From bricklayers to waiters: Reallocation in a deep recession *

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Abstract

This paper explores how local sectoral composition influences workers' ability to adapt to a major economic shock, the massive employment burst in Spain's construction sector. For identification, it exploits regional variation in the decline of the construction sector during the Great Recession and longitudinal administrative data. Workers in the most affected provinces by the shock experienced significant income losses, primarily explained by longer unemployment periods rather than wage cuts. The analysis reveals that worker's labor market adjustment is mainly through intersectoral mobility rather than through geographical migration. To further investigate this adjustment, I construct a novel *reallocation index.* This index captures the degree to which workers from the construction sector can reallocate to other sectors. I provide evidence that workers' likelihood of changing sectors depends on having better outside opportunities in other sectors, which varies across provinces and workers' characteristics. Individuals with more evenly distributed characteristics across sectors were less affected by the shock because they were more likely to change sectors. This implies that, on average, workers are less likely to adapt to shocks when a region has a high sectoral concentration.

Keywords: J23, J31, J61

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1 Introduction

In recent years, workers have faced the significant consequences of two major economic crises—the Great Recession and the COVID-19 pandemic—alongside many economic shocks that have reshaped entire occupations and industries. A growing body of literature quantifies the impact of these disruptions on labor markets. Notable examples include the broad effects of the Great Recession (Mian and Sufi, 2014; Yagan, 2019) and more sector-specific shocks, such as the impact of Chinese import competition and industrial robots on the U.S. manufacturing sector (Autor et al., 2013a, 2014; Acemoglu and Restrepo, 2022).

As a result of these shocks, large disparities in workers' outcomes often emerge, contributing to a widening of wage inequality (Autor et al., 2013b; Goos et al., 2014; Burstein et al., 2019). The diverse impacts stem from the complex interaction between demand shocks and heterogeneity among worker groups. While this complexity has been well-recognized, it is necessary a deeper understanding of how worker heterogeneity—–across factors such as skills, occupations, firm characteristics, and local labor market conditions––affects their ability to adapt to such disruptions in order to create effective policies that help to mitigate the adverse effects of these shocks.

Focusing on Spain, I examine a large employment shift: the massive decline in employment in the construction sector. Over a span of less than five years, the sector's share of the economically active population dropped from nearly 13% to less than 5%. The key question is not only the severity of this shock on workers' economic outcomes but also how they were able to mitigate its negative consequences. In my analysis, I exploit the rich interaction between worker characteristics and regional differences in sectoral specialization to capture variations in the match between workers and available jobs across regions. This approach helps uncover the interplay between economic shocks and the varying supply of skills among workers. Specifically, I provide evidence of workers' adjustments following a major economic shock and introduce a novel reallocation index, which measures the alignment between workers' suitability for different jobs and job availability in their local labor market.

My analysis uses longitudinal administrative data that provides comprehensive information on each worker's entire labor market history, along with detailed and precise individual characteristics. I utilize the *Muestra Continua de Vidas Laborales* (MCVL), best translated as "Continuous Sample of Working Lives.", which provides detailed records for 4% of workers affiliated with Spain's Social Security. This comprehensive dataset tracks earnings and contract changes before and after the crisis, enabling the comparison of the shock's impact on workers' pre-recession earnings and employment trajectories.

In the first part of the analysis, I explore how local labor demand changes, induced by the shrinking of the construction sector, affect workers' earnings and employment outcomes. To capture this economic shock, I exploit the variation in the severity of employment declines in the construction sector across Spanish provinces. I measure workers' exposure to this shock by calculating the relative change in the employment share of the construction sector between 2007 and 2012 in their 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. A key piece of evidence supporting this assumption comes from a placebo analysis of employment probabilities and earnings for construction sector workers prior to the Great Recession. The results reveal no systematic relationship between provincial sectoral decline and worker outcomes before the Great Recession.

The second part of the paper examines how differences in shock intensity across provinces, combined with detailed administrative panel data, can shed light on the role of aligning local sectoral compositions with workers' characteristics in mitigating the impacts of job loss. I developed a *reallocation index* that quantifies the likelihood of workers transitioning from the construction sector to other sectors. This index accounts for the imperfect substitutability of workers across sectors by leveraging variations in sectoral composition and worker characteristics. The construction involves two steps. First, I estimate the likelihood of each worker transitioning from the construction sector to other sectors, with probabilities varying based on individual worker characteristics. In the second step, I calculate the reallocation probabilities by adding the weighted average of these predicted transition probabilities, using the province-level employment share of each respective sector as weights.

My results show that individuals initially employed in the construction sector and working in more exposed provinces earned less and remained employed for fewer days between 2007 and 2012 compared to those in less exposed provinces. Conditional on the initial province of residence, the difference in exposure between the 75th and 25th percentiles led to an additional cumulative earnings loss of 20% of their initial annual income over this period. This impact is driven by a decline in employment probabilities rather than wages. Furthermore, the heterogeneity analysis reveals that young workers experienced the most significant declines in employment. Also, my analysis shows that workers primarily attenuated the shock's impact through intersectoral mobility rather than relocating geographically. By 2015, the number of workers transitioning to different sectors was four times greater than those moving to a different province. In contrast, their likelihood of relocating to a new province remained unaffected. Consistent with recent empirical literature, sectoral mobility proved to be far more common than geographical relocation.

Given the limited adjustment through geographical migration, I investigate another key channel of worker reallocation: intersectoral mobility. The analysis reveals a statistically significant relationship between exposure to the shock and the likelihood of transitioning to another sector. A worker with an average value on the *reallocation index* suffered a 40% weaker average impact on cumulative earnings between 2007 and 2012. Moving from the second to the third quartile of the *reallocation index* results in a 33% milder shock to earnings and employment. Sectoral composition plays an important role in explaining the heterogeneous impact of the employment decline on worker outcomes. Because the value of certain skills differs based on the sectoral composition of the local economy, it is important to consider the size and variance of the shock by worker and region.

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

I contribute primarily to two key areas of the literature: research on the impact of job loss on workers' labor market outcomes and how outside options influence reemployment opportunities. Several studies have established that job losses can have long-term effects on workers' earnings and employment trajectories across various contexts, including 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 increased import competition from developing countries (Autor et al. 2014; Dix-Carneiro and Kovak 2017; Dauth et al. 2014). Despite this extensive research, there still needs to be more understanding of why earnings differentials persist and how workers specifically respond to negative shocks.[1]

This paper aims to address the existing gap in the literature by analyzing the significant shock experienced by the Spanish construction sector. I examine the consequences and adjustment strategies of a well-defined cohort of workers who were directly and indirectly affected by this shock, focusing on the dynamics of their adjustment both during and after the recession. Leveraging high-quality administrative data, I examine how varying exposure to the shock influenced workers' long-term prospects, tracking changes in earnings, employment, and job mobility before and after the Great Recession. This ap-

[1]Certain groups, such as college graduates (Wozniak 2010) and foreign workers (Cadena and Kovak 2016), have been observed to respond more actively to adverse conditions by relocating to less affected regions.

proach offers new insights into the heterogeneous effects of the shock, highlighting how worker and regional characteristics shape the dynamics of its impact.

Additionally, I contribute to the expanding literature that estimates the similarity of job requirements across occupations or industries. Previous studies have examined this by analyzing mobility flows among occupations or industries (Shaw 1987; Schubert et al. 2020), skill and task similarities (Macaluso et al. 2017; Gathmann and Schönberg 2010), and similarities in worker composition and qualifications (Caldwell and Danieli, 2024). Contributing to that literature, I constructed a novel reallocation index that captures the most likely transitions by leveraging worker similarities between sectors. At the regional level, this measure helps estimate how changes in the composition of jobs influence employment opportunities.

Identifying the relevant labor market for each worker is essential for evaluating how job composition influences employment opportunities. Schubert et al. (2019) used worker flows to identify local job opportunities, finding that labor market concentration significantly affects wages. Their approach captures asymmetrical transition probabilities through worker flows but assumes stable job transitions between occupations and industries, an assumption that may not hold during recessions. To address this, I capture industry similarity by comparing sectoral workforces, following the approach of Caldwell and Danieli (2024), who developed an index to measure the value of workers' outside options in Germany. I extend this by creating a reallocation index that predicts the most likely transitions, accounting for sector suitability based on local specialization and worker characteristics.

Beaudry et al. (2012) showed that shifts in the availability of high-wage jobs within a region can have substantial wage spillover effects, impacting workers' outside options and influencing their compensation through wage bargaining. Building on this, I suggest that variations in local sectoral composition may also shape workers' adjustment opportunities, affecting wages in the short term and having a lasting impact as workers face challenges in regaining their previous earnings trajectories.

Two papers closely related to this are Macaluso et al. (2017), which explored how the outcomes of laid-off workers vary depending on the similarity of local occupations, and Yi et al. (2024), that used labor market transitions to show that workers in inflexible labor markets—regions where sectors with similar skill requirements are scarce—experience greater impacts from mass layoffs. The latter study developed an index to capture the potential reallocation of workers from a specific sector, emphasizing the importance of skill transferability across sectors. However, both studies focus on regional differences rather than how workers within the same labor market might respond differently to an identical shock. Contributing to this literature, I show that sector composition significantly influenced the likelihood of finding a suitable job match during the Great Recession, considering worker characteristics and other relevant regional factors.

I begin in Section 2 by providing background information on the contraction of employment in the construction sector. Section 3 details the Spanish data used in this article. In Section 4, I introduce the reallocation index. Section 5 presents the results, focusing on the impact of the employment decline in the construction sector at the worker level. Section 6 analyzes workers' adjustment mechanisms and the outcomes related to reallocation probabilities. Finally, Section 7 presents the robustness checks, and Section 8 concludes.

2 Background

According to the Spanish Labor Force Survey, the construction sector employed 2.7 million workers in the first quarter of 2008. Over the next four years, employment in this sector declined by more than 50%, falling to 1.2 million by 2012. Figure 1 illustrates this decline, showing that the construction sector's employment share dropped from 13% to 6% between 2008 and 2012.

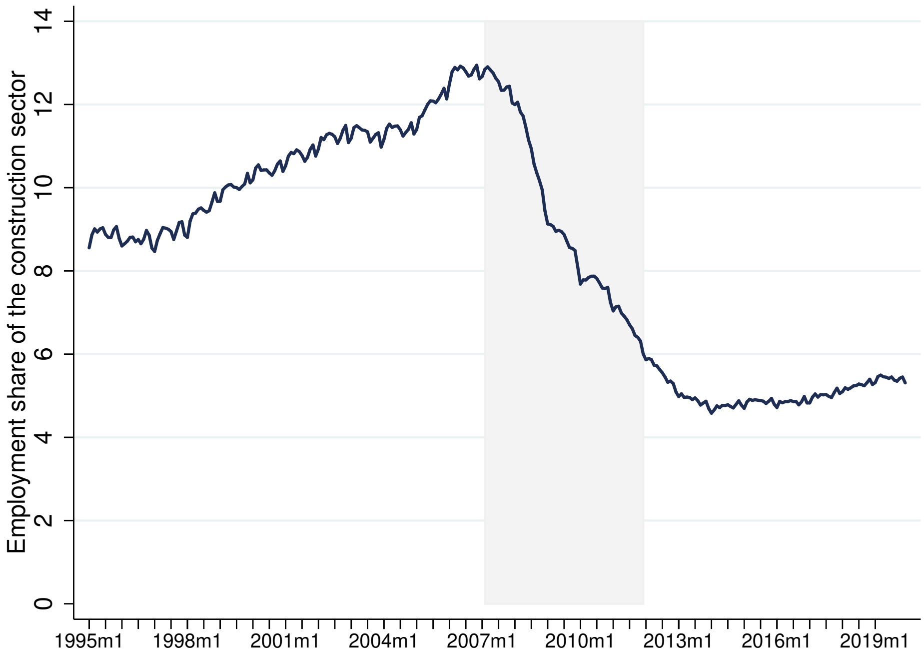
Additionally, this figure indicates that there has been little recovery over the subsequent nine years, with the sector's employment share in 2019 remaining significantly below pre-recession levels. The trajectory of Spain's construction sector, both before and after the Great Recession, contrasts sharply with that of other countries. For instance, Appendix Figure A5 compares Spain's construction employment path with that of the United States, highlighting the employment decline suffered by Spanish workers.

Table A1 provides descriptive statistics for construction workers before and after the Great Recession. In 2007, 64.1% of workers in the sector were employed on fixed-term contracts, but by 2012, this percentage had dropped to 28.6%.[2] As noted by Bentolila et al. (2012), the hiring flexibility offered by fixed-term contracts helped the expansion of the construction sector employment, where temporary contracts align with the cyclical nature of construction activity. However, the sharp employment losses during the Great Recession underline the exposed that are these workers to unemployment risk due to adverse economic conditions.

Additionally, Table A1 shows a decline in the proportion of young, low-skilled, and foreign-born workers employed over the same period. While these demographic groups were among the most affected, concluding that they experienced the largest job losses would be misleading. Although employment within these groups decreased, the overall

[2]Fixed-term contracts in Spain were liberalized in 1984, facilitating the widespread use of sequential temporary contracts.

Figure 1: Employment share of workers in the Spanish construction sector, 1995-2019



Notes: Presents the proportion of workers in Spain's construction sector from January 1995 to December 2019. The data is restricted to monthly observations of workers aged 20-60 employed during the referenced period. The shaded area comprises the years of the Great Recession in Spain, between 2008 and 2014.

workforce composition shifted, driven by both reduced entries and increased exits from the sector from some particular demographic groups. Fewer young workers were entering the sector (as seen in Table A2), and there were significant shifts in the characteristics of those who left (refer to Table A3). Understanding how workers respond to job losses is essential for identifying those most impacted—insights that cannot be captured by analyzing the evolution of employment aggregates. The following sections will explore employment transitions within the sector, highlighting which groups experienced the most significant impacts from the contraction.

2.1 Employment decomposition

Over the past two decades, the construction sector has experienced large employment fluctuations (Figure 1). To identify the underlying causes of these changes, I examine employment trends from 2004 to 2017, focusing on inflows and outflows to the sector. I categorized these changes into transitions between non-employment, unemployment, and shifts to and from other sectors. This approach provides insights into overall employment changes and the patterns of worker movements that contribute to these fluctuations, offering a better understanding of labor market dynamics within the sector, which later will help to understand the adjustment of these workers to the employment decline during the Great Recession.

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

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

where $I_{k,t}$ represents the number of individuals entering the construction sector from status k—whether they are transitioning from unemployment, non-employment, or other sectors at time t. Similarly, the outflow rate from the construction sector at time t is defined as:

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

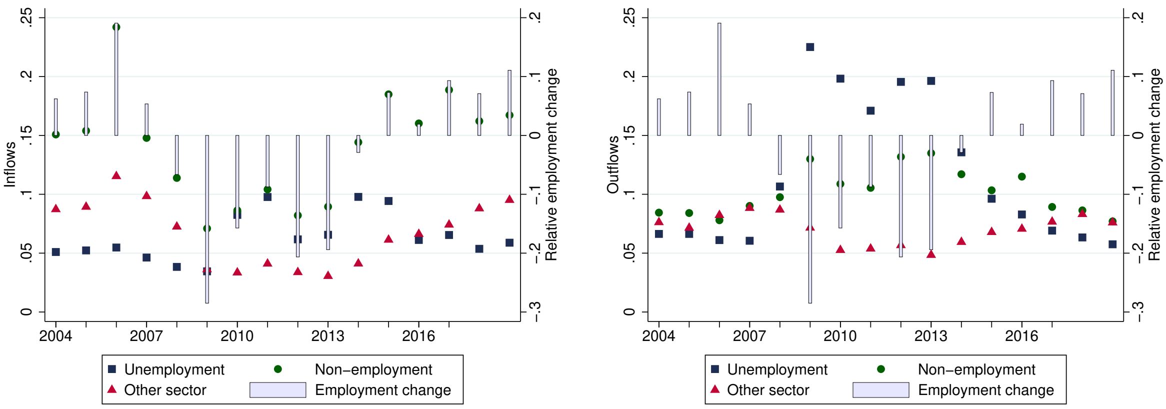
where, $O_{k,t}$ denote the number of individuals leaving the construction sector for status k at time t, where k indicates whether the worker is non-employed, becomes unemployed, or transitions to another sector. In both equations, N_{t-1} represents the total number of workers in the construction sector at time $t-1$. For comparison, I present the yearly employment change in the construction sector. Defined as:

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

The results of this decomposition are illustrated in Figure 2. Panels (a) and (b) display the inflows and outflows, respectively. In both panels, the blue bars represent the relative employment changes in the construction sector.

Panel (a) shows that inflows from unemployment, non-employment, and other sectors followed a similar trend during most years. During this period, inflows from non-employment were the primary drivers of employment growth, especially during the construction boom. Notably, in 2006, the proportion of inflows from non-employment surged from 15% to 22% of the construction sector's workforce, largely due to an increase in the migrant population. This spike can be attributed to the large-scale legalization of foreign-born workers in Spain in 2005 (Moraga et al., 2019), significantly boosting the number of immigrants registered with the Social Security, thereby impacting employment in the construction sector. Table A1 in the appendix shows that the proportion of foreign-born workers rose from 15.7% in 2004 to 27.9% just before the Great Recession. Additionally, during the expansionary period, relatively high wages were offered to low-educated workers, prompting many young individuals to leave education and enter the sector (Lacuesta et al., 2020), further contributing to the large inflows from non-employment before the

Figure 2: Aggregate flows from/to the construction sector



(a) Inflows to the construction sector

(b) Outflows from the construction sector

Notes: Panel (a) presents inflows into the construction sector, representing individuals who, one year before, were employed in another sector, non-employment, or unemployed and then moved into the construction sector, as a proportion of workers in the year $t-1$. Panel (b) depicts outflows from the construction sector, capturing those who were employed in construction one year prior and transitioned to another sector, non-employment, or unemployment in year t, also as a proportion of workers in year $t-1$. The sample is restricted to annual observations between 2003 and 2017 for workers aged 18-60

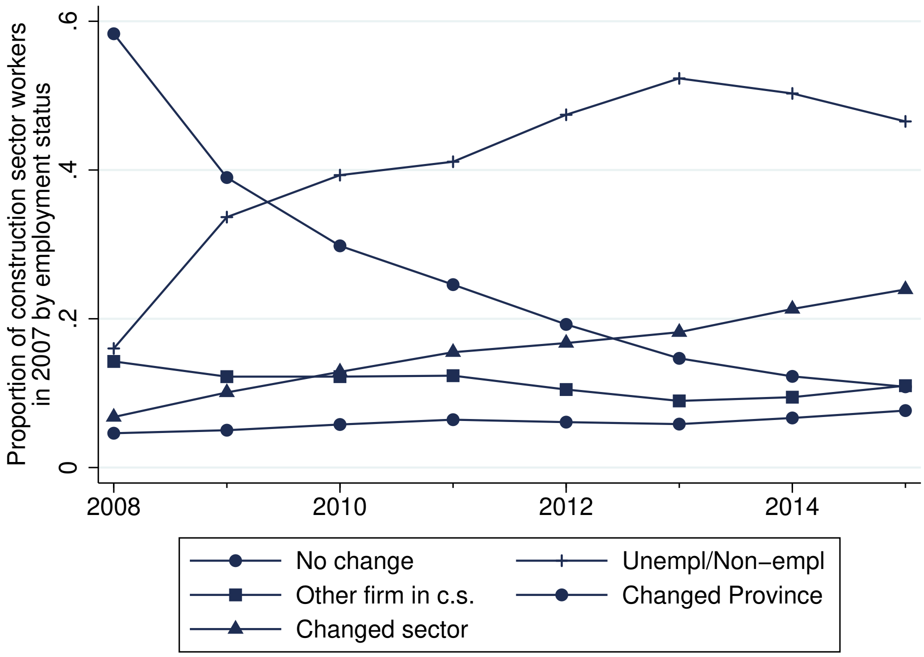
Great Recession.

This analysis serves as an initial step in understanding how workers adjusted to the decline in employment within the construction sector. Figure 2 shows that outflows to other sectors represent only a small percentage of the overall employment decline. However, these aggregate figures mask the individual dynamics behind workers' decisions, complicating the assessment of their adjustment processes. To address this, the next exercise focuses on workers employed in the construction sector in 2007. I tracked their employment status annually, categorizing their transitions into five distinct scenarios: staying with the same firm, moving to a different firm within the same sector and province, relocating to another region, transitioning to a different sector within the same region, or becoming unemployed or non-employed.

The results from this analysis are presented in Figure 3, highlighting three main observations.[3] First, most construction workers lost their jobs during the housing bubble collapse. By 2015, only 10 percent of these workers had retained their 2007 positions, and just 20 percent remained in the construction sector but with another employer. Second, 42 percent of workers in the construction sector in 2007 were no longer employed by 2015. This group includes the unemployed, international migrants, individuals working in the informal sector, and those completely out of the workforce. Finally, the results suggest that moving to another sector becomes more important as overall adjustment increases.

[3] Appendix A6 provides a similar graph for high-skill workers, who were largely unaffected by the shock. Additionally, Appendix A7 shows the same graph for construction sector workers in 2003, offering a comparison of employment status changes before the Recession.

Figure 3: Working status of individuals employed in the construction sector in 2007



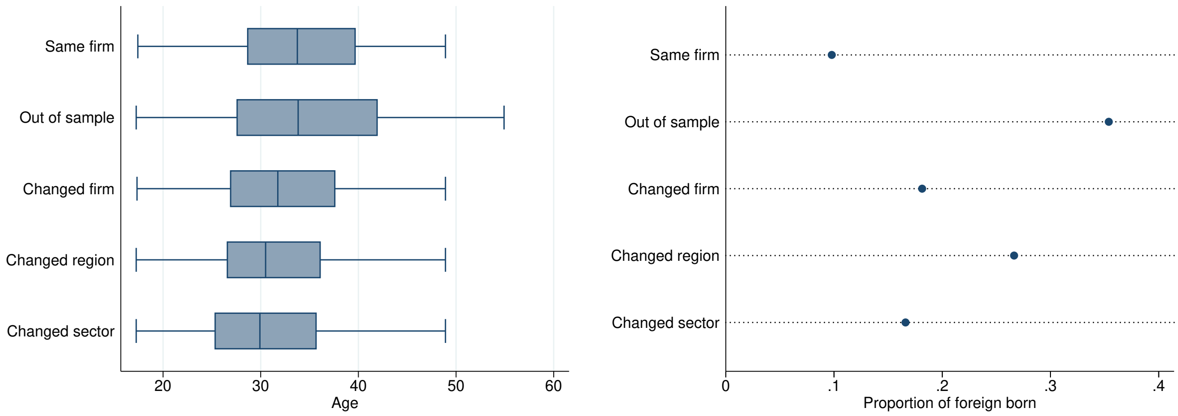
Notes: The shares are computed based on workers in the construction sector in 2007, and every year, I tracked their working status up to 2015. The sample is limited to native workers employed in the construction sector in 2007.

By 2015, approximately 30% of former construction workers had secured employment outside the sector, compared to a smaller proportion who had migrated and are employed in another province. Shortly after the housing bubble burst, a substantial number of workers relocated to different provinces; in 2008, 5.5% of workers resided in a different province than in 2007. However, this percentage showed little change over the next three years, increasing by only three percentage points. In contrast, the proportion of workers who transitioned to different sectors rose significantly, from 9% to 30% of the reference population during the same period.

The decline in employment within the construction sector can be attributed to various factors. However, this analysis does not help to measure long-term earnings or employment losses. It is well-documented that job loss has significant and enduring negative effects on workers' outcomes. Understanding which workers are most vulnerable and how they adjust is crucial for assessing the impact of such negative shocks. Consequently, it is important to determine which types of workers are most likely to occupy different employment statuses following the housing bust.

Figure 4 shows the average age and the proportion of foreign-born workers in the different categories of working status in 2013. As stated 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

Figure 4: Characteristics of workers initially in the construction sector by employment status in 2013



(a) Average age

(b) Share of foreign workers

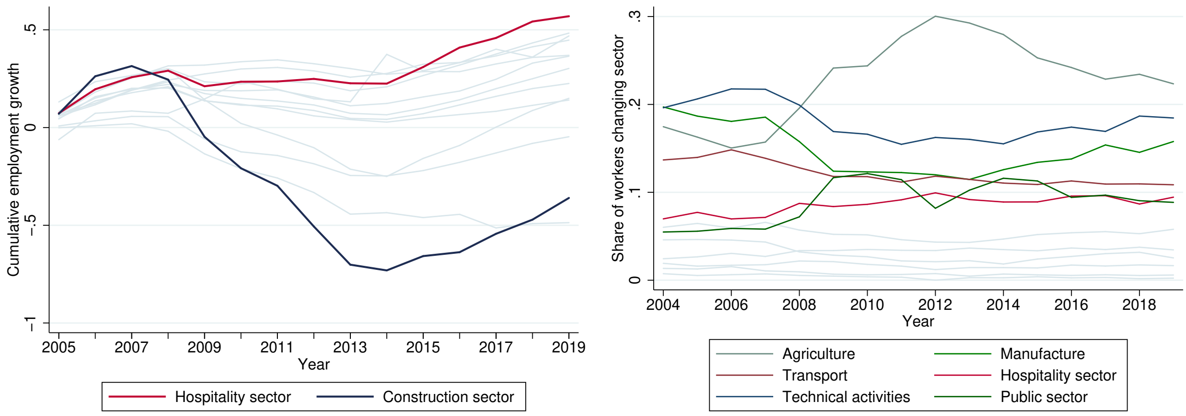
Notes: Panel (a) Average age in 2007 of workers in the construction sector by status in 2013. Panel (b) Share of foreign workers in the construction sector by status in 2012. The sample is restricted to workers in the construction sector in 2007 aged 20-55 years old.

the construction sector or stayed unemployed. Over the past decade, a large fraction of workers have been employed in temporary contracts. The situation is much more prevalent among young workers waiting for permanent positions. Because of this, those workers are more vulnerable to job loss during a recession because they may be dismissed at a much lower cost than similar workers in permanent positions. Still, they also have more flexible human capital due to lower tenure and job-specific experience, which makes them 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) indicates that foreign workers are disproportionately represented among those in non-working conditions and those who changed regions. This aligns with the propensity for foreign workers to migrate more frequently (Cadena and Kovak, 2016). Additionally, the evidence in Appendix D.2 shows that foreign workers in the most affected regions are more likely to be missing from administrative records. Since the Spanish administrative records does not track workers who leave the country, this largely accounts for the higher proportion of unobserved foreign workers during this period, reflecting their in many cases return migration to their home country. The workers who are no longer observed may experience a reduced cumulative earnings as an effect from the shock, not necessarily due to lower wages or reduced working hours, but because they are no longer captured in the data. To mitigate this measurement bias, the remainder of the analysis focuses exclusively on native workers.

Spain's economic expansion triggered significant employment changes, leading to a construction boom and a sharp employment drop during the Great Recession. As previ-

Figure 5: Cumulative employment growth and destination sector of switchers



(a) Cumulative employment growth

(b) Movers by destination sector

Notes: Panel (a) Sector of destination as the proportion of total movers by year from the construction sector, 2004-2019. Panel (b) Cumulative yearly employment growth per sector, 2004-2019.

ously highlighted, many workers shifted to other sectors during this period. The central question remains: where did these workers go, and what factors influenced why not all transitioned to new sectors?

To begin this analysis, Panel (a) of Figure 5 presents the sharp decline in construction employment, measured as cumulative employment growth from 2005 to 2019, alongside the expansion of other sectors—most notably the hospitality sector, represented by the red line. It is important to note, however, that this shift represents a partial reallocation of workers from the contracting construction sector to the expanding hospitality sector, as presented in Panel (b). The impact of the construction downturn was felt across all Spanish provinces. However, each region's sectoral composition and labor market conditions were pivotal in shaping workers' adjustment paths. This topic will be explored in greater detail in the following sections.

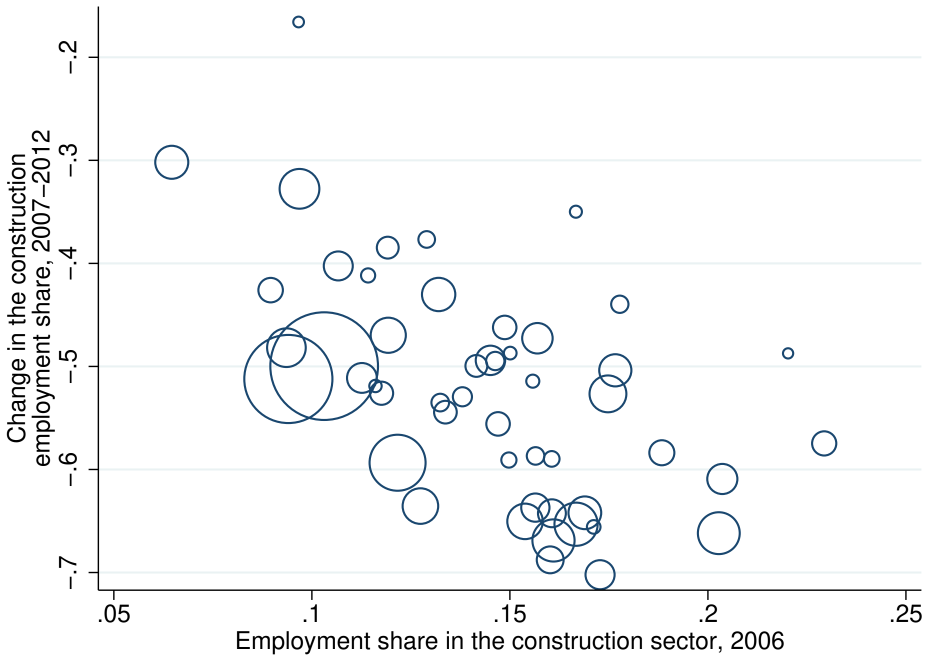
The reallocation of workers into different sectors underscores the importance of individual skills in sectoral reallocation. Adjustments are influenced by the costs or probabilities associated with switching sectors and the relative demand for specific skill sets. The heterogeneity presented in Panel (b) will serve as the basis for developing a reallocation index in the next section.

2.2 Province level impact

The initial employment share and the size of employment contraction in the construction sector during the Great Recession varied significantly across Spanish provinces.[4] My empirical analysis leverages these regional disparities in job opportunities to examine the asymmetric impact of the recession on workers' employment and earnings.

Figure 6 shows that the initial employment share of the construction sector across provinces ranged from 6.8% to 24.14%, with higher shares observed in southern provinces.[5] For example, Gipuzkoa, Araba, and Barcelona had less than 10% construction employment shares, while southern provinces such as Ciudad Real, Huelva, and Malaga had shares exceeding 20%. The figure also illustrates that the contraction in construction employment was not uniform across provinces, with declines ranging from 14.7% to 70.3% relative to 2007 employment levels.

Figure 6: The share of workers in the construction sector by province during the Great Recession.



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

[4]March 2006 is the baseline period because there were no signs of contraction then; the downturn only began to emerge in the fourth quarter of 2007 (see Figure 1).

[5]For easier interpretation, Figure A5 in the appendix presents the same data with the names of each province labeled.

3 Data

The primary data sources are the 2006 to 2021 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 contract conditions.

This rich dataset is built from Spanish administrative data 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 number of observations. Each year, the sample is refreshed by replacing individuals who leave Social Security with new individuals, thus allowing the tracking of the new individuals' complete labor market history.

The MCVL provides detailed earnings information derived from Social Security and tax records. Earnings data from Social Security records are available from 1980 or the beginning of an individual's career for those who entered the workforce later. However, these records are subject to upper and lower limits adjusted yearly based on inflation and labor market conditions. In contrast, tax records offer more comprehensive earnings data and are available only between 2006 and 2021. Despite this limitation, it is a minor issue since my primary analysis focuses on earnings from 2007 to 2013. Therefore, I prioritize using tax record earnings when available. For regions like the Basque Country and Navarre, which manage income taxes independently from the Spanish government, tax records are not available. In these instances, I rely on Social Security earnings data.[6]

Using the MCVL, I build a monthly panel covering 2000 to 2019. This data combines individual, firm, and job characteristics. It includes information on the worker's gender, educational attainment, date of birth, activity sector at the two-digit level, province of the establishment, occupational contribution group, and monthly earnings or unemployment benefits. The raw data has information on each employment spell's entry and exit date, which I use to compute individual 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.

[6] Bonhomme and Hospido (2017) compares earnings from tax and Social Security records, noting that discrepancies primarily affect the top end of the earnings distribution, around the 90th percentile. Since construction workers typically fall below the median of the earnings distribution, both sources of earnings data are deemed comparable.

3.1 Sample restrictions

I restricted my analysis to individuals registered in the general Social Security regime or the special regime for agrarian, seamen, and mining workers. 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 their limited population size.

I created two sub-samples for analysis. The first, the *Complete Sample*, is used to construct all descriptive evidence. This is a monthly panel from January 2000 to December 2019, restricted to active workers aged 18 to 60. The second sub-sample, the *Estimation Sample*, focuses specifically on native workers who were employed in the construction sector before the Great Recession and follows their job history from January 2007 to December 2013.

To estimate and analyze the impact of the shock, I focus on workers with a strong attachment to the construction sector, defined as those who were employed in the sector for at least one year between 2005 and 2006. These individuals are more likely affected by the sector's employment contraction than those with weaker ties. Finally, I calculated cumulative earnings from 2007 to 2012 for the main analysis. To ensure robustness, the sample was restricted to individuals aged 20 to 50 in 2007, minimizing potential bias from early retirements. Additionally, earnings data were adjusted using a price index with 2009 as the base year to account for inflation, ensuring that price fluctuations over the business cycle do not distort the analysis.

4 Reallocation probabilities

I adopt a probabilistic approach to defining the relevant labor market, similar to the method used by Schubert et al. (2020). Job opportunities are determined by workers' matching probabilities to jobs' within each sector and the local employment size of each sector. I assume that workers receive job offers based on how well their characteristics align with the requirements of other sectors' workforces.[7] This alignment is captured by the term:

$$p_{j,i} = \frac{P(X = X_i, J = j)}{P(X = X_i)P(J = j)}. \tag{1}$$

[7]In Section 7, I employ an alternative measure that utilizes transition probabilities conditional on the worker's characteristics.

Equation (1) 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's 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 aggregate the propensities across all sectors, weighting them by each sector's employment share $P(J = j \mid R = r)$. This weighting accounts for the random matching feature of the underlying framework, where the sector's size influences the probability of a worker receiving a job offer conditional to their characteristics X_i. Rearranging the terms, I arrive at the following expression for the reallocation index:

$$\begin{aligned}
Reallocation(X_i, r) &= \sum_j \frac{P(J = j, X = X_i)}{P(X = X_i)P(J = j)} P(J = j|R = r) \\
&= \sum_j \frac{P(J = j, X = X_i)}{P(X = X_i)} \frac{P(J = j|R = r)}{P(J = j)} \\
&= \sum_j P(J = j|X = X_i) \frac{Share_j^r}{Share_j} \qquad (2)
\end{aligned}$$

4.1 Computation of the reallocation index

This section outlines the procedure for estimating the reallocation index, which captures the job options available to each worker during the recession. This index leverages cross-sectional allocations of observably similar workers across sectors before the Great Recession. The baseline assignment captures workers' suitability for positions in each sector based on their observable characteristics, as represented by equation (3). To estimate the probability of employment in each sector, it is necessary to consider both the worker's characteristics and the relative employment size of each sector within each province. Consequently, the estimation process is divided 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, where these characteristics are represented by the vector X_i. The MCVL consists of pairs of matches between workers and employers, allowing me to approximate workers' employment probabilities in each sector. Second, I weigh these probabilities by the sector's employment share in the worker's province of residence before the shock. Given that geographical mobility was limited before the Great Recession, the job distribution in a worker's pre-recession province is a reliable proxy for their local labor market at the moment of the shock.

$$Reallocation(X_i, r) = \sum_{j=1}^{J} \mathbb{P}(J_f = j | X_i) \frac{EmplShare_j^r}{EmplShare_j}. \tag{3}$$

The two-step process is as follows. First, I use actual worker allocations in different sectors from 2000-2004, focusing on the entire population of workers not employed in the construction sector during those years.[8] I regress an indicator variable for the sector of the individual's firm on various worker characteristics, including skill level in the occupation, gender, foreign-born status, and interactions between age categories and educational attainment. I derive the predicted probabilities for the estimated sample from the estimated coefficients. This step captures the likelihood of a plausible match between a worker i and a sector j, and is repeated for each sector.[9]

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 to the employment share of sector j in the entire economy. These weights were measured in 2006 to avoid potential biases from employment changes due to the Great Recession. Finally, to simplify interpretation, the reallocation index is standardized to have zero mean and unitary standard deviation.

Consider a scenario where jobs are randomly allocated across regions. In this situation, the sectoral composition of each region's local economy mirrors that of the aggregate economy. This means that similar workers would face an equivalent set of labor market options, regardless of their province of residence. In such a case, I expect heterogeneity in the shock's impact based on worker characteristics, but not between provinces. However, in reality, worker characteristics do not fully account for the variation in the shock's impact, measured in terms of employment and earnings losses. Workers may be more or less *lucky* depending on how well their characteristics are valued in their region of residence. This variation in local sectoral specialization means that workers might have more or fewer job options that match their observed characteristics. Consequently, even with identical exposure to the shock, similar workers can have vastly different prospects based on their region of residence, underscoring the urgent need to understand and address these disparities.

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

[9]I consider 13 sectors, which are enumerated in Appendix C.

5 Worker level impact: Employment decline in the construction sector

5.1 Static analysis

This section explores the impact of the shock to the construction sector on workers' earnings and employment trajectories. The analysis is based on the estimation sample described in Section 3, which includes native workers with strong attachment to the construction sector before the Great Recession. These highly-attached workers were employed in the sector for at least 12 months between 2005 and 2006. The key assumption is that the local employment contraction in the construction sector is as good as random, conditional on observable characteristics. The estimated impact compares workers with similar characteristics, differing only by their province of residence before the Great Recession.

The baseline specification in this section takes the form:

$$y_i = \theta Shock_i^r + \mathbf{X}_i'\beta + \epsilon_i, \tag{4}$$

where y_i represents the normalized cumulative earnings of individual i. Cumulative earnings are worker's earnings from January 2007 through December 2012, divided by the 2005-2006 average annual earnings. Normalizing by average earnings is equivalent to the approach by Autor et al. (2014) and Yagan (2019), which helps to assess the shock's effect on the earnings evolution and interpret the future results in terms of pre-shock earnings.[10]

$Shock_i^r$ is the change in the employment share in the worker's initial province of residence between 2007 and 2012.[11] X_i represents individual worker and regional characteristics measured at baseline. The full set of controls includes gender, occupational skill level, tenure, experience, an indicator variable for fixed-term and part-time contracts, and interactions between age categories with educational attainment, all these measured at the worker's 2007 values. Additionally, I consider regional controls measured in 2006, including the construction sector's employment share and the unemployment rate in the province of worker residence, a Bartik-type variable that accounts for differential demand shocks in the other sectors,[12] and a Herfindahl-Hirschman Index for the employment concentration in the other sectors, used to capture the overall diversity of the local sectoral

[10] This approach also addresses the undefined log earnings in cases where earnings are zero.

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

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

Table 1: Cumulative earnings impact from the employment decline of the construction sector, 2007-2012

	(1)	(2)	(3)	(4)	(5)
	OLS				IV
	Cumulative earnings, 2007-2012				
Shock	-3.041***	-2.140***	-1.561***	-1.631***	-1.334***
	(0.425)	(0.212)	(0.184)	(0.202)	(0.486)
Constant	4.891***	5.542***	5.612***	5.654***	5.577***
	(0.249)	(0.163)	(0.106)	(0.110)	(0.126)
Observations	47,475	47,475	47,475	47,475	47,475
R^2	.106	.256	.260	.260	.260
Controls	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses are clustered at the province level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 the shock of the change in total workers in the construction sector between 2007 and 2012 a shock. 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.

composition. In the results section, I specify whether different subsets of these controls are included depending on the model specification.

Table 1 present the baseline estimates of equation (4). Column (1) includes the shock variable and a complete set of age dummies and the interaction with the worker's gender and educational attainment to account for variations in life cycle earnings. The results suggest that, on average, workers in the most exposed provinces who were initially employed in the construction sector experienced a stronger drop in cumulative earnings between 2007 and 2012 compared to their counterparts in the least exposed regions. Specifically, cumulative earnings for an average worker in the least affected provinces during the Great Recession decreased by approximately 0.50 (0.16×-3.041) times their initial annual earnings. In contrast, the decrease in the most affected provinces was around 2.13 (0.70×-3.041) times their initial annual earnings. In Column (2), baseline job characteristics such as occupation skill group, contract type, tenure, and experience fixed effects are added. The main coefficient in this regression is reduced by 30 percent compared to the results in Column (1), yet it is still evident the significant impact of the shock on worker's earnings.

Column (3) presents my preferred specification. In this model, I include regional controls and a Bartik-type shock to account for demand shocks in other sectors during the

Great Recession. The Bartik-type variable captures variations in demand across sectors, ensuring that the coefficient for the construction sector shock is not confounded by positive or negative shocks in other sectors during the study period. This approach mitigates concerns about correlated shocks affecting other sectors and provides a more accurate estimate of the impact of the construction sector shock. 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 46.97%. 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) address potential sources of bias that could influence the results. One concern is that changes in the overall population of a province might distort the estimated employment share in the construction sector, leading to measurement bias. To mitigate this issue, I kept the number of workers employed in each province constant between 2007 and 2012. This adjustment ensures that the shock measure reflects changes in the number of workers employed in the construction sector, independent of employment shifts in other sectors.[13]

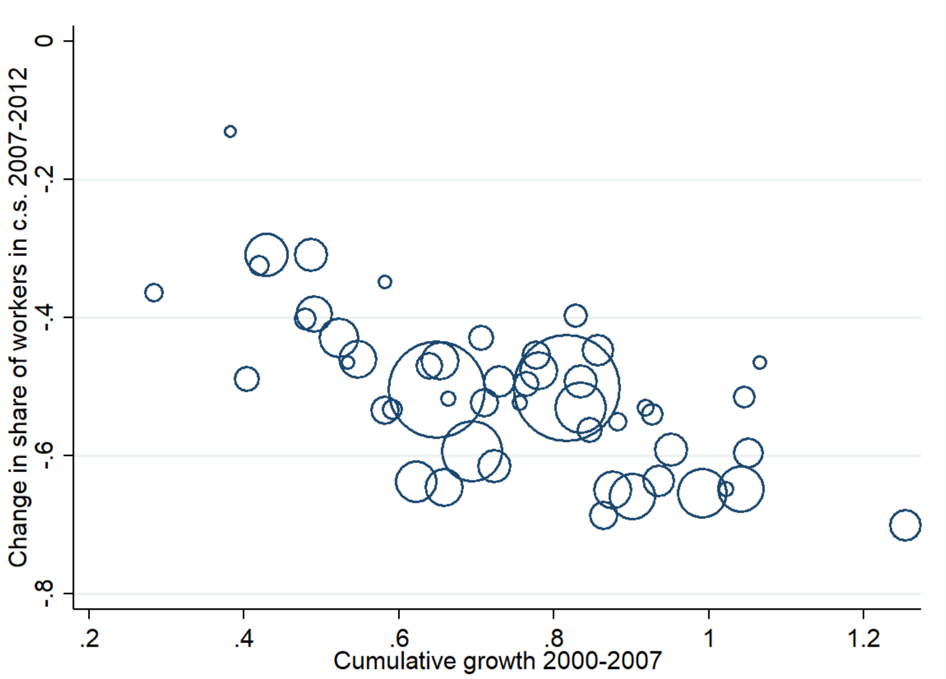
The results of this adjusted measure are presented in Column (4). After this adjustment, the main coefficient is slightly affected, with a 4.3% change in the estimated coefficient. This minor change suggests that while population dynamics may have influenced the original estimates, the overall impact of the construction sector shock remains robust. The adjusted specification ensures that the estimated effect is mainly attributed to changes in construction sector employment rather than broader population or employment shifts.

Supply-side factors are likely to mitigate the impact of the construction sector's employment collapse. When workers either migrate out of the province or leave the formal labor market, the overall decline in job opportunities for those remaining in the construction sector is reduced. This dynamic may distort the estimated effect, and to address this potential bias, I will employ an instrumental variable (IV) approach in the following analysis. In Column (5), I present results that employ an instrumental variable approach to capture the demand-side component of the shock on individual outcomes.

The instrument used in this analysis is based on the cumulative employment growth in the construction sector between 2000 and 2006 in the worker's province of residence. This approach takes advantage of the observation that regions that experienced significant

[13]The adjusted shock is calculated as: $Shock = \frac{Empl.CS_{2012}}{Empl.CS_{2007}} - 1$. 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.

growth during the housing boom are also more likely to face severe downturns. Notably, the cumulative growth in the construction sector before the Great Recession is uncorrelated with earnings during the recession, as demonstrated by the placebo test in Section 7.1, thus satisfying the exclusion restriction. Column (5) shows a 14.5% decrease in the coefficient of interest compared to the estimate from Column (3), indicating a weaker relationship between the demand-side shock and individual outcomes. However, I maintain the results from Column (3) as my preferred estimation since the findings are consistent across both models.

The impact on workers' cumulative earnings may stem from changes in the extensive margin—reflecting a reduction in total years worked—or the intensive margin, indicating a decrease in annual earnings. This distinction is explored in Table 2, where all specifications control for the same variables as those in Column (3) of Table 1. Column (1) presents the impact on normalized cumulative earnings as in Table 1. Column (2) examines the total number of days a worker was formally employed between 2007 and 2012, converting this number into years for easier interpretation. Column (3) analyzes average annual earnings over the same period. To assess the relative magnitude of these effects, Panel (B) conducts similar analyses for a sample of workers who were not employed in the construction sector, allowing for a comparison of how these dynamics differ across sectors and highlighting how much the burst in the construction sector affected worker's employment trajectories.

Table 2: Worker's impact in earnings and employment from the decline in construction employment

	(1) Cumulative earnings	(2) Employment	(3) Average earnings
Panel A: Workers initially employed in the construction sector			
Shock	-1.561***	-1.454***	-0.001
	(0.184)	(0.162)	(0.001)
Constant	5.612***	5.250***	0.088***
	(0.106)	(0.094)	(0.000)
Observations	47,475	47,475	47,475
R^2	.260	.286	.013
Controls	Yes	Yes	Yes
Panel B: Workers initially not employed in the construction sector			
Shock	-0.459***	-0.467***	0.001
	(0.135)	(0.141)	(0.000)
Constant	5.041***	4.762***	0.087***
	(0.072)	(0.083)	(0.000)
Observations	329,145	329,145	329,145
R^2	.279	.301	.017
Controls	Yes	Yes	Yes

Robust standard errors in parentheses are clustered at the province level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 restricted the sample to workers under 50 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.

Column (2) from Panel (A) illustrates that the average worker in the construction sector at the 25th percentile of exposure accumulated 0.17 fewer years of employment than those in a province at the 75th percentile. Meanwhile, Column (2) of Panel (B) indicates that workers outside the construction sector experienced a slight decline in working days between 2007 and 2012 due to the shock. In Column (3), I find no significant difference in average earnings between workers in the construction sector and those in other sectors. This evidence suggests that the impact on workers' earnings trajectories is primarily driven by reduced employment opportunities, highlighting non-employment's significant role in explaining the decline in cumulative earnings.

5.2 Dynamic analysis

The results from the previous section provide an initial look at the impact of the shock on workers' employment and earnings. However, the longitudinal nature of the MCVL dataset allows for a deeper analysis by examining the dynamics of these effects over time. In the following section, I explore how workers' employment and earnings trajectories evolve in response to the shock. Figure 8 illustrates the time series of estimated coefficients from the decline in employment within the construction sector, highlighting its effects on workers' employment status and annual earnings. Each data point in year t represents the coefficients derived from equation (5) within the estimation sample:

$$y_{it} = Shock_i^r \beta_0 + \mathbf{X}_i' \Delta + \epsilon_{it}. \tag{5}$$

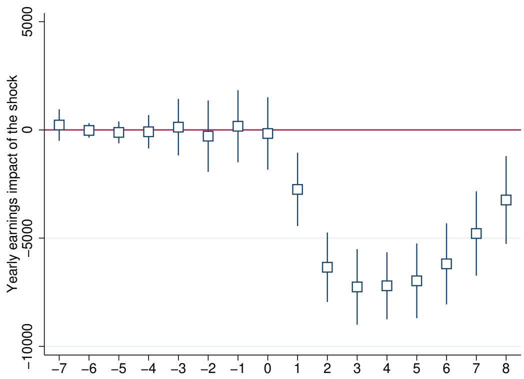
y_{it} represents the labor market outcome for worker i in year t, including the binary employment status and the annual earnings. $Shock_i^r$ denotes the local shock to the individual's i initial province of residence. $\mathbf{X}_i$ is a vector of individuals' observable characteristics measured in 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 used in the baseline regression (Table 1, Column (3)), except that instead of using workers' cumulative earnings over the entire period from 2007 to 2012, each equation now calculates yearly earnings and employment status. Given that this analysis tracks workers over a longer period, I restrict the estimation sample to those aged 29–45 at the baseline, ensuring that the 2000–2015 analysis is confined to individuals within the typical working age range.

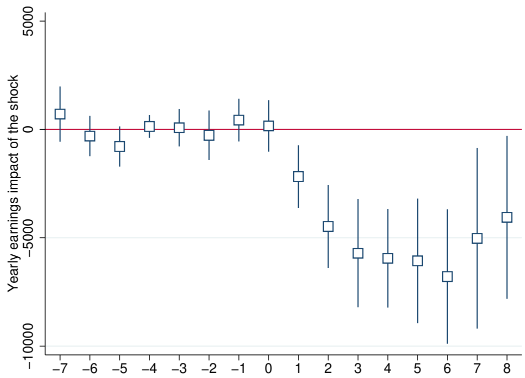
The estimated coefficients are shown in Figure 8. First, the pre-recession estimates support the identifying assumption that the local shock was as good as randomly assigned, conditional on controls. Panel (a) shows how the shock affected the workers' annual earnings. The workers' earnings had a notable negative effect during the Great Recession, consistent with previous findings that workers in more exposed regions accumulated fewer earnings during this period. However, in the years following the recession, earnings in the most affected regions gradually caught up with those in less exposed regions, resulting in weaker differences between them, later almost catching up with the annual earnings of those in the least affected provinces.

The previously documented consequences may stem from workers being unemployed or experiencing lower average earnings during the Great Recession. To disentangle these

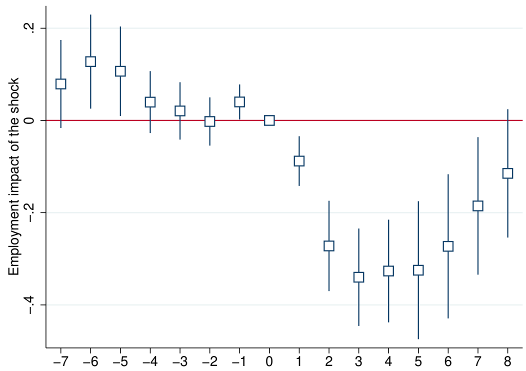
Figure 8: Impact of the contraction in the construction sector employment



(a) Yearly earnings (Full sample)



(b) Yearly earnings (Only employed)



(c) Binary employment status

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

effects, Panels (b) and (c) investigate how the shock impacts employment probabilities and earnings among workers employed each year. Panel (b) examines the effect of the shock on yearly earnings for workers with non-zero earnings, while Panel (c) analyzes its impact on the probability of being employed. Most observed effects can be attributed to decreased employment probabilities during the Great Recession. Specifically, Panel (b) indicates a negative effect on yearly earnings but is less precise than the estimated coefficients in Panel (a). In contrast, Panel (c) reflects a pattern similar to that in Panel (a), revealing a negative impact of the shock on employment probability that diminishes in the later years after the Great Recession and showing that there are no employment differences for workers in the most affected compared to workers in the least affected provinces.

5.3 Heterogeneity of the shock by individual characteristics

As discussed in the previous section, the local employment contraction in the construction sector significantly affected workers' employment and earnings trajectories. In this section, I examine the heterogeneity of these impacts across different individual characteristics. Figure 9 illustrates 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 presents point estimates and 95 percent confidence intervals based on separate regressions for each group of workers. The findings indicate that young, low-tenured, and low-initial earners experienced a larger impact from the shock, suggesting that this shock contributed to increased employment inequality among workers with varying skill levels.

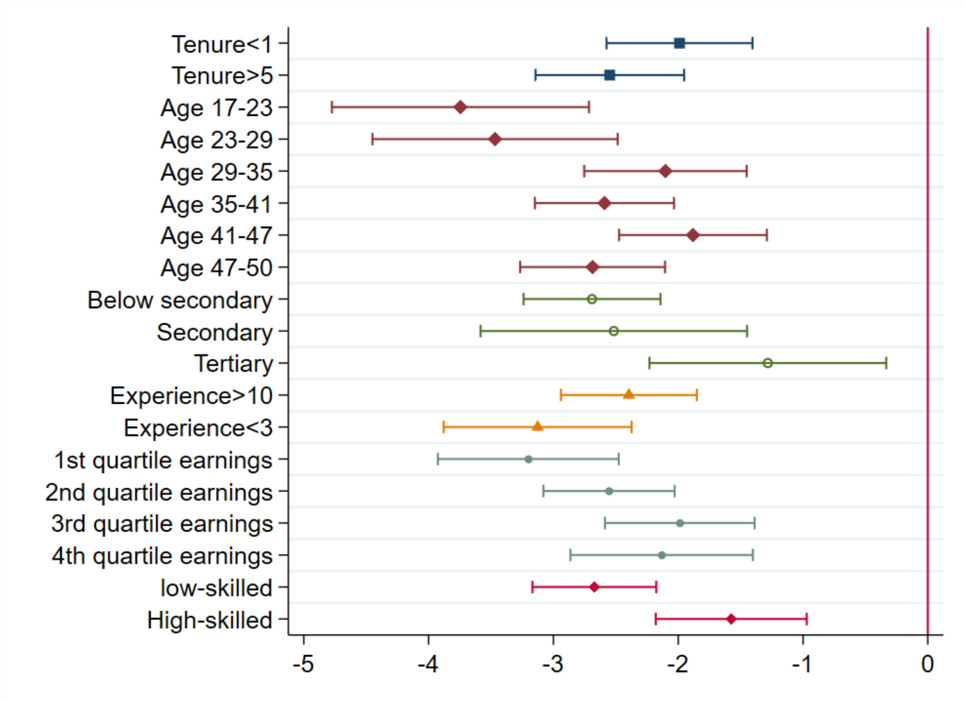
Low initial earners, specifically those in the first two quartiles of the earnings distribution, faced a greater-than-average impact from the economic shock. This finding underscores the potential of economic shocks to exacerbate labor market inequalities. Additionally, there is a significant disparity in the economic consequences for young versus older workers linked to the inequality in employment opportunities across age groups. Most workers in Spain begin their careers with temporary contracts, which may eventually be upgraded to permanent positions. However, this practice creates disparities in job security and exposure to economic shocks between age groups, as younger workers in more unstable jobs are more susceptible to job loss during downturns. Contrary to findings by Yagan (2019) for the U.S., young workers in Spain appear to be less resilient to economic fluctuations.

During the Great Recession, earnings inequality in Spain increased significantly. Bonhomme and Hospido (2017) argues that this increase corresponds with employment cyclicality in the lower middle segment of the wage distribution, highlighting the crucial role of employment trends in the construction sector in this dynamic. As a contribution to this discussion, Figure 9 illustrates that workers initially employed in the construction sector exhibit considerable heterogeneity in their responses to the economic shock. Thus, even within a defined group of workers, economic shocks can exacerbate regional inequalities, as workers across the wage distribution are affected differently.

The following exercise categorizes workers into quartiles based on their earnings in 2007, quantifying the differential exposure to shocks according to their initial position in the earnings distribution. I examine the effects of these shocks on normalized cumulative earnings, employment, and average yearly earnings. The regressions control all worker and regional characteristics used in the previous section.

The results are presented in Table 5. A test of equality among the four coefficients rejects the null hypothesis that they are equal, indicating significant differences based

Figure 9: Heterogeneity of the shock's impact on employment and earnings by characteristics



Notes: The sample is restricted to native workers aged 20-50 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, 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.

on workers' initial earnings. The shock is particularly severe for those with low initial earnings, leading to increased national earnings inequality and a widening of regional disparities. Consequently, workers in the most affected regions experience differential impacts. Notably, there is an 85 percent difference in impact between workers starting in the third quartile of the earnings distribution and those in the fourth quartile.

A milder impact on employment or earnings may account for this difference, as explored in columns (2) and (3). Consistent with the findings from previous sections, a significant portion of the impact is attributed to workers in the most exposed provinces remaining employed for shorter durations during the Great Recession. Consequently, the recession substantially and significantly affects earnings distributions, exacerbating employment inequalities. According to Column (2), high-earning workers experience a lesser impact on their employment than their lower-earning counterparts in the same province.

Table 3: Heterogeneity of the shock's impact on employment and earnings

	(1) Cumulative earnings	(2) Employment	(3) Average earnings
$Q_1^{earnings} \cdot Shock$	-3.446***	-3.332***	-0.006***
	(0.268)	(0.261)	(0.001)
$Q_2^{earnings} \cdot Shock$	-1.886***	-1.724***	-0.002*
	(0.232)	(0.221)	(0.001)
$Q_3^{earnings} \cdot Shock$	-0.934***	-0.812***	-0.0002
	(0.247)	(0.237)	(0.001)
$Q_4^{earnings} \cdot Shock$	-0.140	-0.116	0.002*
	(0.254)	(0.240)	(0.001)
Constant	4.829***	4.510***	0.085***
	(0.170)	(0.170)	(0.000)
Observations	47,475	47,475	47,475
R^2	.341	.366	.027
Controls	Yes	Yes	Yes

Robust standard errors in parentheses are clustered at the province level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

5.4 Geographical vs. sectoral reallocation

Transitions between sectors and geographic locations serve as mechanisms for workers to adapt to negative shocks' impacts. However, evidence regarding the responsiveness of geographical mobility to such shocks is mixed. Worker adjustment across regions appears to be slow and incomplete (Autor et al., 2014; Dix-Carneiro, 2014). This sluggishness is more pronounced among less-educated workers, a subset of workers over-represented in the construction sector. Additionally, workers often have significant sector-specific human capital, hindering their ability to secure employment in other sectors. Consequently, a worker's adjustment is complex, motivating the need to explore both mechanisms further.

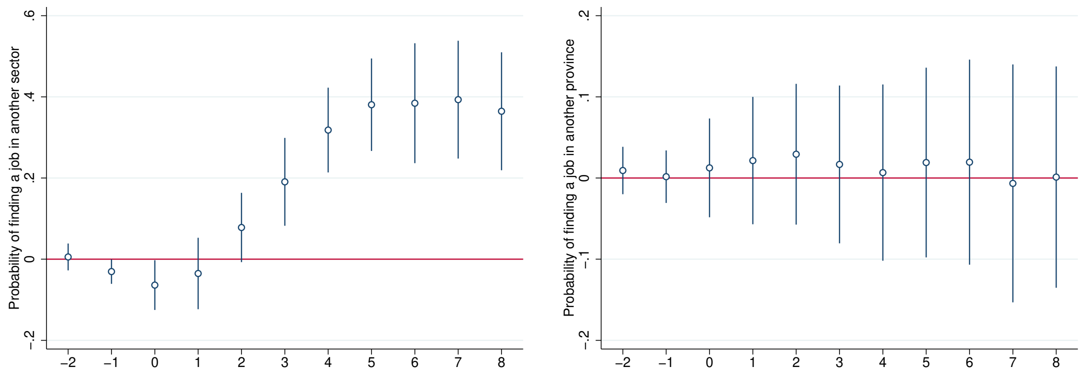
This section analyzes the mobility responses of construction workers to the employment shock resulting from the contraction in construction employment between 2007 and 2012 in their initial province of residence. Figure 10 illustrates how these shocks influence the probability of workers changing provinces or sectors. The results are derived from separate regressions of a binary variable indicating sector and regional changes, conditioned on the shock and a comprehensive set of individual and regional controls. A dynamic approach enables comparisons of coefficients before and during the Great Recession while also testing for the absence of differential pre-trends.

Figure 10 shows that workers in the most affected regions are more likely to change sectors, reflecting a decrease in construction employment opportunities. When comparing magnitudes, a worker at the 75th percentile of shock exposure is 4.03 percentage points more likely to change sectors than a worker at the 25th percentile. Conversely, 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), the spatial correlation of demand shocks attenuates migration responses to negative shocks. Workers consider local shocks and their impacts on alternative locations, which can influence the estimates. An effective strategy is to incorporate shocks from interconnected locations. This concept of regional interconnectedness is also examined by Bertoli and Moraga (2013), who frame it as multilateral resistance to migration, a notion widely utilized in migration literature. Based on this understanding, I developed an adjusted shock measure that includes migration flows between provinces.

The adjusted shock is presented in equation (6). Here, $Shock_m$ denotes the decline in construction employment from 2007 to 2012 in province m, while $\mu_{r \to k}$ represents the probability that a worker from province r migrates to province k, conditional on a change of residence. I construct the adjusted measure in two steps. First, I estimate transition probabilities between provinces using migration data for observed workers from 2001 to

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 the initial share of construction sector employment, Bartik type variable, demographic characteristics, and interactions.

2006. In the second step, I create the shock variable by comparing the local shock to a weighted average shock across provinces, utilizing the previously estimated transition probabilities. When assessing the effect of a shock on a given province, I compare it to the shocks experienced by all other provinces, assigning greater weight to those provinces that are typical migration destinations.

$$Shock_r^{adj} = Shock_r - \sum_{k \neq r} \mu_{r \to k} Shock_k \tag{6}$$

Table 4 presents the effects of employment decline in the construction sector on the likelihood of individuals changing their sector or province of employment. The first three columns focus on the probability that an individual will be employed in a different province in 2012 compared to 2007. The fourth to sixth columns examine the likelihood of an individual transitioning to a sector other than construction by 2012. Notably, Columns (3) and (6) adjust the shock measure to account for shocks in other provinces.

According to Column (1), the employment shock in the construction sector has a negative but statistically insignificant effect on the probability of workers changing provinces. When individual and regional controls are added in Column (2), the relationship between the shock and migration turns positive, though it remains statistically insignificant. Column (3) further refines the analysis by considering the adjusted shock. Even with this adjustment, no significant relationship is found between the decline in the construction sector and interprovincial migration.

Table 4: Geographical vs. sectoral reallocation due to the economic shock

	(1)	(2)	(3)	(4)	(5)	(6)
	Change province			Change sector		
Shock	-0.030	0.005		0.391***	0.405***	
	(0.085)	(0.064)		(0.058)	(0.052)	
AdjustedShock			0.025			0.339***
			(0.091)			(0.078)
Constant	0.276***	0.230***	0.278***	0.293***	0.284***	0.428***
	(0.043)	(0.035)	(0.054)	(0.037)	(0.033)	(0.036)
Observations	33,399	33,399	33,399	33,399	33,399	33,399
R^2	.041	.139	.041	.143	.169	.168
Controls	YesNo	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses are clustered at the province level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The outcome measures the number of individuals employed in a province different from their baseline province in 2007, with the sample further restricted to native workers employed in 2012. 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. Columns (2) and (5) control for average mobility at the province and sector levels, respectively.

Column (4) shows that workers initially employed in the construction sector started transitioning to other sectors in response to declining job opportunities. Column (5), including individual and regional controls, slightly increases the coefficient, indicating that workers with higher exposure to the shock are more likely to transition to a different sector than those with lower exposure. Finally, Column (6) reveals that the adjusted shock has a positive and statistically significant effect on the probability of workers changing sectors.

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

The access to diverse job opportunities and the potential to switch between sectors play a crucial role in a worker's decision to leave an exposed sector. On average, individuals with a broader set of relevant job options can secure better job matches and experience shorter periods of unemployment. As a result, they are likely to face a smaller earnings penalty after a job loss.

The reallocation index reflects the job opportunities available to workers within their labor market, positioning it as an important factor in explaining the variation in earnings penalties observed after a job loss. Traditionally, empirical studies define a local labor market by a geographic boundary.[14] Alternatively, labor markets can be delineated by exploring worker flows within a region (Nimczik, 2020). However, any binary definition that treats local jobs as close substitutes while excluding those outside the region fails to capture the nuances of individual job preferences. Therefore, I adopt a probabilistic definition of the labor market, as suggested by Schubert et al. (2020), which acknowledges that even similar jobs may be valued differently depending on a worker's skills and characteristics.

The next section incorporates the reallocation index into the analysis, exploring how sectoral composition impacts workers' job opportunities and influences their adjustment to a massive negative shock. The reallocation index, which reflects the job options available to workers, is constructed by comparing sectors based on the similarity of their workforce. This approach is consistent with the methodology used by Caldwell and Danieli (2024) and aligns with the framework outlined in Section 4. In the robustness section, I demonstrate that constructing the reallocation index using transition probabilities between sectors, rather than solely relying on workforce similarity, produces comparable results.

6.1 Reallocation index

This subsection builds on equation (4) by introducing the reallocation index as an additional control variable. The probability that a worker with characteristics X_i in region r secures employment in a different sector influences the extent to which the impact of a shock is mitigated. Accordingly, a higher reallocation index will indicate a greater capacity for workers to offset the shock's effects on their earnings trajectories. I test and quantify this hypothesis by examining workers' adjustment as a response to the employment burst of the construction sector.

The results of this analysis are presented in Table 5. Column (1) shows that workers in provinces at the 25th percentile of shock exposure lost 1.19 times their initial average annual earnings (-2.35×0.5081). In comparison, those in provinces at the 75th percentile lost 1.51 times their initial earnings (-2.35×0.6463). This exercise indicates that the impact on annual earnings is nearly 21 percent greater for workers in high-exposure provinces than those in low-exposure provinces.

Additionally, the coefficient in Column (1) shows the effect of the reallocation index

[14] Examples include states Acemoglu and Angrist (2000), metropolitan areas Moretti (2004), and commuting zones Autor et al. (2013a).

Table 5: 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	-1.571***	-1.566***	-1.465***	-1.461***	-0.001	-0.001
	(0.178)	(0.172)	(0.156)	(0.155)	(0.001)	(0.001)
Reall.Index	0.039***	-0.110**	0.029**	-0.091*	0.0001	-0.0005
	(0.013)	(0.052)	(0.013)	(0.049)	(0.0001)	(0.0004)
$Shock \cdot Reall.Index$		0.269***		0.217**		0.001
		(0.098)		(0.089)		(0.0009)
Constant	5.281***	5.298***	4.935***	4.949***	0.087***	0.087***
	(0.108)	(0.104)	(0.099)	(0.097)	(0.0007)	(0.000)
Observations	47,475	47,475	47,475	47,475	47,475	47,475
R^2	.265	.265	.291	.291	.012	.012
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses are clustered at the province level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

on workers' cumulative earnings. To facilitate interpretation, the index was standardized to a mean of zero and a standard deviation of one. As a result, a one standard deviation increase in the reallocation index corresponds to a 6 percent rise in initial annual earnings, accounting for nearly 30 percent of the earnings gap between workers at the 25th and 75th percentiles of exposure. Column (2) incorporates both the shock's impact and the reallocation index, capturing their interaction to evaluate the significant role of sectoral composition in worker adjustment. While the shock affects all workers within the same province, the results reveal a positive and statistically significant effect on cumulative earnings for those with higher reallocation index values. This result suggests that aligning with the regional sectoral composition can enhance the employment prospects of affected workers.

The interaction between the reallocation index and shocks reflects mitigating adverse conditions resulting from a better alignment between workers' characteristics and the local sectoral composition. The analysis reveals that a one standard deviation increase in the reallocation index results in a 17.9% reduction in the shock's impact (0.432/2.420). This suggests that workers are more likely to fare better in the event of a significant shock if they are in a region where their skills and attributes are well-aligned with local job opportunities.

Columns (3) and (4) present the effects of the shock and reallocation index on workers' employment between 2007 and 2012. The evidence suggests that exposure to the shock negatively affects workers' employment probabilities. However, strong prospects in other sectors can help cushion the impact of such significant shocks. In other words, opportunities in alternative sectors can partially counterbalance the decline in employment probabilities within the affected sector.

Column (3) shows that the reallocation probabilities index had a positive and statistically significant impact on employment during the Great Recession. A one-standard-deviation increase in the index is associated with a 4% rise in employment during the reference period. Additionally, Column (4) indicates that workers with higher reallocation indexes were better able to mitigate the shock's impact, with the importance of this mitigation increasing with the shock's magnitude.

Finally, Columns (5) and (6) show that workers in more exposed areas did not experience a substantial decline in their average yearly earnings. The decrease in average earnings between 2007 and 2012 for a worker in a province at the 75th percentile of exposure amounts to 84 real Euros relative to their initial annual earnings in 2009.[15] While this effect is statistically significant, its economic magnitude is relatively small.

[15] Calculated as $0.0857 \times 0.6463 \times 1596$; the average monthly real earnings are 1596 real Euros.

6.1.1 Heterogeneous impact of the reallocation index

As discussed in the previous section, a diverse regional sectoral composition provides workers with different opportunities to mitigate the effects of economic shocks. In this section, I expand on that analysis by examining how the impact of this shock varies across the distribution of the reallocation probability index, as captured by the following specification:

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

The set of controls remains as in the previous specifications, with the addition of dummy variables for each quartile of the reallocation probabilities. The coefficients $\{\beta\}_{k=1}^4$ capture the differential effects of the shock across these quartiles. Consequently, the impact on a worker varies depending on the interaction between their characteristics and region.

The results are presented in Table 6. Columns (1) and (3) show the impact of the shock without including the reallocation index, revealing that the decline in construction employment between 2007 and 2012 had a significant effect on the cumulative earnings and employment of workers initially employed in that sector. Columns (2) and (4) explore how these effects vary based on the mismatch between workers' characteristics and job opportunities in other sectors within the region. As shown in Column (2), workers with a lower reallocation index—indicative of fewer high-quality or suitable jobs in the region —experience a more pronounced negative impact on their earnings trajectories. An equality test for the four coefficients is rejected at the 0.2% confidence level, underscoring the heterogeneity of the shock's effects.

In terms of economic significance, moving a worker from the first to the third quartile of the reallocation probability index reduces the intensity of the shock by 20%. Similarly, shifting a worker from the first to the highest quartile results in a 40% less severe impact. Comparable findings are observed in Column (4), where workers in the lowest quartile experience a 35% stronger shock from the decline in the construction sector compared to those in the highest quartile.

Next, I evaluate whether sectoral composition affects workers' willingness to switch sectors. Workers may relocate to less affected regions or jobs in different sectors to attenuate the consequences of negative economic shocks. In Section 5.4, I provide evidence that workers primarily adjusted through sectoral reallocation. Building on this, I present suggestive evidence that sectoral composition influences the likelihood of sectoral transitions, thereby shaping workers' labor market adjustments.

Table 6: Sectoral composition and the consequences from the contraction of the construction sector

	(1)	(2)	(3)	(4)	(5)	(6)
	Cumulative earnings		Employment		Average earnings	
Shock	-1.582***		-1.474***		-0.002	
	(0.179)		(0.157)		(0.001)	
$Q_1 \cdot Shock$		-2.254***		-2.151***		-0.004**
		(0.294)		(0.275)		(0.002)
$Q_2 \cdot Shock$		-1.389***		-1.192***		-0.001
		(0.321)		(0.288)		(0.001)
$Q_3 \cdot Shock$		-1.347***		-1.264***		-0.0003
		(0.210)		(0.214)		(0.001)
$Q_4 \cdot Shock$		-1.304***		-1.262***		-0.001
		(0.183)		(0.182)		(0.001)
Observations	47,475	47,475	47,475	47,475	47,475	47,475
R^2	.265	.265	.290	.291	.012	.012
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses are clustered at the province level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

Here, I discuss the influence of sectoral concentration on local economic performance, considering two main theories. According to Marshall (1890), agglomeration forces enhance local economic performance by facilitating intra-industry knowledge transfer, reducing transportation costs, and creating more efficient labor markets through the proximity of related industries. On the other hand, Jacobs and Jane (1969) explains that economic diversity drives innovation and prosperity by fostering knowledge exchange across different industries. Building on this discussion, my research provides evidence of how the composition of local economic activities affects workers' labor market adjustments, adding a new dimension by considering not only the immediate outcomes but also how workers cope with economic shocks. Specifically, it examines how a diverse labor market offers a wider range of opportunities for workers facing negative shocks.

In the aftermath of a major economic shock, workers are likely to have more options if the labor market is diverse. While the Herfindahl-Hirschman Index (HHI) is a commonly used measure of sectoral and occupational diversity, it treats all sectors as equally viable from the worker's perspective, regardless of individual characteristics. In contrast, the reallocation index emphasizes sectors that align closely with workers' skills and attributes. This measure more accurately reflects the relevance of local job opportunities to the worker, as it considers the alignment between the worker's characteristics and the available jobs in the local sectors, thereby providing a more nuanced understanding of labor market diversity.

I estimate a probit regression model to analyze the probability that a worker will switch sectors, focusing on the reallocation index as my primary coefficient of interest. To provide a comparative perspective, I also include the Herfindahl-Hirschman Index (HHI) to evaluate the impact of this conventional measure of diversity on sectoral mobility. Subsequently, I contrast the effects of local job opportunity diversity on sectoral transitions by examining both the reallocation index and the HHI, thereby assessing how each measure influences the likelihood of workers changing sectors.

Table 7 presents estimates of the probability that workers in the construction sector transitioned to other sectors between 2007 and 2012. The results reveal a statistically significant positive relationship between the decline in construction employment and the likelihood of workers leaving the sector. In contrast, the Herfindahl-Hirschman Index (HHI) does not show a statistically significant relationship between sectoral mobility and concentration.

Column (2) in Table 7 includes the reallocation index, which, as discussed earlier, measures the alignment between a worker's characteristics and the available job opportunities in other sectors. The results indicate a positive relationship between the probability of sectoral mobility and the reallocation index: workers are more likely to switch sectors in provinces where local job opportunities closely match their skills and attributes.

Column (3) decomposes the reallocation index into quartiles, allowing for a more detailed analysis of the heterogeneity and facilitating the interpretation of the coefficients. An equality test rejects the null hypothesis that the coefficients are equal across quartiles. Comparing the coefficients reveals that the highest quartile has the biggest influence on sectoral mobility. Workers moving 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, showing that they have limited job options in other sectors.

Table 7: Sectoral composition and the probability of change sector

	(1)	(2)	(3)
		Change sector	
Shock	0.391***	0.394***	
	(0.058)	(0.053)	
HHI	0.287	0.457	0.490
	(0.648)	(0.704)	(0.639)
Reall. Prob. $\times$ Shock		0.090***	
		(0.033)	
$Q_1 \times Shock$			0.357***
			(0.085)
$Q_2 \times Shock$			0.220*
			(0.114)
$Q_3 \times Shock$			0.486***
			(0.088)
$Q_4 \times Shock$			0.490***
			(0.083)
Constant	0.293***	0.284***	0.233***
	(0.037)	(0.041)	(0.045)
Observations	33,399	33,399	33,399
R^2	.144	.144	.144
Controls	Yes	Yes	Yes

Robust standard errors in parentheses are clustered at the province level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

6.2 Residualized reallocation probabilities

The previous results raise the concern that specific individual characteristics may be driving the correlation between the reallocation index and its impact on earnings. This implies that the reallocation index might only be reflecting the effect of the worker's attributes on the worker's adjustment. To alleviate this concern, I present the residualized reallocation index. This measure, derived from the residuals of a regression of the reallocation index on the characteristics used to compute it, effectively removes the influence of individual characteristics. By doing so, the residualized index isolates the interaction between individual traits and local conditions. This refined measure is designed to accurately capture the effect of local economic conditions on labor market adjustments, independent of individual attributes, thereby enhancing the validity of the previous results.

Table 8 shows the results of including the residualized reallocation index in the estimating equation. Column (1) presents 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 higher reallocation probability positively affects workers' employment prospects during the Great Recession.

Table 8: Residualized reallocation probabilities

	(1)	(2)	(3)	(4)	(5)	(6)
	Cumulative earnings		Employment		Average earnings	
Shock	-1.571***	-1.568***	-1.465***	-1.463***	-0.001	-0.001
	(0.178)	(0.172)	(0.156)	(0.155)	(0.001)	(0.001)
Resid.Reall	0.038***	-0.085	0.028**	-0.073	0.000	-0.0003
	(0.013)	(0.056)	(0.013)	(0.054)	(0.000)	(0.000)
Shock × *Resid.Reall.*		0.220**		0.181*		0.0008
		(0.103)		(0.0957)		(0.0008)
Constant	5.287***	5.301***	4.939***	4.950***	0.087***	0.087***
	(0.108)	(0.104)	(0.0989)	(0.0964)	(0.001)	(0.001)
Observations	47,475	47,475	47,475	47,475	47,475	47,475
R^2	.265	.265	.291	.291	.012	.012
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

7 Basic robustness

7.1 Falsification of the decline in construction employment

In this section, I explore whether the decline in construction employment during the Great Recession is associated with the labor market outcomes of workers employed in the sector during the housing boom. Specifically, I assess whether the employment contraction from 2007 to 2012 can help predict worker outcomes before the Great Recession. Following

Table 9: 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	0.074	-0.108	0.002
	(0.206)	(0.147)	(0.003)
Constant	4.410***	3.447***	0.106***
	(0.143)	(0.073)	(0.002)
Observations	25,455	25,455	25,455
R^2	.067	.116	.063
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 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

a similar approach to previous sections, I constructed a sample of construction workers in 2003 and estimated their cumulative earnings from 2003 to 2007, which serve as my dependent variable.

Table 9 presents the results of this analysis, incorporating both the regional shock as an independent variable and the same set of individual and regional controls used in Table 1. The table provides evidence neglecting that the shock is related to the pre-recession outcomes. Column (1) shows a positive but statistically insignificant effect of the shock on cumulative earnings, consistent with the insignificant effects observed in Columns (2) and (3). This evidence helps alleviate potential concerns that the shock reflects a regional component that led to worse employment opportunities during the Great Recession. If that were the case, I would expect to see some correlation between workers' outcomes and the same regional variation used in the main analysis, which is not observed.

7.2 Reallocation index from transition probabilities

This section explores an alternative approach for constructing the reallocation index. Instead of relying on workforce similarity, it utilizes sector transition probabilities. By focusing on worker movement between sectors, this method captures the likelihood that a worker from the construction sector would transition to another sector. It is motivated by the work by Schubert et al. (2019) and analyzes the actual mobility patterns of construction workers from 2000 to 2006. While this exercise provides useful insight into alternative methods for capturing likely mobility patterns among similar workers, it has a potential limitation: relying on pre-recession mobility patterns may be less informative during the recession period.

The estimation follows a two-step approach, leveraging data on sectoral worker transitions in the MCVL from 2000 to 2006. The probability that a worker moves from the construction sector to sector s, denoted as $\pi_{cs \to p}$, is defined as follows:

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

The transition probabilities are calculated under the condition that an individual leaves the construction sector and are modeled as a function of worker characteristics, denoted by X_i. The vector X_i includes variables such as occupation skill group, gender, foreign-born status, and interactions between age categories and educational attainment. [16]

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

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

Using a probit model, I estimate the transition probabilities for individuals leaving the construction sector between 2000 and 2006. The analysis is based on monthly data from this period, with the dependent variable indicating the sector in which individual i is employed after exiting the construction sector.[17] From this first step, I derive the predicted probabilities. In the second step, these probabilities are averaged and weighted by the size of each sector within each province as in equation 7.

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

Therefore, the final measure is:

$$\sum_j \widehat{\pi}_{cs \to j} * \frac{EmplShare^r_j}{EmplShare_j}. \tag{7}$$

The main analysis shows that workers initially employed in the construction sector within provinces severely impacted by the Great Recession accumulated lower earnings

[16] To account for potential seasonal variations that might lead to temporary sectoral shifts, the estimation also incorporates month-fixed effects.

[17] For instance, if worker i is in the construction sector in period t and transitions to another sector in $t+1$, this change is reflected in the dependent variable.

Table 10: Reallocation probabilities from transition probabilities

	(1)	(2)	(3)	(4)
	Cumulative earnings		Employment	
Shock	-1.582***		-1.474***	
	(0.179)		(0.157)	
$Q_1 \times Shock$		-1.525***		-1.432***
		(0.185)		(0.163)
$Q_2 \times Shock$		-1.564***		-1.447***
		(0.185)		(0.162)
$Q_3 \times Shock$		-1.577***		-1.457***
		(0.193)		(0.166)
$Q_4 \times Shock$		-1.453***		-1.336***
		(0.209)		(0.182)
Constant	5.421***	5.408***	5.038***	5.033***
	(0.107)	(0.110)	(0.0952)	(0.102)
Observations	47,475	47,475	47,475	47,475
R^2	.265	.265	.290	.291
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 who were 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**.

during the economic downturn than those in less affected regions. This result is consistent with labor market frictions hindering workers from transitioning smoothly to new job opportunities. This paper examines explicitly the frictions that individual workers face when changing sectors. The likelihood of movement is influenced by worker characteristics and the match between those characteristics and the province's sectoral composition. The underlying idea is that a worker's profile must appeal to hiring firms, and the local sectoral composition must provide enough contracting firms within that sector to facilitate the transition.

The previous section exploits the similarity between a moving worker and those in the receiving sector to estimate the likelihood of a worker transitioning to a firm in a particular sector. In contrast, this section focuses on the transitions of similar workers from the construction sector to other sectors during the pre-shock period, as previously outlined.

Table 10 presents results using the transition probabilities to construct the reallocation index. Column (1) shows the shock's impact on cumulative earnings, while Column (2) breaks down this effect by quartiles of the new reallocation index. The results reveal a similar pattern to the results in the previous sections: workers whose characteristics align more closely with the local sectoral composition experience a reduced earnings impact. However, the differences between quartiles are very weak. An equality test across the four coefficients fails to reject the hypothesis that all coefficients are statistically equal. As previously discussed, this is likely because sectoral transitions lose predictive power during the recession due to typical job-to-job mobility patterns disruptions.

7.3 Labor market adjustment and internal migration

As discussed in Section 2.1, the unexpected nature of the shock would typically lead to low levels of internal migration. Despite this, workers from the most affected regions are still likely to migrate to mitigate the adverse effects of the shock on their employment trajectories.

This subsection emphasizes the relevance of sectoral and regional mobility for construction workers. It employs a similar two-step approach to assess how geographical mobility contributes to mitigating the impact of the shock.

As a result, I assess the likelihood that a worker will migrate in response to the shock. To achieve this, I first estimate the conditional probability of a worker with specific characteristics changing provinces, using data from 2002 to 2006. Subsequently, I predict the probability of regional change for workers within 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, 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 shown in Table 11. Column (1) presents the baseline specification from Section 6. In Column (2), the predicted probability of migration is included as a control. Notably, workers with higher migration probabilities experience worse outcomes in the most affected regions. Migration probabilities were standardized to have a mean of zero and a standard deviation of one. An increase of one standard deviation in migration probabilities is associated with a 2 percent decrease of the initial annual earnings on the total 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 through this mechanism. The Great Recession limited workers' geographical mobility, and this section confirms that more adjustment needs to be made through this mechanism. Cumulative earnings and the interaction of the shock do not show a statistically significant relationship.

Table 11: Labor market adjustment: Geographical and sectoral mobility

	(1)	(2)	(3)
	Cumulative earnings		
Shock	-1.571***	-1.605***	-1.604***
	(0.178)	(0.194)	(0.188)
Reall.Index	0.039***	0.039***	-0.112**
	(0.013)	(0.013)	(0.053)
MigrationProb.		-0.020	-0.013
		(0.025)	(0.081)
Reall.Index × *Shock*			0.274***
			(0.099)
MigrationProb. × *Shock*			-0.018
			(0.126)
Constant	5.281***	5.299***	5.320***
	(0.108)	(0.117)	(0.112)
Observations	47,475	47,475	47,475
R^2	.265	.265	.265

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The sample comprises workers aged 20-50 in 2007 who were employed in the construction sector before the crisis. Column (1) imposes no additional restrictions. Column (2) incorporates the probability of migration. Column (3) includes interactions between the shock, the reallocation index, and the probability of migration. All regressions control for gender, age, education, skill group, interactions between age and education, and Bartik-type shock and regional controls.

8 Conclusion

In this paper, I examined the impact of the decline in construction sector employment on Spanish workers from 2007 to 2012. During the Great Recession, Spain experienced one of the most severe economic downturns, with the construction sector being especially hard-hit. The contraction was unevenly distributed across Spanish provinces, leading to significant earnings losses for workers initially employed in the sector and an increase in regional earnings inequality. To quantify the shock's effects on earnings and employment, I employed a regression model that accounts for regional and individual heterogeneity and incorporates the asymmetric decline in construction sector employment across Spanish provinces.

The results indicate that employment losses were most severe in the early years of the Great Recession, with the employment probabilities of workers in the most exposed provinces eventually aligning with those in less affected regions during the subsequent recovery. The sectoral reallocation of workers in highly impacted regions partially explains the mitigation of the initial impact. The findings suggest that workers primarily adjusted through sectoral mobility, with geographical mobility playing a relatively minor role.

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. Specifically, I analyze how differences in sectoral composition impact workers' ability to transition to new roles by addressing two key factors: (i) the suitability of sectors based on worker characteristics and (ii) the availability of job opportunities across regions due to spatial specialization patterns. To capture these dynamics, I construct a *reallocation index* that reflects the likelihood of transitioning from the construction sector to other industries. This index accounts for the imperfect substitutability of workers between sectors by leveraging variations in sectoral composition and worker characteristics across provinces.

Finally, the results remain consistent across various robustness checks. Crucially, falsification tests using pre-Great Recession data and outcomes show no statistically significant relationships, confirming the specificity of the findings to the actual recession period. The relevance of reallocation probabilities in mitigating the impact of the construction sector downturn remains robust, even when employing alternative definitions of reallocation probabilities or using an instrumental variable approach using the sector's cumulative growth during expansionary periods.

References

Acemoglu, D. and J. Angrist (2000): "How large are human-capital externalities? Evidence from compulsory schooling laws," *NBER macroeconomics annual*, 15, 9–59.

Acemoglu, D. and P. Restrepo (2022): "Tasks, automation, and the rise in US wage inequality," *Econometrica*, 90, 1973–2016.

Amior, M. and A. Manning (2018): "The persistence of local joblessness," *American Economic Review*, 108, 1942–70.

Autor, D. H., D. Dorn, and G. H. Hanson (2013a): "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103, 2121–68.

——— (2013b): "The China syndrome: Local labor market effects of import competition in the United States," *American economic review*, 103, 2121–2168.

Autor, D. H., D. Dorn, G. H. Hanson, and J. Song (2014): "Trade adjustment: Worker-level evidence," *The Quarterly Journal of Economics*, 129, 1799–1860.

Bachmann, R., P. Bechara, A. Kramer, and S. Rzepka (2015): "Labour market dynamics and worker heterogeneity during the Great Recession–Evidence from Europe," *IZA Journal of European Labor Studies*, 4, 1–29.

Beaudry, P., D. A. Green, and B. Sand (2012): "Does industrial composition matter for wages? A test of search and bargaining theory," *Econometrica*, 80, 1063–1104.

Bentolila, S., P. Cahuc, J. J. Dolado, and T. Le Barbanchon (2012): "Two-tier labour markets in the great recession: France Versus Spain," *The Economic Journal*, 122, F155–F187.

Bertoli, S. and J. F.-H. Moraga (2013): "Multilateral resistance to migration," *Journal of development economics*, 102, 79–100.

Blanchard, O. J., L. F. Katz, R. E. Hall, and B. Eichengreen (1992): "Regional Evolutions," *Brookings Papers on Economic Activity*, 1992, 1–75.

Bonhomme, S. and L. Hospido (2017): "The cycle of earnings inequality: evidence from Spanish social security data," *The Economic Journal*, 127, 1244–1278.

Borusyak, K., R. Dix-Carneiro, and B. Kovak (2022): "Understanding Migration Responses to Local Shocks," *Available at SSRN 4086847*.

Burstein, A., E. Morales, and J. Vogel (2019): "Changes in between-group inequality: computers, occupations, and international trade," *American Economic Journal: Macroeconomics*, 11, 348–400.

Cadena, B. C. and B. K. Kovak (2016): "Immigrants equilibrate local labor markets: Evidence from the Great Recession," *American Economic Journal: Applied Economics*, 8, 257–90.

Caldwell, S. and O. Danieli (2024): "Outside Options in the Labour Market," *Review of Economic Studies*, rdae006.

Dauth, W., S. Findeisen, and J. Suedekum (2014): "The rise of the East and the Far East: German labor markets and trade integration," *Journal of the European Economic Association*, 12, 1643–1675.

Dix-Carneiro, R. (2014): "Trade liberalization and labor market dynamics," *Econometrica*, 82, 825–885.

Dix-Carneiro, R. and B. K. Kovak (2017): "Trade liberalization and regional dynamics," *American Economic Review*, 107, 2908–46.

Dustmann, C., U. Schönberg, and J. Stuhler (2017): "Labor supply shocks, native wages, and the adjustment of local employment," *The Quarterly Journal of Economics*, 132, 435–483.

Farber, H. S. (2017): "Employment, hours, and earnings consequences of job loss: US evidence from the displaced workers survey," *Journal of Labor Economics*, 35, S235–S272.

Gathmann, C., I. Helm, and U. Schönberg (2020): "Spillover effects of mass layoffs," *Journal of the European Economic Association*, 18, 427–468.

Gathmann, C. and U. Schönberg (2010): "How general is human capital? A task-based approach," *Journal of Labor Economics*, 28, 1–49.

Goos, M., A. Manning, and A. Salomons (2014): "Explaining job polarization: Routine-biased technological change and offshoring," *American economic review*, 104, 2509–2526.

Gulyas, A., K. Pytka, et al. (2019): "Understanding the sources of earnings losses after job displacement: A machine-learning approach," Tech. rep., University of Bonn and University of Mannheim, Germany.

Jacobs, J. and J. Jane (1969): *The Economy of Cities*, A Vintage book, V-584, Random House.

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan (1993): "Earnings losses of displaced workers," *The American economic review*, 685–709.

Lacuesta, A., S. Puente, and E. Villanueva (2020): "The schooling response to a sustained increase in low-skill wages: evidence from Spain 1989–2009," *SERIEs*, 11, 457–499.

Macaluso, C. et al. (2017): "Skill remoteness and post-layoff labor market outcomes," in *2017 Meeting Papers, Society for Economic Dynamics*, vol. 569.

Marshall, A. (1890): "Principles of Economics, 8th edn (1920)," *London, Mcmillan.*

Mian, A. and A. Sufi (2014): "What explains the 2007–2009 drop in employment?" *Econometrica*, 82, 2197–2223.

Molloy, R., C. L. Smith, and A. Wozniak (2011): "Internal migration in the United States," *Journal of Economic perspectives*, 25, 173–96.

Monras, J. (2018): "Economic shocks and internal migration," .

Moraga, J. F.-H., A. Ferrer-i Carbonell, and A. Saiz (2019): "Immigrant locations and native residential preferences: Emerging ghettos or new communities?" *Journal of Urban Economics*, 112, 133–151.

Moretti, E. (2004): "Workers' education, spillovers, and productivity: evidence from plant-level production functions," *American Economic Review*, 94, 656–690.

Nagore García, A. and A. van Soest (2017): "Unemployment exits before and during the crisis," *Labour*, 31, 337–368.

Neal, D. (1995): "Industry-specific human capital: Evidence from displaced workers," *Journal of labor Economics*, 13, 653–677.

Nimczik, J. (2020): "Job mobility networks and data-driven labor markets," Tech. rep., Working Paper.

Schubert, G., A. Stansbury, and B. Taska (2019): "Getting labor markets right: Outside options and occupational mobility," Tech. rep.

——— (2020): "Employer Concentration and Outside Options," .

Shaw, K. L. (1987): "Occupational change, employer change, and the transferability of skills," *Southern Economic Journal*, 702–719.

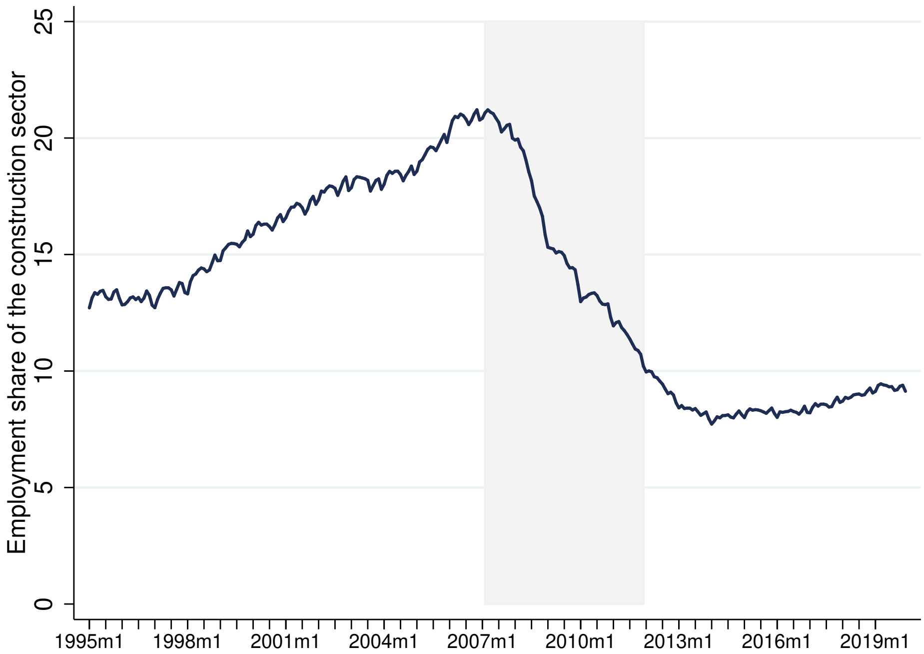
Wozniak, A. (2010): "Are college graduates more responsive to distant labor market opportunities?" *Journal of Human Resources*, 45, 944–970.

Yagan, D. (2019): "Employment hysteresis from the great recession," *Journal of Political Economy*, 127, 2505–2558.

Yi, M., S. Müller, and J. Stegmaier (2024): "Industry mix, local labor markets, and the incidence of trade shocks," *Journal of Labor Economics*, 42, 000–000.

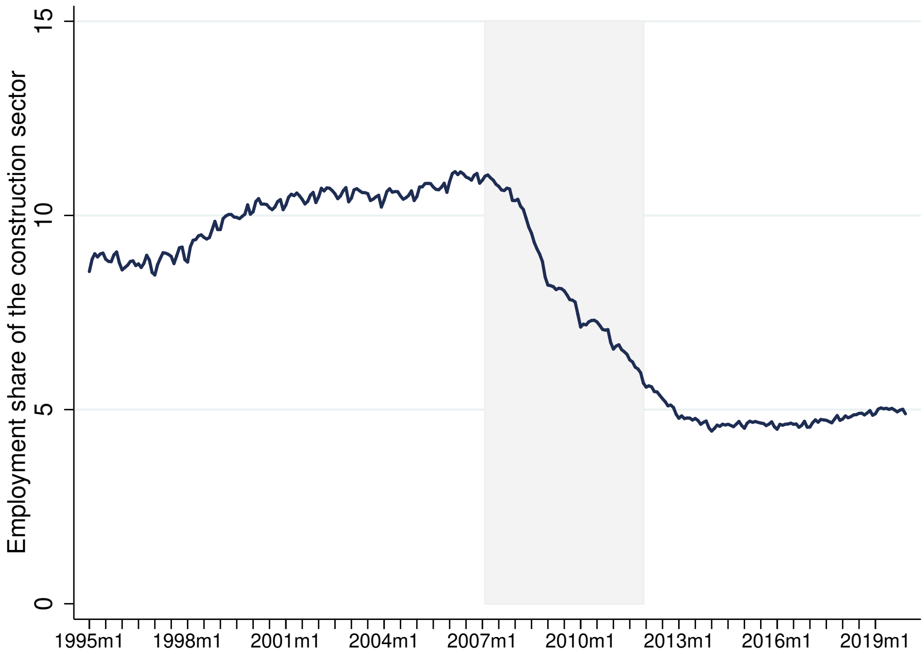
A Appendix: Figures

Figure A1: Employment share of the construction sector, 1995-2019



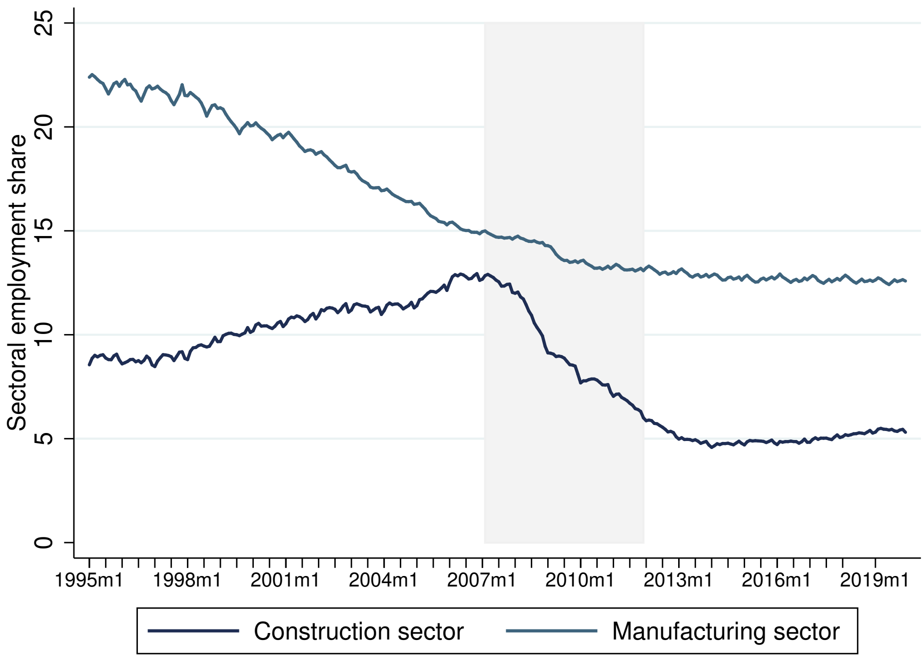
Notes: Presents the proportion of male workers in Spain's construction sector from January 1995 to December 2017. The data is restricted to male workers aged 20-60 and employed during the referenced period employed during the referenced period. The shaded area comprises the years of the Great Recession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

Figure A2: Employment share of the construction sector, 1995-2019



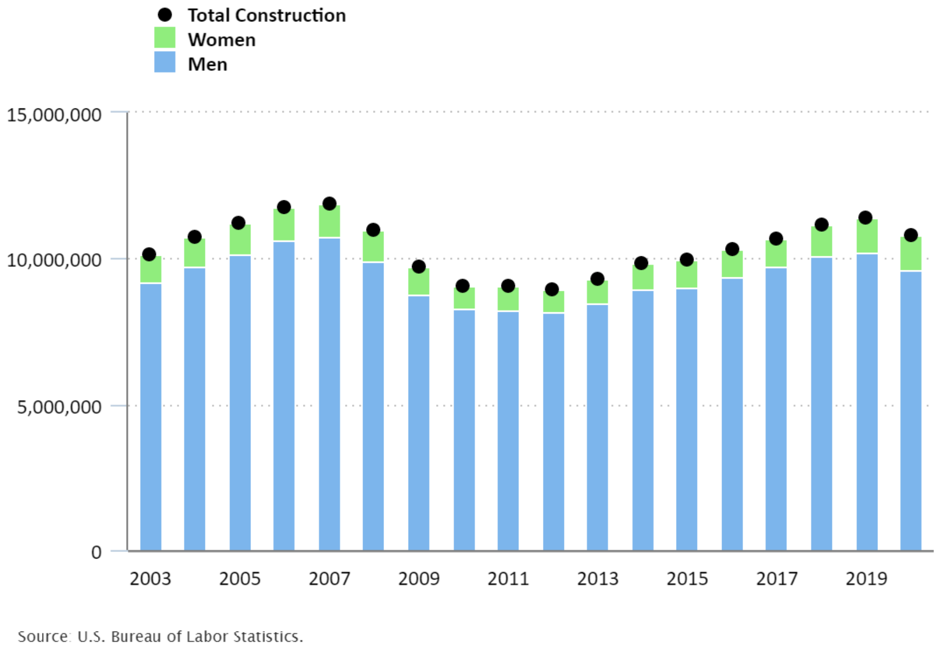
Notes: Presents the proportion of native workers in Spain's construction sector from January 1995 to December 2017. The data is restricted to native workers aged 20-60 and employed during the referenced period employed during the referenced period. The shaded area comprises the years of the Great Recession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

Figure A3: Manufacturing and construction employment shares, 1995-2019



Notes: Employed workers in the construction and manufacturing sector as a percentage of all employed workers, January 1995 to December 2019. Data is restricted to workers employed during the referenced period. The shaded area comprises the years of the Great Recession in Spain, between 2008 and 2014.

Figure A4: 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

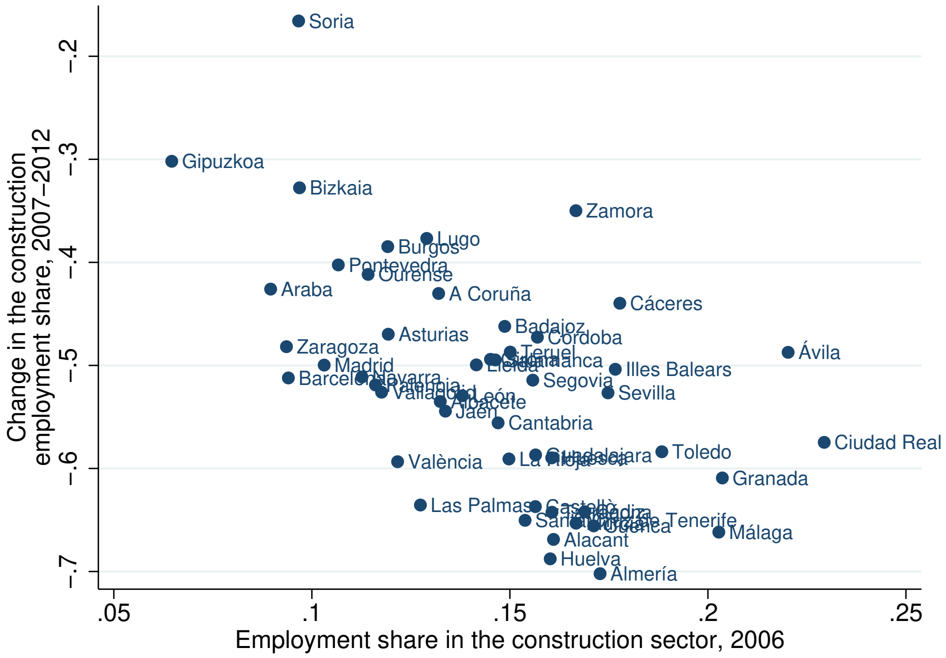
B Appendix: Tables

Table A1: Descriptive statistics of workers in the construction sector

	2004	2007	2012	2017
Age				
<24	0.151	0.123	0.039	0.026
24-35	0.450	0.445	0.360	0.231
35-45	0.242	0.268	0.369	0.412
45<	0.157	0.165	0.232	0.330
Average age	34.02	34.73	38.24	40.93
Education				
Below secondary	0.758	0.746	0.656	0.671
Secondary	0.156	0.161	0.199	0.189
Tertiary	0.086	0.092	0.146	0.141
Type of contract				
Part-time	0.037	0.035	0.074	0.088
Fixed-term	0.724	0.659	0.472	0.508
Foreign born	0.163	0.275	0.182	0.184
Occupations				
Very-high skilled	0.019	0.021	0.046	0.040
High skilled	0.044	0.047	0.079	0.070
Medium-high skilled	0.054	0.056	0.086	0.074
Medium-low skilled	0.590	0.608	0.636	0.647
Low skilled	0.292	0.267	0.153	0.168

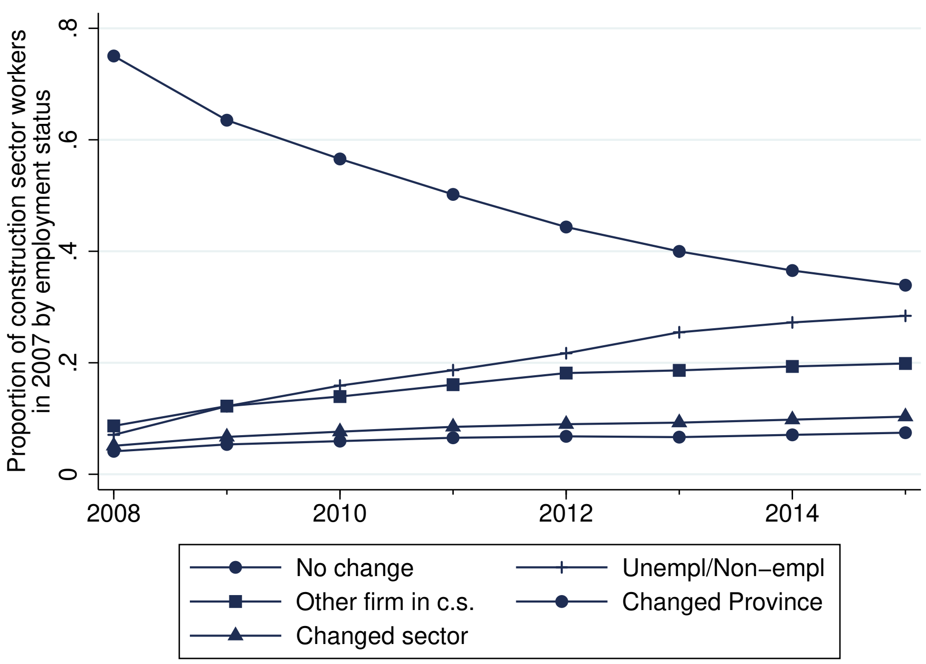
Notes: The table above presents the key characteristics of workers in the construction sector for the years 2004, 2007, 2012, and 2017

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



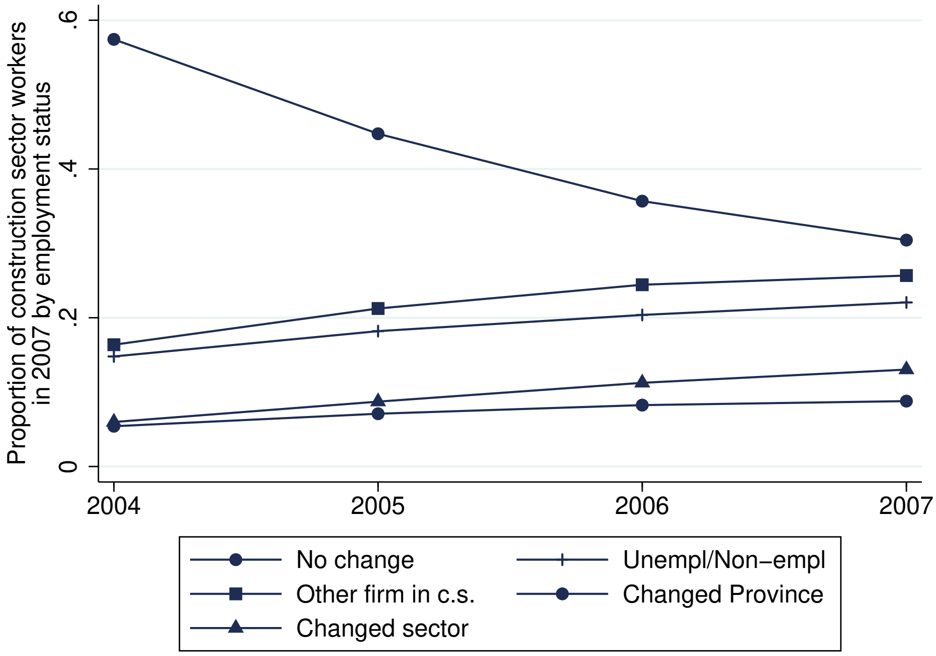
Notes: Change in the employment share of the construction sector by province between 2007 and 2012 against construction employment share in 2006. The sample considers the 50 Spanish provinces.

Figure A6: Working status of highly skilled individuals in 2007



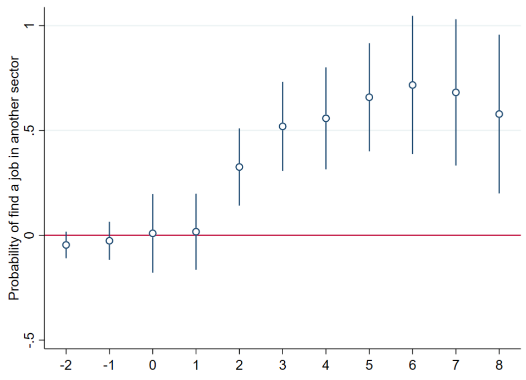
Notes: The shares are computed based on highly skilled workers, and every year, I tracked their working status up to 2015.

Figure A7: Working status of workers in the construction sector in 2003

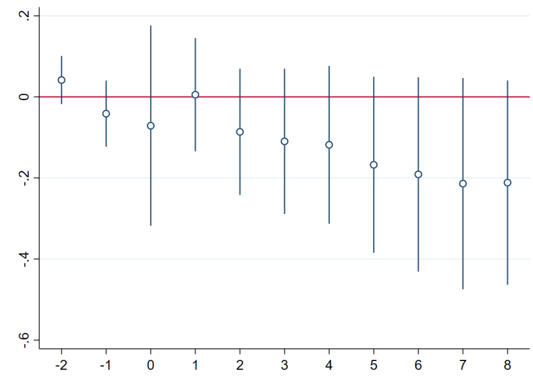


Notes: The shares are computed based on native workers employed in the construction sector in 2003, and every year I tracked their working status up to 2007.

Figure A8: Impact of contraction of the construction sector employment. Weighted shock



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



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

Notes: Sample restricted to workers aged 29-42 working in the construction sector in 2007. Coefficients of the shock were used as an outcome variable and an indicator of 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 residence in 2007. Additional controls by initial share of construction sector employment, Bartik type variable, demographic characteristics, and interactions

Table A2: Descriptive evidence of new workers in construction sector

	2004	2007	2012	2017
Age				
<24	0.383	0.335	0.251	0.291
24-35	0.393	0.401	0.355	0.395
35-45	0.153	0.179	0.246	0.185
45<	0.071	0.084	0.149	0.128
Average age	28.74	29.77	32.95	31.22
Education				
Below secondary	0.682	0.685	0.623	0.631
Secondary	0.190	0.190	0.212	0.211
Tertiary	0.128	0.124	0.165	0.158
Type of contract				
Part-time	0.099	0.092	0.226	0.195
Fixed-term	0.883	0.842	0.848	0.817
Foreign born	0.300	0.427	0.234	0.271
Occupations				
Very-high skilled	0.016	0.019	0.028	0.024
High skilled	0.030	0.030	0.033	0.042
Medium-high skilled	0.042	0.045	0.060	0.055
Medium-low skilled	0.398	0.437	0.440	0.446
Low skilled	0.514	0.468	0.439	0.433

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

Table A3: Descriptive evidence of leavers from the construction sector

	2004	2007	2012	2017
Age				
<24	0.269	0.255	0.158	0.187
24-35	0.429	0.406	0.393	0.330
35-45	0.194	0.218	0.284	0.269
45<	0.108	0.121	0.165	0.213
Average age	31.17	31.87	34.48	35.12
Education				
Below secondary	0.592	0.598	0.600	0.590
Secondary	0.196	0.191	0.188	0.203
Tertiary	0.212	0.211	0.212	0.208
Type of contract				
Part-time	0.217	0.218	0.282	0.317
Fixed-term	0.845	0.813	0.799	0.821
Foreign born	0.148	0.237	0.203	0.200
Occupations				
Very-high skilled	0.021	0.021	0.030	0.026
High skilled	0.043	0.043	0.057	0.055
Medium-high skilled	0.113	0.117	0.128	0.129
Medium-low skilled	0.456	0.474	0.448	0.445
Low skilled	0.368	0.345	0.337	0.345

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

Table A4: Impact of the employment contraction in the construction sector on worker's outcomes. By foreign born status.

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

Standard errors in parentheses

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

Notes: In each regression, I control for gender, occupation skill level, education, age, and foreign-born status. I restricted workers under 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 are the accumulated days worked from 2007 to 2012 and converted into years. Average yearly wage is the average yearly wage from 2007 to 2012.

Table A5: Impact of the employment contraction in the construction sector on worker's outcomes. By age group.

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

Standard errors in parentheses

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

Notes: In each regression, I control for gender, occupation skill level, education, age, and foreign-born status. I restrict workers under 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 are the accumulated days worked from 2007 to 2012 and converted into years. Average yearly wage is the average yearly wage from 2007 to 2012.

Table A6: Impact of the employment contraction on workers wage and employment trajectories

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

Standard errors in parentheses

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

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

C Definitions

C.1 Bartik

Workers may experience variation in employment opportunities as the construction sector in their initial province of residence declines and as employment fluctuations occur in the other sectors. To account for such fluctuations, I construct a Bartik-type shock.

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

Employment growth in each sector is weighted by the local employment share, which 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:

$$y_i^s = X_i\beta + \varepsilon_i$$

The estimation is based on the following sectors:

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

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

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

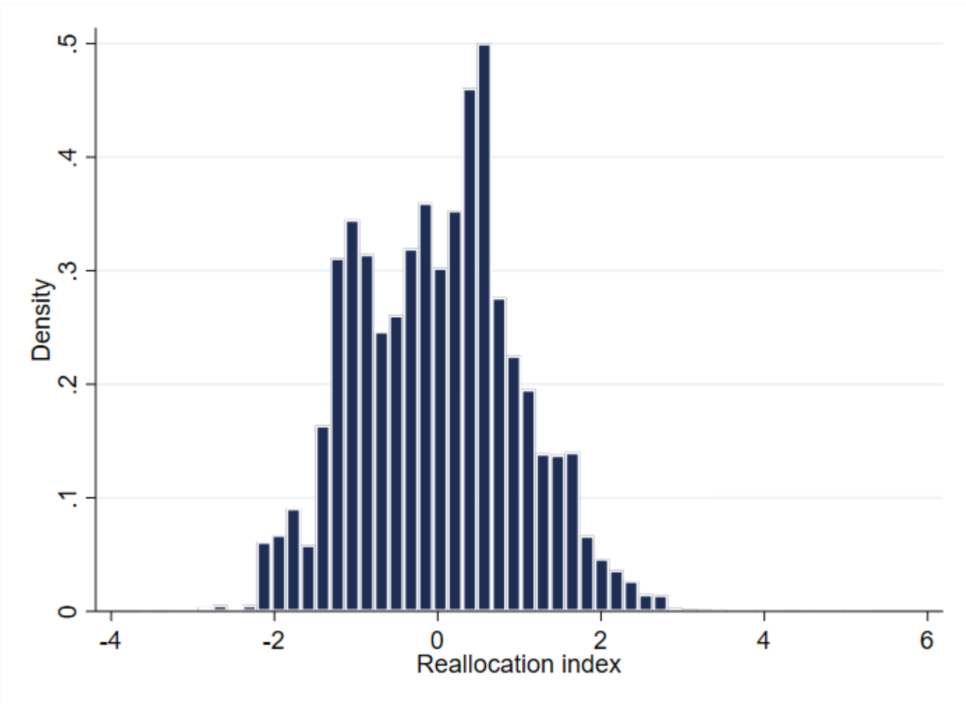


Figure A9: Histogram of the reallocation probabilities

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

C.3 Description of outcomes

Table A7 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 and 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.

Table A7: 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

D Migration

D.1 Internal migration

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

Figure A10 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) shows 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 time. However, Figure A10 shows a decrease during the Great Recession in movers' share. This claim is in line with recent evidence. After a negative shock, exposed regions experience a decrease in inflows and not necessarily a strong response on outflows, Dustmann et al. (2017), Molloy et al. (2011).

However, this aggregate description of worker flows hides compositional changes. For instance, on the type of migrants before and after the crisis. So, to study this further, the following results change the scope of regional movements. 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:

$$\frac{L_{m,t} - L_{m,t-1}}{L_{m,t-1}} = \Big[\frac{I^r_{m,t}}{L_{m,t-1}} - \frac{O^r_{m,t}}{L_{m,t-1}}\Big] + \Big[\frac{I^u_{m,t}}{L_{m,t-1}} - \frac{O^u_{m,t}}{L_{m,t-1}}\Big] \tag{8}$$

The sub-index m is applied for the region, and t for the 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[18].

[18]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

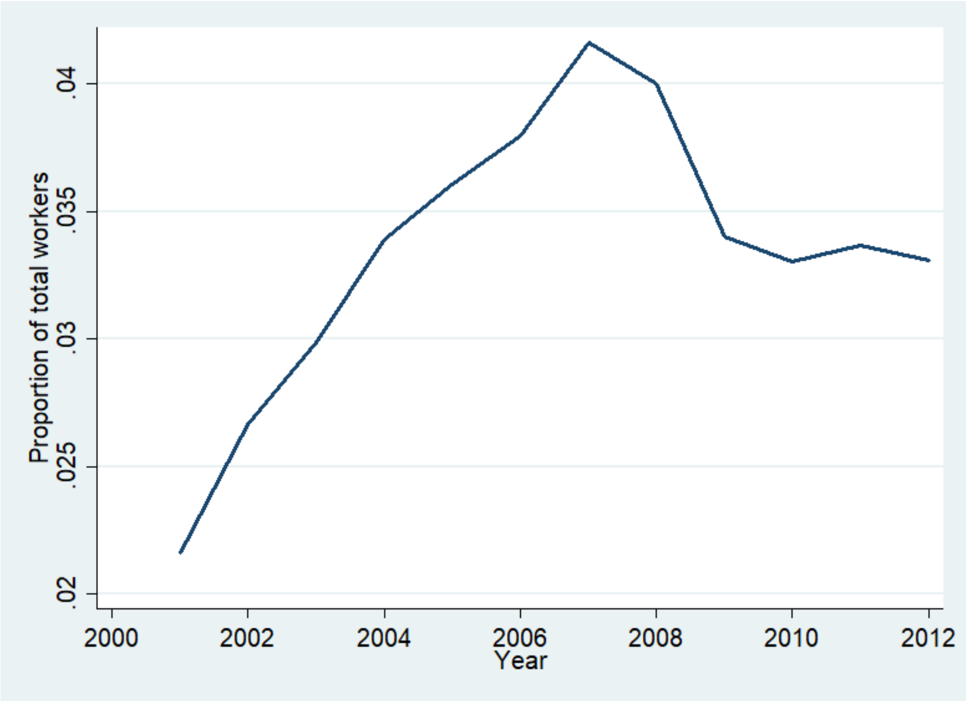


Figure A10: Share of workers change job's province
Notes: Share of individuals working in a different province concerning the previous year, 2001-2012. The sample of workers between 2000-2012, based on a sample of workers in MCVL

$I^r_{m,t}$ 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. Conversely, $I^u_{m,t}$ accounts for the number of workers that come to region m and previously were unemployed or non-employment. Finally, $O^u_{m,t}$ shows outflows to unemployment or non-employment.

Given equation 8 is an exact decomposition, I can decompose the variance as how much of the population growth rate in region m is explained by in-migration rates and how much by out-migration rates (Dustmann et al. 2017; Monras 2018).[19]

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 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 A8 shows worker flows from and to the non-working condition are relatively

[19]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 covariance properties $\beta_1 + \beta_2 = 1$, we can interpret β_1 and β_2 as a variance decomposition of A

Table A8: 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

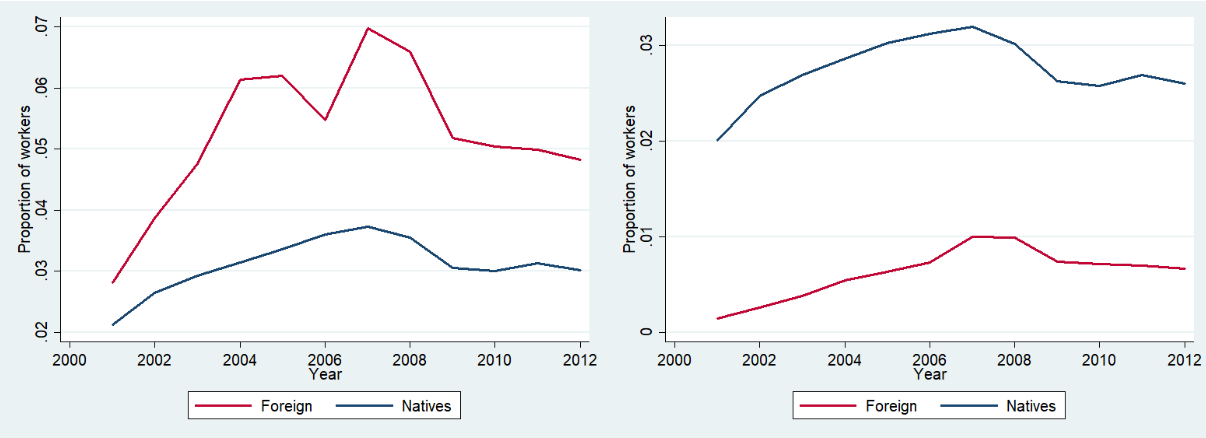
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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

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

The common idea is that foreign workers are more predisposed to migrate. This includes a more significant propensity to international and interregional migration. I will start by analyzing the proportion of foreign workers in the interregional flows. Figure **??** 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 likelier to change location. Considering the population of foreign workers each year, the proportion of workers who changed location 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).



(a) Movers by group (b) Movers from total

Figure A11: Interregional movements

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

D.2 International migration

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

Given this constraint, I could, at most, analyze the probability that a worker will be unemployed for a considerable amount of time. In the case of foreign workers, this would suggest that they return to their home country.

In native workers, there is a strong familial link and wealth accumulation, which could maintain a long non-employment time. This force is likely less critical in foreign workers 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 A9 shows results from the probability a worker is not seen from some time into the future. As assumed in the previous discussion, them being a foreign worker implies a higher probability of disappearing 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 was higher than in years before the Great Recession and also during the recovery period (Figure A13)

Table A9: 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 disappeared from my sample between 2007 and 2012 conditional on worker characteristics. The probability is computed from a linear probability model on a dummy that takes value one if workers disappear between 2007 and 2012, controlled by education, age, foreign status, occupational skill group, a decrease of local construction sector share, and initial share of the construction sector. The sample was constrained to individuals in the construction sector in 2007 and was based on a yearly panel with observations from 2005 to 2017.

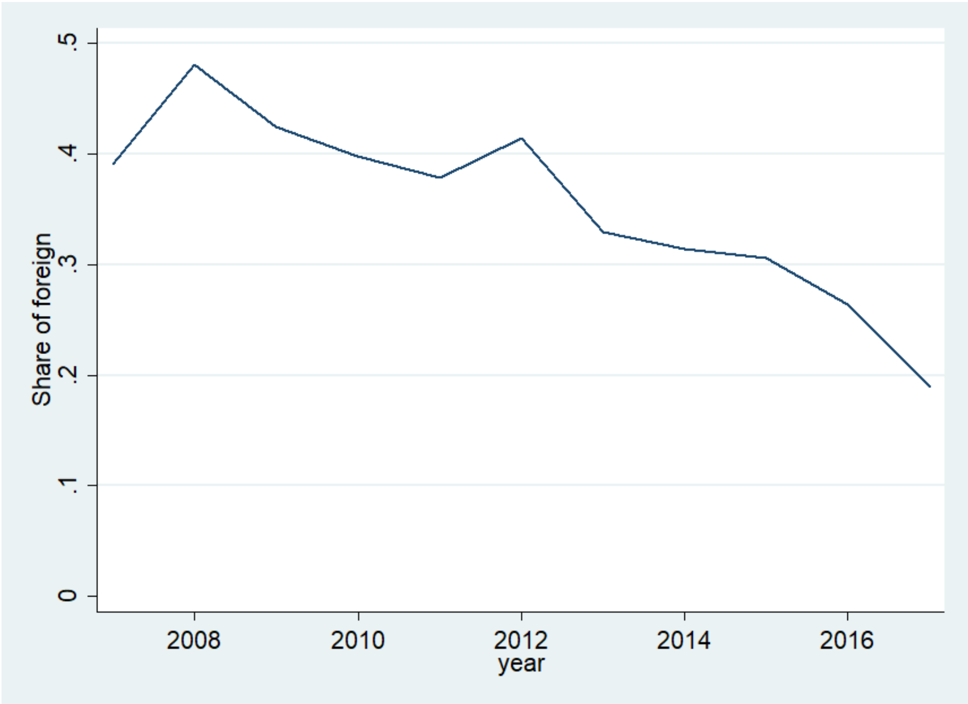
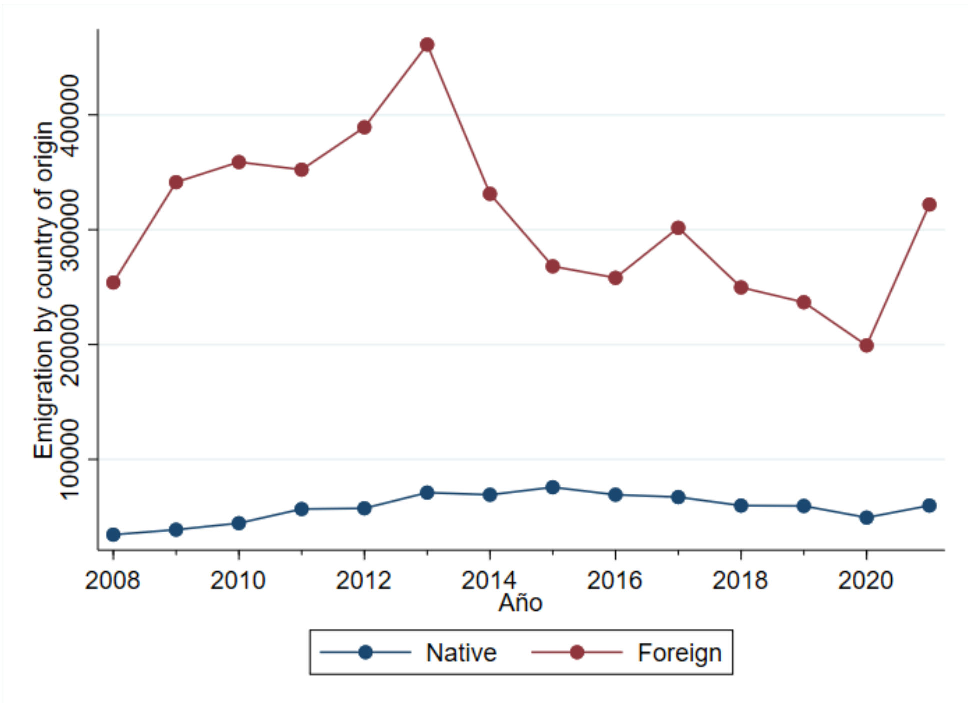


Figure A12: Share of foreign workers leaving the ss records
Notes: Share of foreign workers by year of exit from social security records of workers in the construction sector during 2007.

Figure A13: Emigration by country of birth, 2008-2021



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