: province-level unemployment rate at 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.
Source: MCVL 2006-2017

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 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 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
Source: MCVL, 2006-2017

7 Basic robustness

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 10 provides evidence neglecting that the shock is related to the pre-recession outcomes. Column (1) shows a positive but insignificant effect of the shock on both employment and earnings.

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 workforce. 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.[26]

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

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

I compute the transition probabilities between 2000 and 2006 for the group of leavers from the construction sector using a probit model. 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, Iuse 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:

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

[26]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.

Table 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**.
Source: MCVL, 2006-2017

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 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.

7.3 Labor market adjustment and internal migration

As argued in Section 4.1, given the nature of the shock, which was highly unexpected, low internal migration would be expected. However, workers would still leave the most exposed regions to alleviate the impact of the shock on their labor market career outcomes.

According to Figure 3, even though workers migrated from the exposed region during the Great Recession, the number of individuals who changed sectors surpassed those who changed provinces. This article has not studied these two forces simultaneously, given the focus on local sectoral composition and sectoral change. In this case, I will consider that some workers might move from one province to another to adjust, then consider the likelihood of them changing provinces and sectors.

This subsection highlights the importance of sectoral and regional mobility for construction workers. A similar two-step approach was used to study geographical mobility's contribution to alleviating the shock's impact in this section.

As a result, I capture the likelihood that a worker will migrate in response to the shock. In order to do so, I estimate the conditional probability that a worker with given characteristics would change province; this is estimated for 1995-2007. Then I predict the probability of change sector on the set of workers in the estimation sample. This conditional probability is given by:

$$Prob(migrate_i) = \sigma_r + X_i'\beta + \epsilon_{it}.$$

Where σ_r is a province fixed effect, and X_i is a vector of worker characteristics which includes: occupational skill groups, indicators for part-time and fixed-term contracts,

Table 12: Labor market adjustment: Geographical and sectoral mobility

	(1)	(2)	(3)
	Cumulative earnings		
Shock	-2.338***	-2.560***	-2.628***
	(0.243)	(0.261)	(0.248)
Reall.Index	0.0652***	0.0741***	-0.225*
	(0.0174)	(0.0170)	(0.0852)
MigrationProb.		-0.134***	-0.117
		(0.0302)	(0.0910)
Reall.Index × *Shock*			0.542***
			(0.134)
MigrationProb. × *Shock*			-0.0409
			(0.143)
Constant	6.584***	6.630***	6.672***
	(0.144)	(0.160)	(0.162)
Observations	46375	46375	46375
R^2	.2349	.2358	.2363

Standard errors in parentheses

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

labor market experience, interactions of age and gender, and interactions of age and education attainment. Following this estimation, the second step predicts the conditional probability that a worker would change the region on the set of workers in the estimation sample. I also consider the interaction between migration probability and shock for comparison with the reallocation probabilities.

Results are presented in Table 12. Column (1) presents the baseline specification from section 6. The predicted probability of migration is added as a control in column (2). Interestingly, workers more likely to migrate have worse outcomes in the most affected regions. The migration probabilities were standardized to have a zero mean and unitary standard deviation. The increase of one standard deviation in migration probabilities is related to the decrease of 13.4 percent in the initial annual earnings between 2007 and 2012.

The third column examines the interaction between migration probabilities and the shock to determine how well workers in more affected regions attenuate the shock's impact. The Great Recession limited workers' geographical mobility, and this section confirms that there has been little adjustment through this mechanism. Cumulative earnings and the interaction of the shock do not show a statistically significant relationship.

8 Conclusion

In this paper, I have analyzed the effect of the employment decline of the construction sector on Spanish workers during the period 2007-2012. During the Great Recession, Spain was one of the most affected countries. The construction sector was particularly affected, with the contraction unevenly distributed among Spanish provinces. I initially show how the exposure to the burst of the Spanish construction sector led to large earnings losses. 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. Next, I explore how workers react to such a large shock and the evolution of workers' responses during the recovery. 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.

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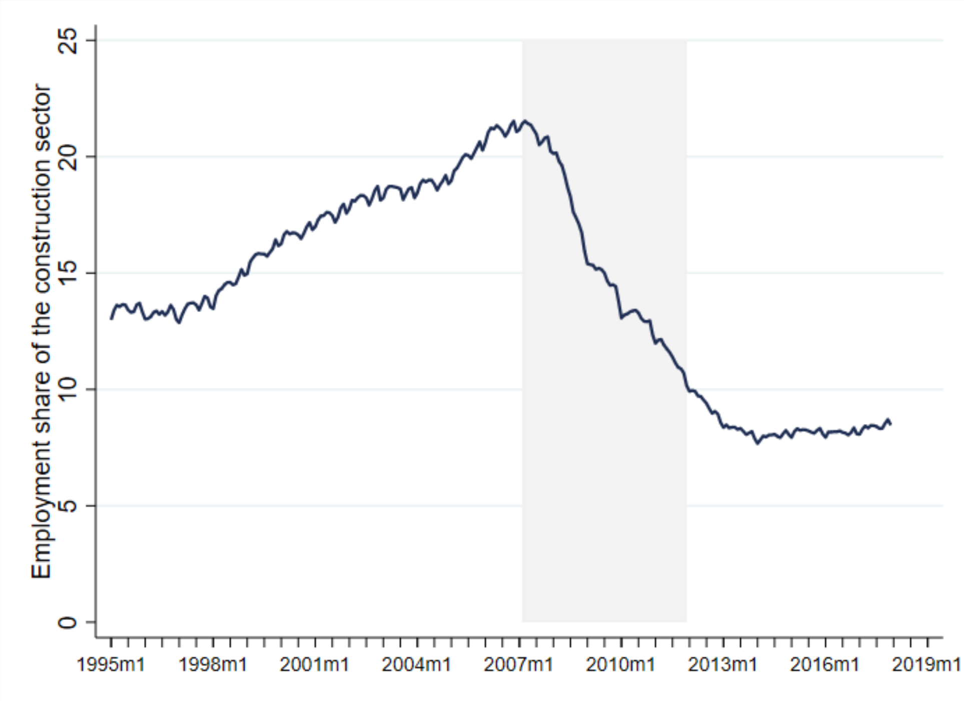
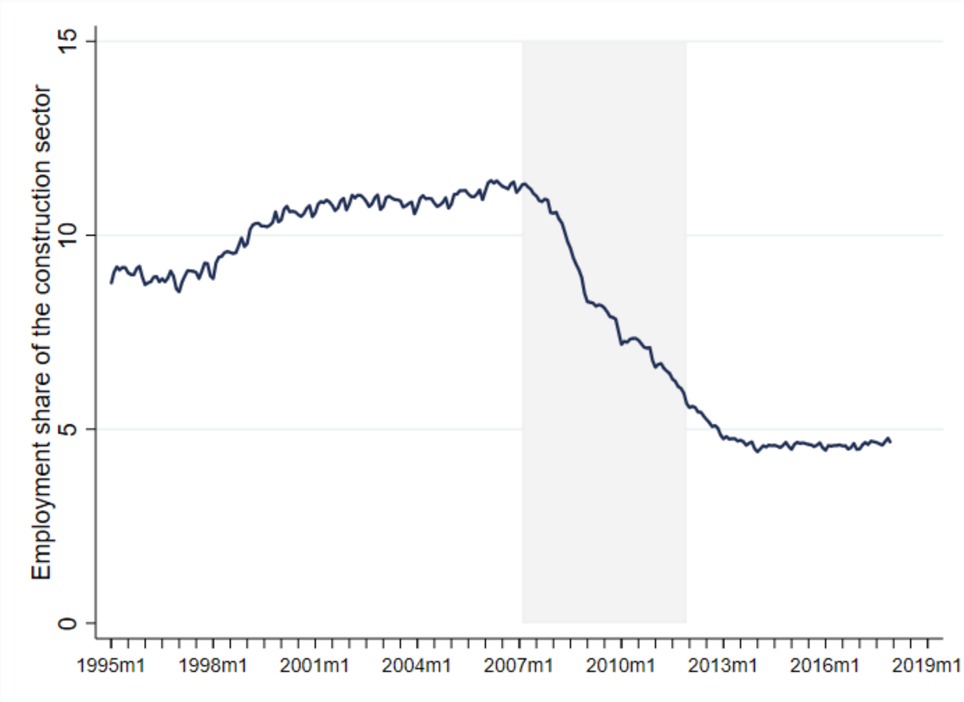
A Appendix: Figures

Figure A1: Employment share of the construction sector, 2000-2017



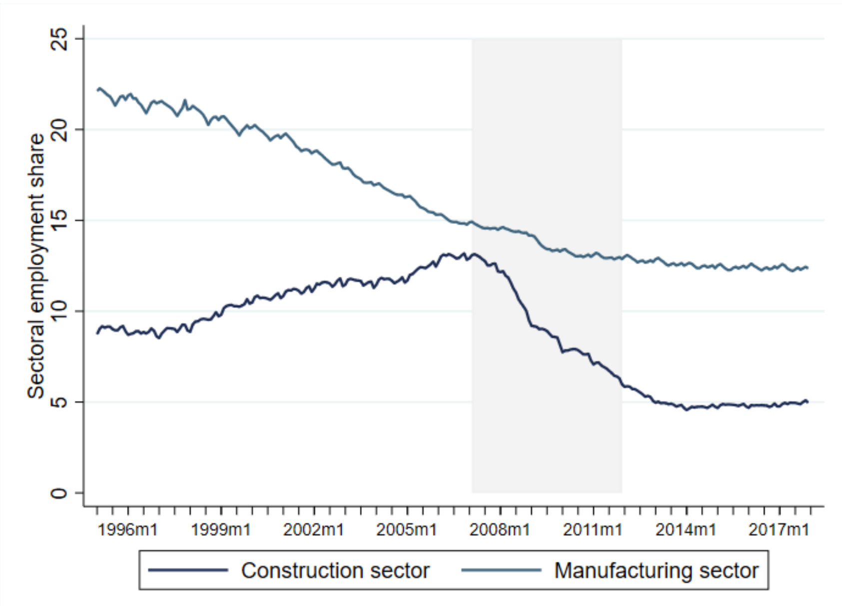
Notes: Men employed in the construction sector as a percentage of all male employed, January 2000 to December 2017. Data restricts to male workers employed during the referenced period.
Source: MCVL 2006-2017

Figure A2: Employment share of the construction sector, 2000-2017



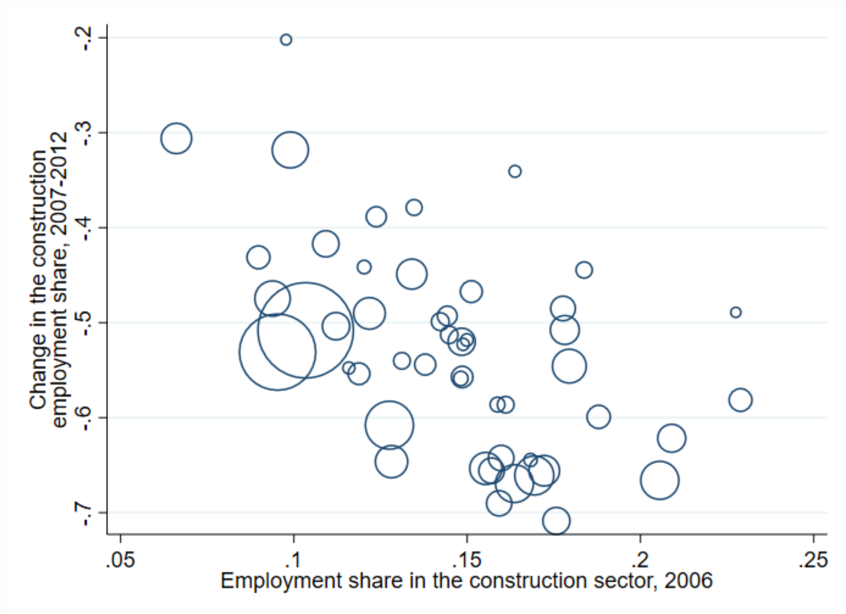
Notes: Native employed in the construction sector as a percentage of all Native employed, January 2000 to December 2017. Data restricts to Native workers employed during the referenced period. The gray area represents the period from January 2007 to December 2012
Source: MCVL 2006-2017

Figure A3: Manufacturing and construction employment shares, 2000-2017



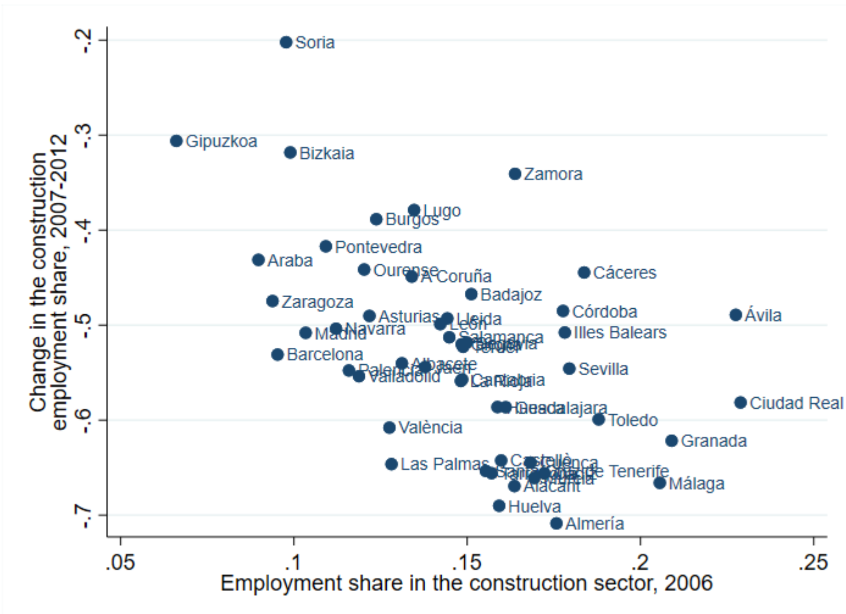
Notes: Employed workers in the construction and manufacturing sector as a percentage of all employed workers, January 2000 to December 2017. Data restricts to workers employed during the referenced period. The gray area represents the period from January 2007 to December 2012
Source: MCVL 2006-2017

Figure A4: Change in the construction employment share by province, 2007-2012



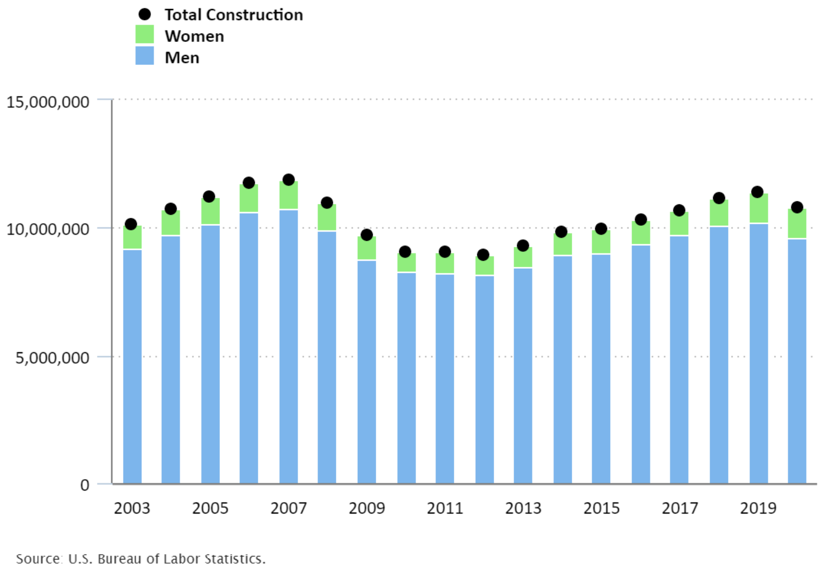
Notes: Change in the employment share of the construction sector by province between 2007 and 2012 against construction employment share in 2006. Sample considers the 50 Spanish provinces. The circles represent 2006 employment for each province.
Source: MCVL 2006-2017

Figure A5: Change in the construction employment share by province, 2003-2020



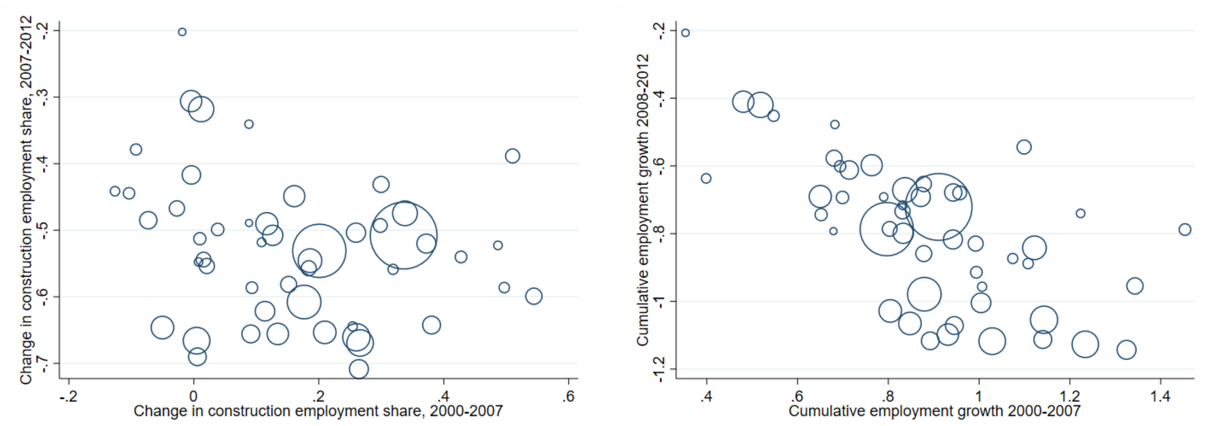
Notes: Change in the employment share of the construction sector by province between 2007 and 2012 against construction employment share in 2006. Sample considers the 50 Spanish provinces.
Source: MCVL 2006-2017

Figure A6: Construction sector employment in the US, 2003-2020



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

Figure A7: Employment evolution of the construction sector by province, 2007-2012

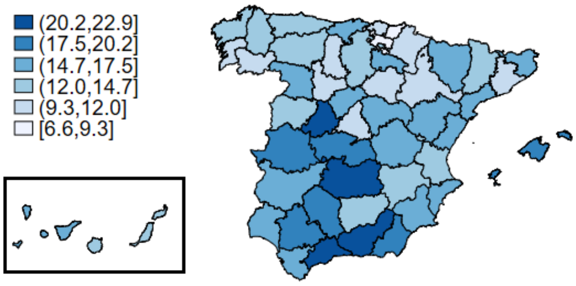


(a) Employment change in the construction sector by province

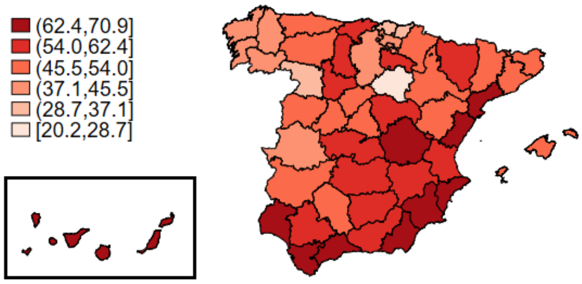
(b) Cumulative employment growth in the construction sector by province

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.
Source: MCVL 2006-2017

Figure A8: Employment evolution of the construction sector by province, 2007-2012



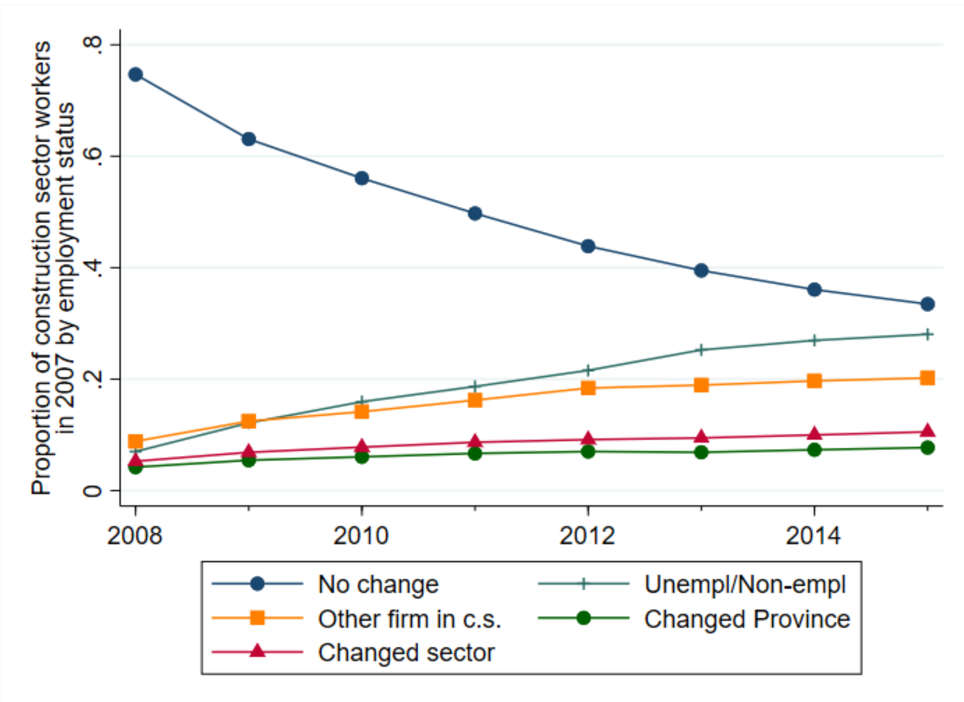
(a) Employment share in the construction sector by province, 2006



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

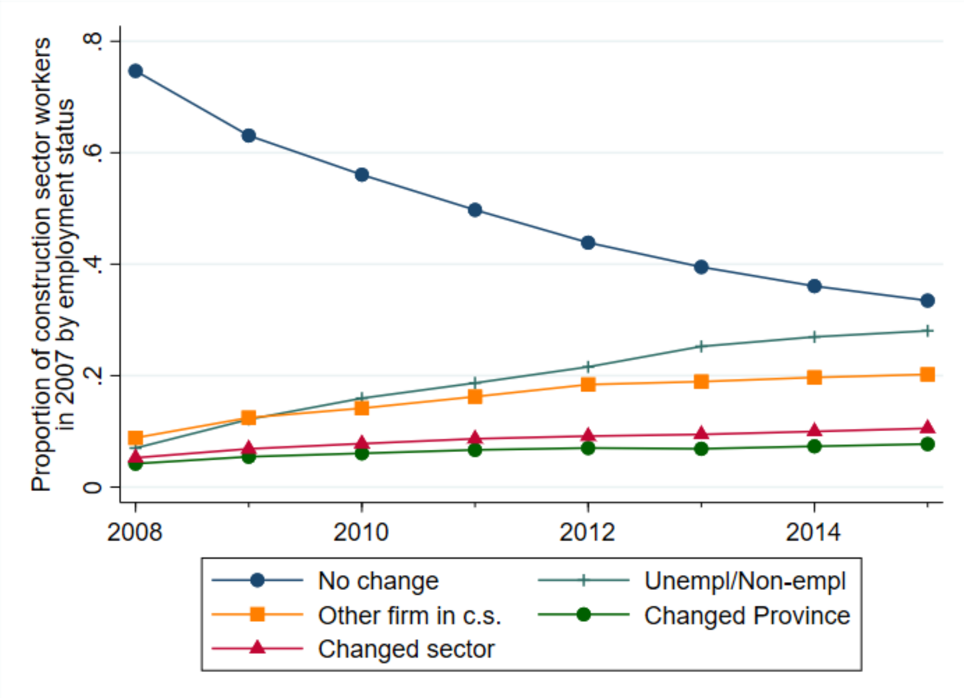
Notes: Panel a) Initial share of workers in the construction sector, shares are based on workers in the complete sample. Panel b) Relative decrease in the share of workers in the construction sector by province between 2007 and 2012. The sample considers 50 Spanish provinces.
Source: MCVL 2006-2017

Figure A9: Working status of individuals employed in the construction sector in 2007



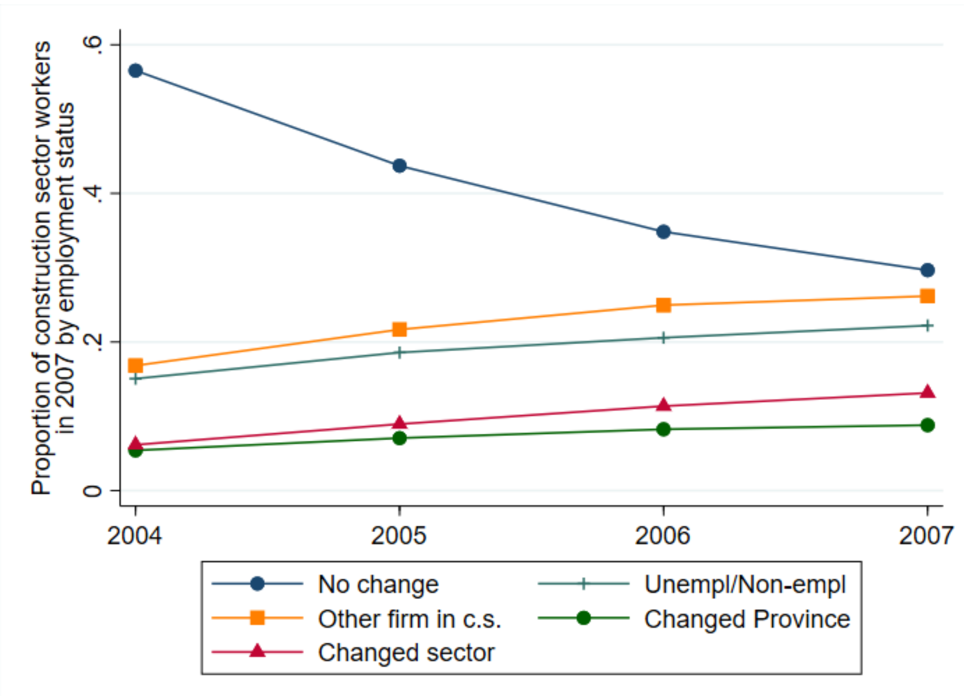
Notes: The shares are computed based on workers in the construction sector in 2007, and every year I tracked their working status up to 2015. Sample includes native and foreign workers
Source: MCVL 2006-2017

Figure A10: Working status of high skilled individuals in 2007

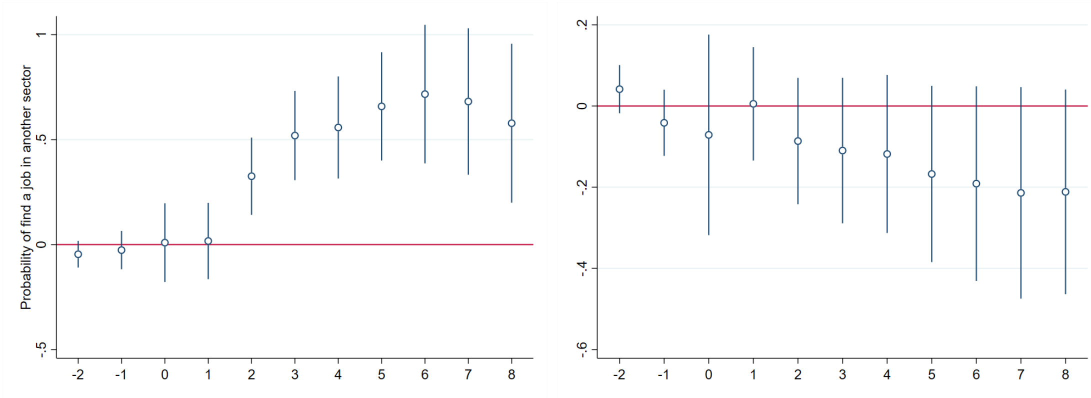


Notes: The shares are computed based on high skilled workers, and every year I tracked their working status up to 2015.
Source: MCVL 2006-2017

Figure A11: 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.
Source: MCVL 2006-2017



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

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

Figure A12: 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 outcome variable an 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

Source: CSWL 2006-2017

B Appendix: Tables

Table A1: 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: Table reports characteristics of new workers in construction sector per year.
Source: MCVL, 2006-2017

Table A2: 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 does not appear more, or those who leave the construction sector and move to another sector

Source: MCVL, 2006-2017

Table A3: 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 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.
Source: CSWL 2006-2017.

Table A4: Impact of the employment contraction in the construction sector on worker's outcomes. By age group.

	(1)	(2)	(3)
	Cumulative wage	Cumulative years	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.

Source: CSWL 2006-2017.

Table A5: 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: 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 of months with non zero earnings. Every regression controls by: gender, age, education, skill group, and foreign status, and interactions between age and educations. 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 Source: MCVL, 2006-2017

C Definitions

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 on each sector weighted by the local employment share. The employment share is computed without the construction sector.

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 education 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 steem 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.

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

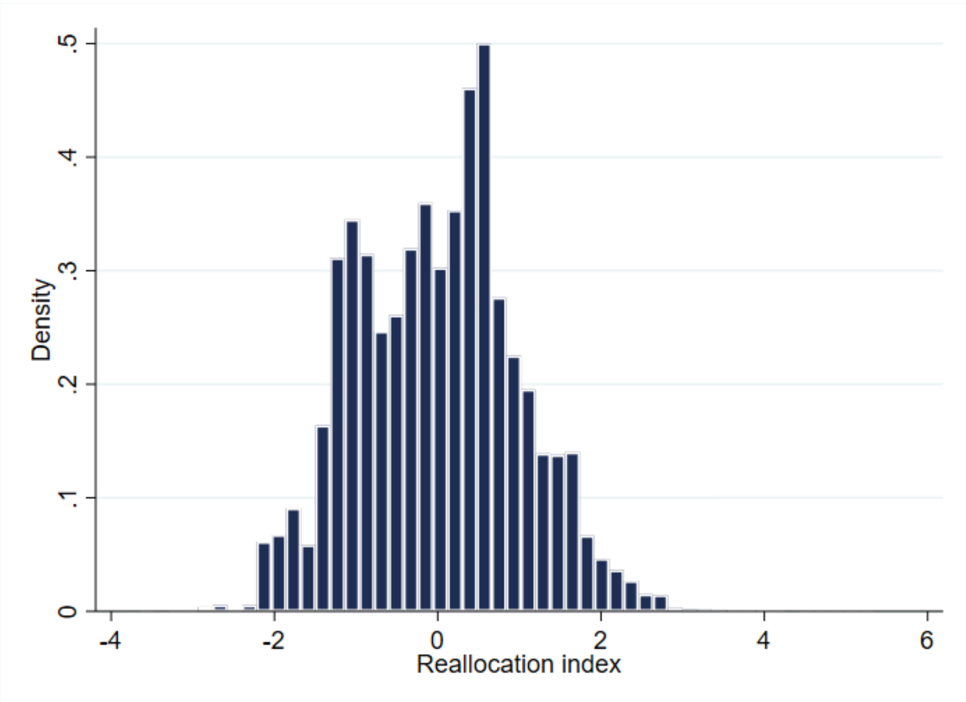


Figure A13: Histogram of the reallocation probabilities
Notes: Reallocation probabilities of workers employed in the construction sector in the year 2007.
Source: CSWL, 2006-2017

C.3 Description of outcomes

Table A6 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 4.6 out of a maximum of 6 years and earned 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.

D Migration

Geographical mobility depends on many factors, including the availability of credit and labour market security, which are 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 labour 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 A14 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 A14 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).

Table A6: 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
Source: MCVL 2006-2017

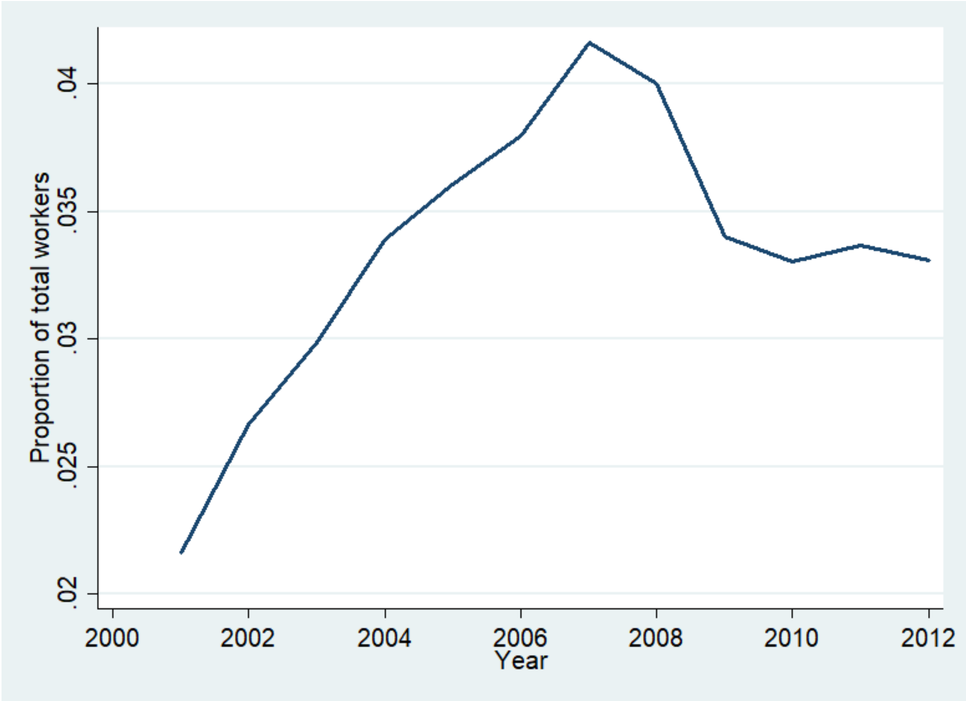


Figure A14: Share of workers change job's province
Notes: Share of individuals working in a different province with respect to the previous year, 2001-2012. The sample of workers between 2000-2012, based on sample of workers in MCVL Source: MCVL, 2006-2017

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

$$\frac{L_{m,t} - L_{m,t-1}}{L_{m,t-1}} = \Big[\frac{I^r_{m,t}}{L_{m,t-1}} - \frac{O^r_{m,t}}{L_{m,t-1}}\Big] + \Big[\frac{I^u_{m,t}}{L_{m,t-1}} - \frac{O^u_{m,t}}{L_{m,t-1}}\Big] \tag{10}$$

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[27].

$I^r_{m,t}$ 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 was in unemployment or non-employment. Finally, $O^u_{m,t}$ shows outflows to unemployment or

[27]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 A7: Decomposition variance of local population growth

	(1) I^r_m	(2) I^u_m	(3) O^r_m	(4) O^u_m
	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. Sample considers the 50 Spanish provinces between 2005 and 2008 in panel A, and after 2008 in panel B. Source: MCVL, 2006-2017

non-employment.

Given equation 10 is an exact decomposition, I can decompose the variance as how much of population growth rate in region m is explained by in-migration rates and how much by out-migration rates (Dustmann et al. 2017; Monras 2018).[28] .

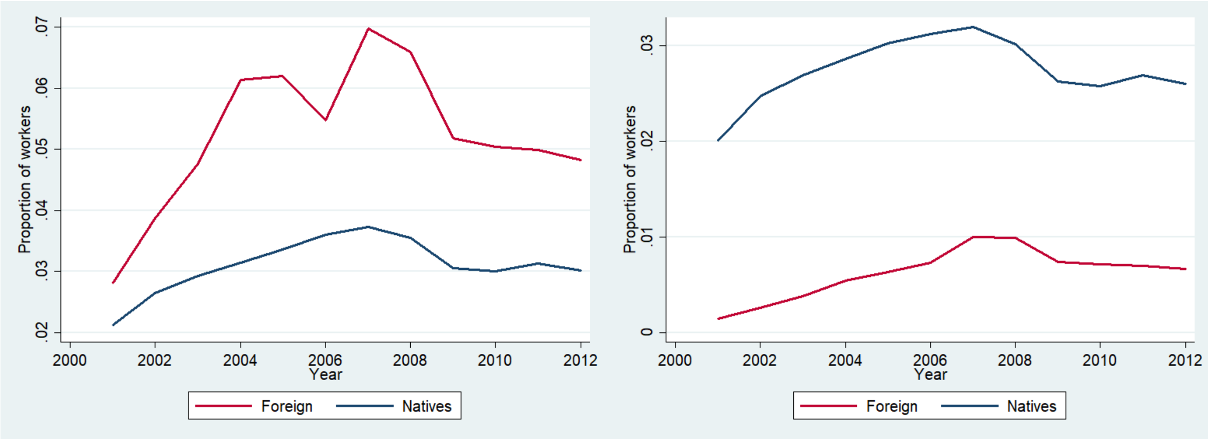
Consider the following regression:

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

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 A7 shows worker flows from and to the non-working condition are relatively more important explaining local population growth. More than 50% of population growth variation is explained from 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.

[28]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



(a) Movers by group

(b) Movers from total

Figure A15: Interregional movements

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

Source: MCVL 2006-2017

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 **??** presents the share of movers as a proportion of all workers, divided by 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 **??** 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).

D.0.1 International migration

The data in CSWL does not allow to track 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

Table A8: 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 worker disappear between 2007 and 2012 controlling by education, age, foreign status, occupational skill group, decrease of local construction sector share and initial share of construction sector. Sample is constrained to individuals in the construction sector in 2007, and is based on a yearly panel with observations from 2005 to 2017 .

Source: MCVL 2006-2017

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 familiar link and wealth accumulation, which could maintain a long time of non-employment. In foreign workers, this force very 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 A8 shows results from the probability a worker is not seen from sometime 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 years before the Great Recession, and also during the recovery period (Figure A17)

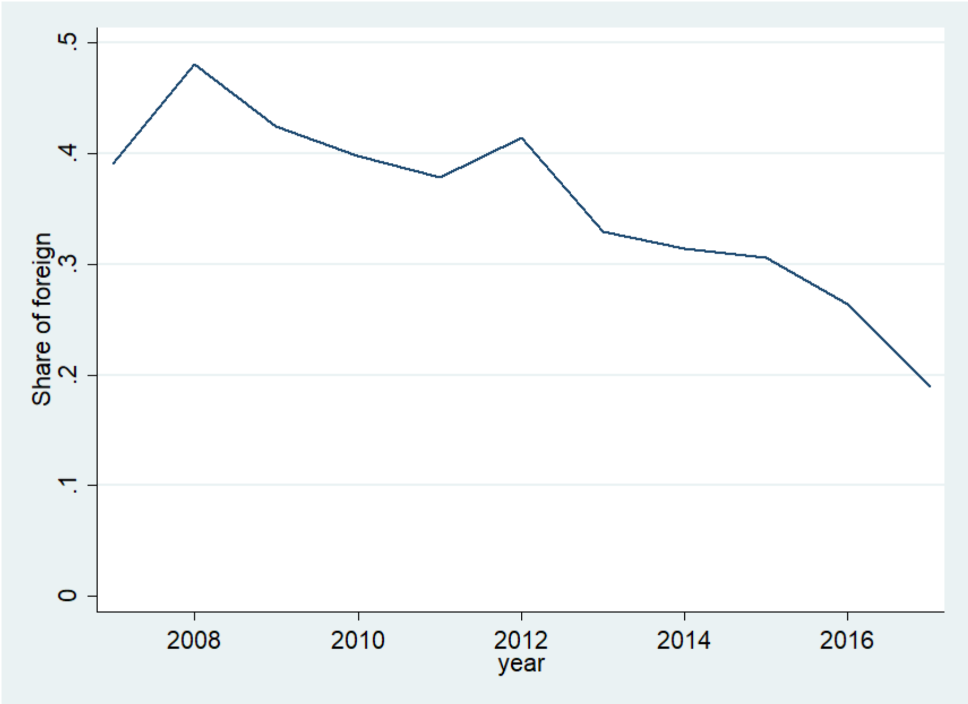
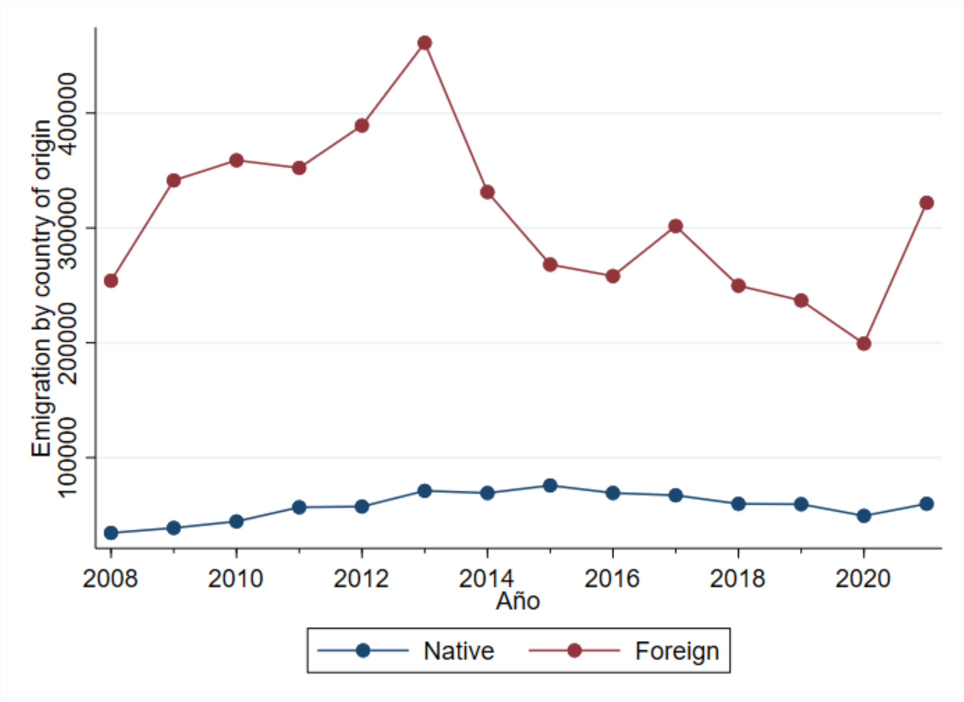


Figure A16: Share of foreign workers leaving the ss records
Notes: Share of foreign workers by year of exit from social security records of workers in the construction sector during 2007. Source: MCVL, 2006-2017

Figure A17: Emigration by country of birth, 2008-2021



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