From bricklayers to waiters: Reallocation in a deep recession

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October 7, 2022

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Abstract

Is diversification of local economic activities associated with a faster adjustment of workers to negative shocks? This paper explores how the local sectoral composition influence the worker's adjustment to a large economic shock. The identification strategy relies on regional variations in employment contraction of the construction sector across Spanish provinces and administrative panel data that tracks all the workers' labor market histories (MCVL). The construction workers in heavily exposed provinces suffered a significant decline in total earnings between 2007 and 2012. This effect is explained by workers experiencing long periods of unemployment rather than wage cuts. I provide evidence that the local sectoral composition influences workers' likelihood of changing sectors. I construct a reallocation index based on worker characteristics and local employment size within the sector. This index captures the degree to which workers from the construction sector can reallocate into other sectors. Then, I examine how sectoral composition contributes to ameliorating the shock's impact. Individuals with more evenly distributed characteristics across sectors are less affected by the shock because they are more likely to change sectors. It implies that workers are less likely to adapt to shocks when a region has a high level of sectoral concentration. I find evidence that short-term labor market adjustment is intersectoral rather than interregional, even under asymmetric exposure.

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1 Introduction

Today, workers face the pervasive consequences of two deep economic crises in less than a decade—the Great Recession and the COVID-19 pandemic. [1] Affected workers may relocate to different sectors, occupations, or regions to offset the loss of employment opportunities. Understanding workers' obstacles in attenuating the impact on their labor market outcomes is crucial to mitigating employment fluctuations. The first step is to identify the consequences and heterogeneity of the individual impact. The evidence suggests that young and low-tenured workers often suffer the largest burden from adverse economic conditions. However, a better understanding of these heterogeneous impacts is still required. By examining the interaction between workers' characteristics and local conditions, we can better understand workers' consequences of negative shocks and adjustment opportunities.

In a classical contribution, Blanchard et al. (1992) found that the impact of labor demand shocks on regional wages and employment rates disappear in less than ten years, suggesting geographical mobility as the dominant regional adjustment mechanism. Recent studies found a slower response (Amior and Manning (2018); Dao et al. (2017)) and that mobility plays a minor role in mitigating job loss consequences (Autor et al. (2014); Dix-Carneiro and Kovak (2017)).

Geographical mobility is an incomplete mechanism for mitigating the impact of a demand shock on workers' earnings. As a result, sectoral mobility should be further explored as an alternative adjustment mechanism. [2] Sectoral mobility allows workers to relocate to a less affected or growing sector and is the subject of a growing body of literature. [3] For example, Yi et al. (2016), Artuç et al. (2010), and Dix-Carneiro (2014) As a result of trade shocks, workers who left the manufacturing sector reported a smaller earnings disruption than workers who changed jobs but remained in manufacturing.

Sectoral mobility may mitigate the individual's consequences from negative shocks; however, large flows out of the most affected sectors remain largely unobserved. One reason is that workers accumulate sector-specific human capital (Neal (1995)), making it more costly for them to leave the shrinking sectors. Furthermore, workers may face a

[1] Job loss tends to have large and very persistent effects on the earnings trajectories of workers. Generally observed under diverse circumstances: Mass-layoffs Jacobson et al. (1993); Davis and Von Wachter (2011);Farber (2017). Great Recession: Yagan (2019); Mian and Sufi (2014); Rothstein (2021). COVID-19 pandemic: Adams-Prassl et al. (2020); Gulyas et al. (2020)

[2] Sectoral reallocation has been widely discussed, mainly as part of the trade literature (Mayer (1974); Kambourov (2009)), and less often but equally important, as an adjustment mechanism to large economic shocks Carrington (1996). This literature considers how sectoral mobility affects the reallocation and the earnings costs of workers affected by a shock Artuç et al. (2010)

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

shortage of jobs suited to their skills and preferences, which creates a mismatch between their characteristics and the available jobs.

This paper examines how a large economic shock impacts workers' outcomes and their geographic and sectoral reallocations as a response to the shock. Specifically, I examine workers initially employed in the construction sector before the Great Recession and exploit local differences in intensity to the burst of the Spanish property bubble between 2007 and 2012.

The paper is divided into two main sections. I begin by leveraging variation in the employment contraction of the construction sector across Spanish provinces to determine how changes in local labor demand induced by the shrinkage of the sector impact the workers' earnings and employment. [4] I define the workers' exposure as the relative change in the employment share of the construction sector between 2007 and 2012 in the workers' initial province of residence. I exploit quasi-random variations in its intensity of the employment decline between regions.

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

My analysis relies on longitudinal data covering a worker's entire labor market history and unique characteristics. The Continuous Sample of Working Lives (MCVL) [5] includes the working history of a 4% of the workers affiliated with Spain's Social Security. This rich data source tracks earnings and contract changes before and after the crisis, allowing me to compare the shock's consequences to pre-recession earnings and employment trajectories.

There are two main literature strands to which I contribute. First, to the literature on worker level adjustment to economic shocks (Autor et al. (2014), Dix-Carneiro and Kovak (2017)) and job displacement (Jacobson et al. (1993)). This extensive literature offers evidence about job loss's negative and persistent consequences on workers' earnings trajectories, but little is known about workers' mitigation strategies. A key aspect of this paper is the analysis of the influence of local sectoral composition on worker adjustment. As a contribution to this literature, I explore the decline in construction employment as a large decline in job opportunities that were largely unexpected at the time and did not

[4] I follow the approach by Autor et al. (2014), and Yagan (2019) who study the impact of the Great Recession and the China shock on worker's earnings and employment trajectories respectively

[5] Muestra Continua de Vidas Laborales (MCVL) in Spanish

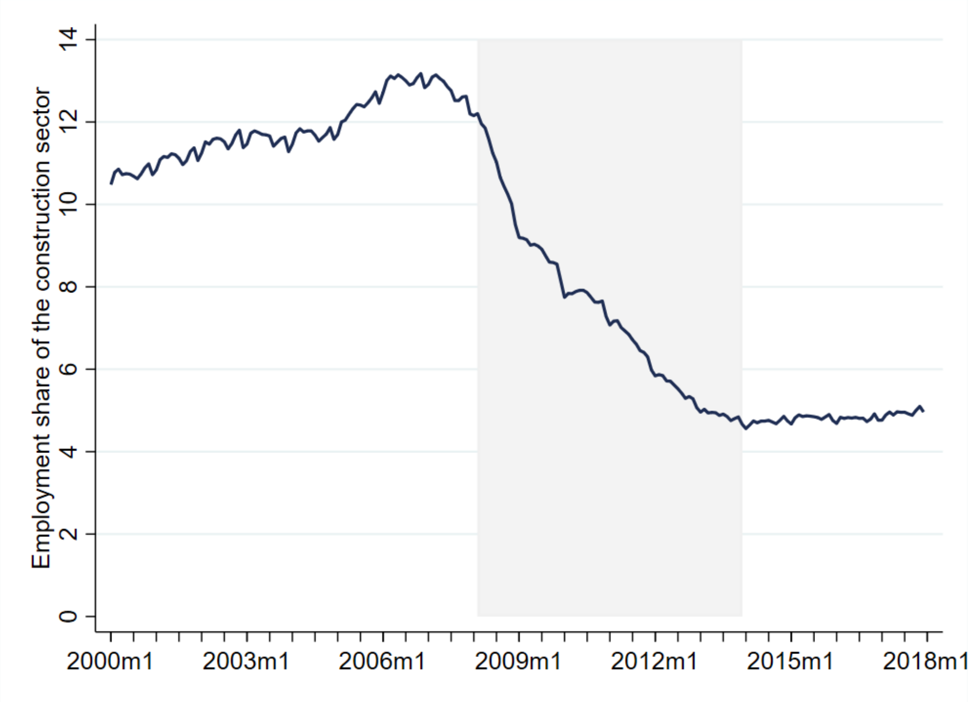


Figure 1: Employment share of workers in the Spanish construction sector, 2004-2017
Notes: Presents the proportion of workers in the construction sector from January 2004 to December 2017. The data restricts to monthly observations of workers aged 20-60 years old and employed during the referenced period. The shaded area comprises the years of the Great Recession in Spain, between 2008 and 2014.
Source: MCVL 2006-2017

recover after the Great Recession, resulting in some adjustment for workers previously employed there.

Secondly, to the literature on the estimation of occupation/sector similarity (Schubert et al. (2019), Beaudry et al. (2012), Caldwell and Danieli (2018)). My contribution focuses on how adjustment opportunities are closely related to the similarity of workers' skills within their regions of residence. In line with Caldwell and Danieli (2018) framework for estimating outside options, I estimate the reallocation index to capture the value of job opportunities outside the construction sector. Using the estimated reallocation index, I study the effects of a shock on workers' sectoral reallocation.

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

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

Construction experienced the biggest employment decline during the Great Recession, as well as large changes in the composition of workers. Fixed-term and young workers' shares declined due to large layoffs and a significant decline in hiring. In line with Lacuesta et al. (2020), who reports dropout rates increased during the boom, I complement such evidence by documenting that the proportion of young workers in the construction sector increased, which plunged during the recession.

In light of insufficient adjustment via geographical migration, I found a statistically significant relationship between exposure to shock and the likelihood of leaving the construction sector. A worker with the average value of the reallocation index suffered a 40% weaker average impact on the 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. The sectoral composition plays an important role in explaining the heterogeneous impact of the employment decline on worker outcomes. In light of this, it is important to consider the size and variance of the shock by worker and region because the value of a worker's skills differs depending on the sectoral composition of the local economy.

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 identification. Irrespective of the reallocation probabilities definition, transition probabilities within sectors show similar results compared to the main specification. Furthermore, the results remain mostly unaffected when the sector's cumulative growth before the recession instruments the shock.

Related literature and contribution: I contribute primarily to two lines of literature: the consequences of job loss on worker's labor market outcomes and the role of outside options in wage determination and reemployment opportunities.

Several studies have shown that job losses have long-term effects on workers' earnings and employment trajectories in the context of: mass layoffs (Jacobson et al. (1993); Neal (1995); Farber (2017); Gulyas et al. (2019)), economic downturns (Yagan (2019); Mian and Sufi (2014); Bachmann et al. (2015); Nagore García and van Soest (2017)), and the growth of import competition from developing countries (Autor et al. (2014); Dix-Carneiro and Kovak (2017); Dauth et al. (2014)). Despite a large number of studies, little is known about how workers react to negative shocks [6]. This paper contributes to filling that gap by taking advantage of a massive construction shock in Spain. Having a well-defined group of workers affected by the shock allows comparison of its consequences and adjustment margins for directly and indirectly affected workers. Additionally, I am able to compare how different degrees of exposure to the shock and the labor market adjustment affect workers' prospects by using high-quality administrative data.

After adverse economic events, why do studies find large earnings and employment differentials between exposed and less exposed workers? The workers' impact to negative demand shocks could be mitigated if workers reallocate to less-affected regions (Topel (1986)). Blanchard et al. (1992) argues that regional differences in exposure to adverse shocks trigger a migration response among workers, therefore equalizing differences in employment and wages among regions [7]. Recent evidence suggests, that out-migration is not the main response of workers to economic shocks [8]. Amior and Manning (2018) find that despite the large migratory response, adjustment to shocks is incomplete within a decade. Dix-Carneiro and Kovak (2019) studying trade liberalization in Brazil emphasizes the importance of geographic location explaining outcome differentials, implying that the worker adjustment occurs primarily within the region. Following previous evidence, I demonstrate that workers in more exposed regions are not more likely to migrate to less affected regions, which persists even after controlling for individual and regional characteristics.

Research supports the equalizing role of geographical mobility in reducing regional disparities. At the worker level, however, the efficacy is less clear. In particular, when comparing regions affected differently by economic shocks, it has been found that the primary effect is a decline in in-migration rates (Dustmann et al. (2017); Gathmann et al. (2020)), in contrast to classical references, which suggests increasing out-migration rates as the equalizing force. Additionally, Marinescu and Rathelot (2018) and Manning and Petrongolo (2017) found that worker's job search is discouraged by the distance to open vacancies, contributing to the low geographical mobility observed during economic

[6] For some groups of workers, it is documented they are highly responsive to negative conditions, such as college graduates (Wozniak (2010)), foreign workers (Cadena and Kovak (2016)). Individuals who are generally more geographically mobile move to less affected regions in response to negative conditions

[7] Monras (2018) study the consequences of the Great Recession across locations, the author documents that around 60 percent of the initial differences potentially dissipate across space within ten years

[8] There are several explanations for the minor role of geographical mobility in turbulent labor market conditions. Amior (2020) argues that immigration crowds out the contribution of internal mobility to the adjustment process. Also, Huttunen et al. (2018) claims that individuals' life circumstances influence this adjustment process. Fertility, divorce, and new relationships correlate with geographic mobility after a job loss, which partly accounts for the large income losses following a mass layoff.

downturns. Additional sources of adjustment, which may also play a larger role in the worker's adjustment, should be deeply studied. Utar (2018) in Denmark, Dix-Carneiro (2014) in Brazil, and Walker (2013) in the U.S. found that even though adjustment through sectoral mobility is small compared to the number of workers hit by a shock, sectoral mobility plays a significant role in the labor market adjustment of workers, already documented in the past by Carrington (1996). Using regional characteristics and detailed worker characteristics, I contribute to this debate by documenting the relevance of both adjustment margins after a large shock.

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

Identifying the relevant labor market for each worker is crucial to assessing how job composition affects employment opportunities. Worker flows are used by Schubert et al. (2019) to identify local job opportunities. According to the study, labor market concentration has a significant effect on wages. In this approach, worker flows capture that transition probabilities are not symmetrical. However, it relies on the stability of the transitions between occupations/industries and assumptions which could be violated during recessions. I capture industry similarity by following Caldwell and Danieli (2018), they construct an index of the value of workers' outside options in Germany based on the diversity of jobs and locations in which similar workers are observed and show it is strongly associated with individual wages.

Beaudry et al. (2012) show that changes in the availability of high-wage jobs within the region have considerable wage spillover effects. Those changes impact workers' outside options and workers' compensation through wage bargaining. I propose that variation in the local sectoral composition may affect workers' adjustment opportunities, which affects wages immediately and persists as workers are harder-pressed to bounce back to previous earnings trajectories.

Two papers that are closely related to mine are Macaluso et al. (2017), which examines how laid-off workers' outcomes differ based on the similarity of local jobs, and Yi et al. (2016) who use labor market transitions to capture that workers in inflexible labor markets [9] will have a larger impact from mass layoffs. The index captures the potential reallocation

[9] i.e., those in regions where the sectors with a similar skill requirement are scarce

of workers from a particular sector and focuses on the relevance of skill transferability among sectors. However, both articles focus primarily on regional differences rather than considering that workers within the same labor market can respond differently to the shock. As a contributor to this literature, I demonstrate that sector composition affects the likelihood of finding a good match based on the characteristics of the worker and other relevant regional characteristics during the Great Recession.

2 Theoretical framework

Workers affected by a negative shock are assumed to leave the affected sector to minimize disruptions to their earnings and employment. According to empirical evidence, however, these shocks are incompletely attenuated, and workers seldom recover their previous earnings trajectory. It is important to note that the implied earnings losses depend on several factors, including the worker's characteristics, which inform about workers' flexibility in finding new jobs. This section aims to provide a theoretical background for the worker's transition process after a shock and how these costs differ by region and individual characteristics.

Workers and firms: Consider an economy characterized by S sectors (indexed by s) and R regions (indexed by r). Each region is an open economy; workers are mobile across sectors but immobile across regions. The total measure of workers and firms is fixed and normalized to one. Workers are identified by the vector of characteristics $X \in \mathcal{X}$, and firms are grouped into J sectors. Following this notation, X_i represents the characteristics of worker i and j_f the sector of firm f.

Workers live for T periods after labor market entry, and firms live forever. Newborn workers begin their working life in the construction sector ($s = 1$); if employed in the construction sector, workers face a region-specific probability of losing their job μ_r; in such case, workers search for a job in the construction sector or the other sectors within the region.

Matching: Firms and workers are brought together through a search process, which takes time, and is random. Firms post vacancies to fill positions that have been vacated. Posted vacancies contain a take-it-or-leave-it wage offer, the posted wage is the same as the national wage for workers with similar characteristics X_i. The prior implies that in the absence of the shock, workers know with certainty their earnings trajectories. The function $w^{cs}(X_i)$ captures the wage of a worker in the construction sector with characteristics X_i, wages in other sectors are equal but vary by region $\tilde{w}(r)$. [10]

[10]This assumption is later relaxed in the empirical results allowing wages to differ by sector and region

In the spirit of Burdett and Mortensen (1980) I assume job seekers randomly receive job offers within their labor market [11]. In addition, as in Schubert et al. (2020) I follow a probabilistic definition of the relevant labor market for the individual. The intuition is that defining the relevant labor market as the whole local area or particular occupations within the same region overstates the set of possible jobs a worker may accept. Therefore, I consider that workers receive random offers that depend on the sector's relative size and the likelihood that the worker may be matched in equilibrium with a firm in that sector. The last is captured by using the probability that a worker with characteristics X_i is matched to a firm in each given sector.

For simplicity, I first present the framework considering that workers have the option to reallocate into another sector and receive offers depending on the probability $\mathbb{P}(X_i, r)$. I later expand this probability, accounting for the composition of workers and firms in each local labor market.

Timing: Time is discrete and infinite. At the beginning of the period, employed workers collected their wages. Unemployed workers get job offers randomly, and in case they receive an offer, they accept it [12]. Assume the probability that worker i receives an offer from the construction sector depends on the employment share of the construction sector in the region (σ^r_{cs}); this is used as a proxy for the local sectoral size [13]. The probability that the worker receives an offer from another sector is $\mathbb{P}(X_i, r)$. This probability captures the worker's likelihood of being matched to a firm in each sector and the employment share of each sector at the local level. If they are not matched, I assume workers get a zero payoff, and the period ends.

Framework: The per-period utility of the individual in period t is represented by the value function $V_t(X_i, r)$:

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

Where $\tilde{V}(X_i, r)$ denotes the continuation value if the shock hits the worker, this function displays the probability of finding a job in another sector and the present value of the wages in that sector $\tilde{W}(r)$ [14]. The probability that workers may receive offers from firms in the construction sector is captured by the employment share of the sector in the region

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

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

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

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

σ^r_{cs}. If the worker did not receive an offer from a construction firm or another company. In that case, the worker remains unemployed and has a payoff equal to zero during that period.

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

Combining expression (1) and (2):

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

A worker's shock attenuation depends on the opportunity to reallocate into another sector and reemployment opportunities in the construction sector. In the absence of the shock, workers know with certainty the earnings they will receive in the construction sector, which evolve along with their characteristics following their life cycle profile. On the other extreme, if workers cannot change sectors, they alternate between employment and unemployment periods; therefore, the shock's impact is just the future earnings discounted by the probability of losing their current job.

Equation 3 has a natural representation in terms of pre-shock levels. Let $W_0(X_i)$ the initial wage of agent i. Then, dividing both sides of the equation by $W_0(X_i)$, the following expression is obtained:

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

Then, for agent i, I could re-express the shock's impact in terms of pre-shock wages, which captures the disruption on their earnings trajectories due to μ_r, and it is appreciated how the probability of finding a job in another sector interacts with the shock which attenuates the disruption on the earnings trajectories of the workers. Empirically this is going to be analyzed by considering both the shock on the worker's opportunities and the probability that the workers may find a job in another sector:

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

.

In the previous expression, X_i is the vector of worker's characteristics which captures that for a given worker, in the absence of a shock, the worker's earnings trajectory is perfectly defined by the worker characteristics. $Shock_i^r$ represent the shock on the worker's opportunities given by the employment decline in the construction sector. $EmplShare_i^{cs}$ and $Prob_i$ capture the reemployment probabilities on the construction sector and another sector, respectively. The parameters of interest are δ and Γ, which measure the impact of pre-shock earnings on the labor market trajectories and the attenuation of the shock for individual i.

The probability of finding a job in another sector is the key element in studying the interaction of workers' characteristics and the local sectoral composition. In what follows, I briefly discuss this measure, which will later be used in the empirical results.

In a classic model, it is assumed that workers are perfectly mobile between regions. In such a case, the labor market would be all the occupations with a similar skill requirement. In practice, workers have very little regional mobility as workers search for open vacancies close to their homes, as revealed by Marinescu and Rathelot (2018). Next, I will propose the measure for reallocation probabilities, exploiting the similarity between the worker's characteristics and the sectoral composition at the province level. This approach considers that workers' opportunities are defined by the relative size of each sector and the likelihood that workers would move to each sector, conditional on their characteristics.

Reallocation probabilities: Determine the range of options that workers hit by a negative shock have required to define what is their appropriate labor market. Local labor markets are thought to capture most workers' job mobility patterns in practice. However, it does not consider the possibility of workers changing occupations or sectors. Additionally, not all occupations are equally relevant for the worker as options. I follow a probabilistic approach similar to Schubert et al. (2020) and determine that for a worker i, the job opportunities are a function of the sector's size and the likelihood that similar workers to i are matched in equilibrium to a firm in that sector. Next, I define the reallocation probabilities assuming that workers receive offers that match their region of residence and characteristics.[15]

The reallocation probabilities depend on the employment size in sector j, which captures the probability of getting an offer from sector j and the likelihood that a worker with given characteristics may move to that sector, which is absorbed by the probability that workers with similar characteristics are employed in each sector. The last assumption is applied to simplify this comparison. Therefore, assume workers with equal characteristics are perfect substitutes for the same job. Define $f(x, j)$ as the density of matches between workers with characteristics x and firms in sector j; intuitively, this is the joint density of

[15]In the section 8 I apply another measure that exploits the transition probabilities conditional on the worker's characteristics.

observing a worker with characteristics x and a firm in sector j matched in equilibrium. Which is defined as:

$$f(x,j) = \int_{X_i=x}\int_{j_f=j} g(i,f)\, di df.$$

This measure determines the conditional probability of finding a worker i matched to a firm in sector j, expressed as $P(f|i)$. Under the assumption of perfect substitutability between workers implies that $P(f|i) = P(f|i')$. Essentially, two workers with identical characteristics are equally likely to be hired in sector j.

Exploiting that both the firms and workers have a unitary measure $P(f|i) = P(f,i)$ [16].

I pinned down $P(f,i)$ directly from the definition of $f(x,j)$ and the assumption that workers with the same characteristics are equally likely to be matched to the same job. Hence, $P(j|i) = \frac{P(J=j,X=X_i)}{P(X=X_i)P(J=j)}$. [17]

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

The equation 4 captures the likelihood that a worker i will receive an offer from a firm in sector j. $P(X_i = x; J = j)$ is the probability of observing a match between a worker with characteristics X_i and a job in sector j. $P(X_i = x)P(J = j)$ is the product of the marginal distributions for worker characteristics and firm sector. This 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 that workers and jobs with such observables are matched, accounting for the total measure of workers and jobs with these observables.

I add up the propensities across all the sectors and weigh them by their employment share. Based on the worker's characteristics X_i, employment shares capture the framework's random matching aspect, as the worker's chances of being offered work in the sector depend on the sector's size.

[16] $P(f|i) = \frac{P(f,i)}{P(i)} = P(f,i)\cdot I = P(f,i)$. The last steps come from I having a unitary measure

[17] $P(X_i = x, J = j) = \int_{X_i=x}[\int_{j_f=j} g(i,f)\, di]df = \int_{X_i=x} \frac{P(J=j)}{J^{-1}} g(i,f)\, df = \frac{P(X_i=x)}{I^{-1}}\frac{P(J=j)}{J^{-1}} g(i,f) \Rightarrow g(i,f) = \frac{P(J=j,X=X_i)}{P(X=X_i)P(J=j)} \Rightarrow P(j|i) = \frac{P(J=j,X=X_i)}{P(X=X_i)P(J=j)}$

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

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

2.1 Empirical predictions

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

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

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

3 Data

The primary data sources are the 2006 to 2017 Continuous Sample of Working Lives (MCVL) editions. [18] The raw data represents 4% of the Spanish population registered with Social Security (workers, unemployed receiving benefits, and pensioners). The observational unit is a labor market spell, which is updated whenever a worker's contract changes.

This rich dataset is built from Spanish administrative files matching social security, income tax, and census records. The data has a longitudinal design: those initially sampled are also selected each following year, subject to them still having a relationship with Social Security. The benefit of using several waves of the MCVL is the expansion of the sample. Each year, the sample is refreshed by replacing individuals who leave the social security records, ensuring representativeness. These changes allow for tracking the new individuals' complete labor market history.

[18] In Spanish *Muestra Continua de Vidas Laborales*

The MCVL offers earnings information derived from social security and tax records. Earnings information from Social Security records is available from 1980 or the beginning of the worker's career for later entrants. The earnings from the Social Security Administration is restricted by upper and lower limits, which are updated based on inflation and overall labor market conditions. On the other hand, tax records are not bounded but are only available for each wave of the MCVL from 2006 to 2017.

The limited availability of the tax information is a minor concern, as the analysis focuses primarily on 2007-2013 earnings. For this reason, I rely on earnings from tax records, except when it is unavailable. The autonomous communities of Basque Country and Navarre collect income taxes independently of the Spanish government. Consequently, tax records cannot be obtained from those regions. I use earnings information from social security records for workers in those regions. [19]

From the MCVL, I built a monthly panel covering 2000 to 2017. This data combines individual, firm, and job characteristics. It includes gender, educational attainment, date of birth, activity sector at the two-digit level, province of the establishment, occupational contribution group, and monthly earnings or unemployment benefits. The raw data has information on each spell's entry and exit date, which is used to compute individual experience and 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 wages, simplifying the comparison with the monthly earnings available from Social Security records.

3.1 Sample restrictions

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

I construct two sub-samples: i) The complete sample, from which I derive all the descriptive evidence. This dataset is a monthly panel from January 2000 to December 2017, and I limit it to active workers aged 20 to 60. ii) The second sample is labeled the estimation sample, which I limit to native workers employed in the construction sector before the Great Recession. Following their information from January 2007 to December 2013.

[19] Bonhomme and Hospido (2017) shows a comparison of earnings from tax and social security records suggesting it is primarily a concern at the top of the distribution, around the 90th percentile. Construction workers are below the middle of the earnings distribution, which makes both sources of earnings comparable.

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

3.2 Computation of the reallocation index

This section describes the procedure for estimating the reallocation index. The method exploits cross-sectional allocations of observably similar workers across sectors before the recession. It is used to estimate the relevant job options for each worker. The baseline assignment captures the worker's suitability for jobs within each sector based on their observable characteristics.

According to equation (6), it is necessary to determine the probability of being employed in each sector conditional on the worker's characteristics and the relative employment size of each sector by province. As a result, I divide the estimation process into two steps.

First, I estimate the likelihood of observing a match between a worker and a firm in each sector based on a given set of worker characteristics X_i. The MCVL consists of pairs of matches between workers and employers, allowing to approximate worker's employment probabilities in each sector. Second, the prior probabilities are weighted by the sector's employment share in the worker's province of residence before the shock. During the Great Recession, workers' geographical mobility was limited. As a result, the distribution of jobs in the province of residence before the recession are a good proxy for the individual's local labor market. [20]

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

The two-step process is as follows. I used actual worker allocations in different sectors

[20] In Section 8.3, the likelihood that each worker will migrate to another province is also taken into account. However, the main results remain largely unchanged

before the Great Recession, specifically for 2000-2004. [21] I regress an indicator variable of the individual's job sector on an array of worker's characteristics. The control variables are occupation's skill level, gender, foreign-born status, and interactions of age categories with education attainment. Based on the estimated coefficients, I use the estimation sample to determine the probability of finding a plausible match between a worker i and a sector j. I repeat this process for each sector. In the second step, I combine the predicted values using as weights the ratio of the employment share of sector j in the province r and the employment share of sector j in the entire economy, both measured in 2006, to avoid potential bias caused by employment changes driven by the Great Recession. As a final step, the reallocation index is standardized so that the mean is zero and the standard deviation is unitary in order to simplify interpretation.

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

4 Description of the Construction Sector

Table 1 provides descriptive statistics of construction workers before and after the Great Recession. Fixed-term contract employees constituted 64.1% of total employment in 2007 but were down 28.6% by 2012. [22] According to Bentolila et al. (2012), fixed-term contract's hiring flexibility promoted construction sector growth. During the implementation of this policy, temporary contracts increased employer flexibility and decreased unemployment. However, workers with such contracts are more vulnerable to economic fluctuations, as evidenced by the decline in their employment shares during the Great Recession.

Additionally, Table 1 shows that the proportion of young, low-skilled, and foreign workers decreased during the Great Recession. Despite this, does this evidence show that

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

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

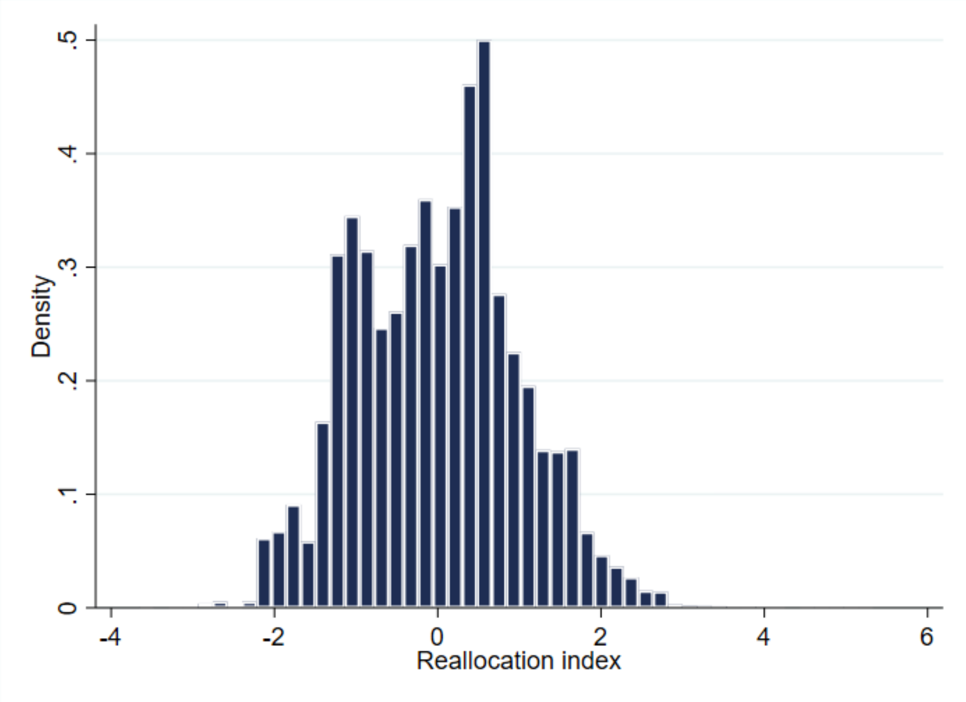


Figure 2: Histogram of the reallocation probabilities
Notes: Reallocation probabilities of workers employed in the construction sector in the year 2007.
Source: CSWL, 2006-2017

these workers were the most affected by the Great Recession? Not necessarily; workers with those characteristics were the most vulnerable, evident from each sub-group's employment decline. However, the sector also experienced a change in the composition of newcomers (Table 15) as well as leavers (Table 16) Both tables reveal that fewer young workers enter the sector and the proportion of workers leaving shifts over time. Additionally, answering who are the most affected requires a consideration of how the workers adjusted to the job loss. Within the following sections, I explore the employment changes experienced by the sector and which individuals were most affected by the employment contraction in more detail.

4.1 Employment decomposition

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

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

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

Table 1: Descriptive statistics of workers in the construction sector

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

Notes: The Table shows the main characteristics of workers in the construction sector in 2004, 2007, 2012, and 2017.
Source: MCVL, 2006-2017

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

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

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

where, $O_{k,t}$ denotes the number of individuals leaving the construction sector to status k at time t. k represents the outflows under consideration, whether it stays in non-employment, unemployment, or moved into another sector at time t. In both equations, N_{t-1} is the population in the construction sector at time $t-1$.

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

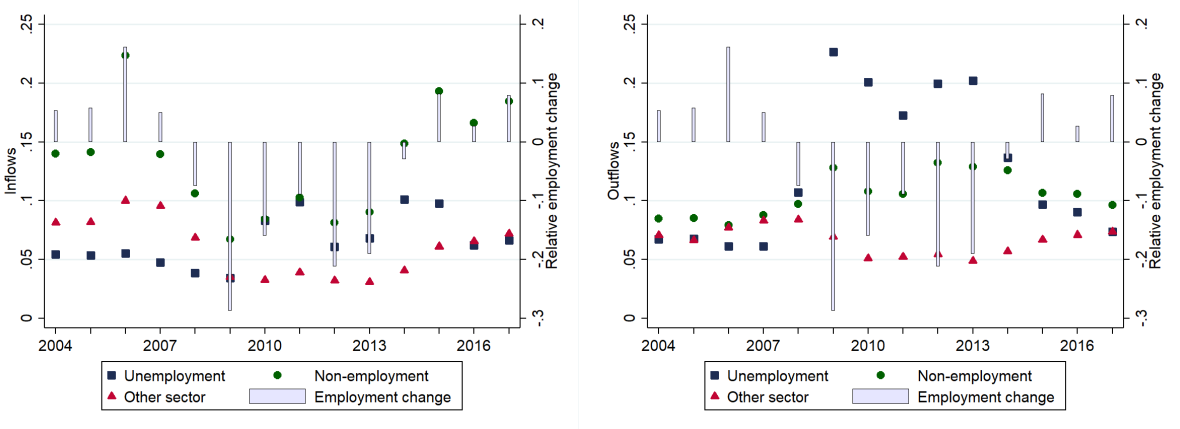
$$EmploymentChange_t = \frac{Empl.Construction_t}{Empl.Construction_{t-1}} - 1.$$

I show the results of this decomposition in Figure 3. Panels (a) and (b) present inflows and outflows, respectively. The blue bars in both figures show the relative changes in construction employment.

According to Panel (a), inflows from unemployment, non-employment, and other sectors had a similar evolution. During the period, inflows from non-employment accounted for most of the employment growth, which is more evident during the expansion period. In 2006, non-employment inflows spiked from 15 to 22 percent of the construction sector's population, primarily explained by an increase in the migrant population at that time. In 2005, there was large legalization of foreign-born workers in Spain (Moraga et al. (2019)). This event resulted in a significant increase in the number of immigrants in Social Security records, impacting the number employed in the construction sector. Table 1 shows that 15.7% of workers were foreign-born in 2004, increasing to 27.9% right before the Great Recession.

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

As shown in Figure 3, outflows into other sectors do not account for a large fraction of the observed employment decline. However, workers' dynamic decisions during this period



(a) Inflows to c.s.

(b) Outflows to c.s.

Figure 3: Aggregate flows from/to construction sector

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

Source: CSWL 2006-2017

are hidden by aggregate flows, making it difficult to gauge the worker's adjustment process from there. In the following exercise, I restrict my analysis to workers in the construction sector in 2007 and track their working status yearly, considering five scenarios: if they stay in the same firm, work in another firm in the same sector and province, move to another region, move to another sector within the same region, or stayed unemployed/non-employed.

The results are presented in Figure 4, in which I emphasize three main points. [23] Most construction workers lost their jobs during the housing bubble bust. As of 2015, only 10 percent of workers held the same job as in 2007, while only 20 percent remained employed in the construction sector. Second, 42 percent of workers in the construction sector in 2007 were no longer employed in 2015. Among those individuals are unemployed workers, international migrants, people working in the informal sector, or those out of work. A large increase in long-term unemployment is one of the major consequences of the Great Recession, contributing to that 42 percent. It is important to note, however, that this situation also affects non-construction workers as documented by Bentolila et al. (2017).

The results suggest that moving to another sector becomes more important as overall adjustment increases. About 30% of construction workers found a job outside the sector in 2015, as opposed to the lower percentage of internal migration. Within a year of the housing bubble burst, there was a large fraction of workers moving to a different

[23]The share of workers non-employed seems exceptionally high. To study this Figure, 16 tracks workers using a more restrictive sample; the sample considers native workers ages between 20 and 45 years old and employed in the construction sector in 2007. Using this sample, the qualitative results are maintained

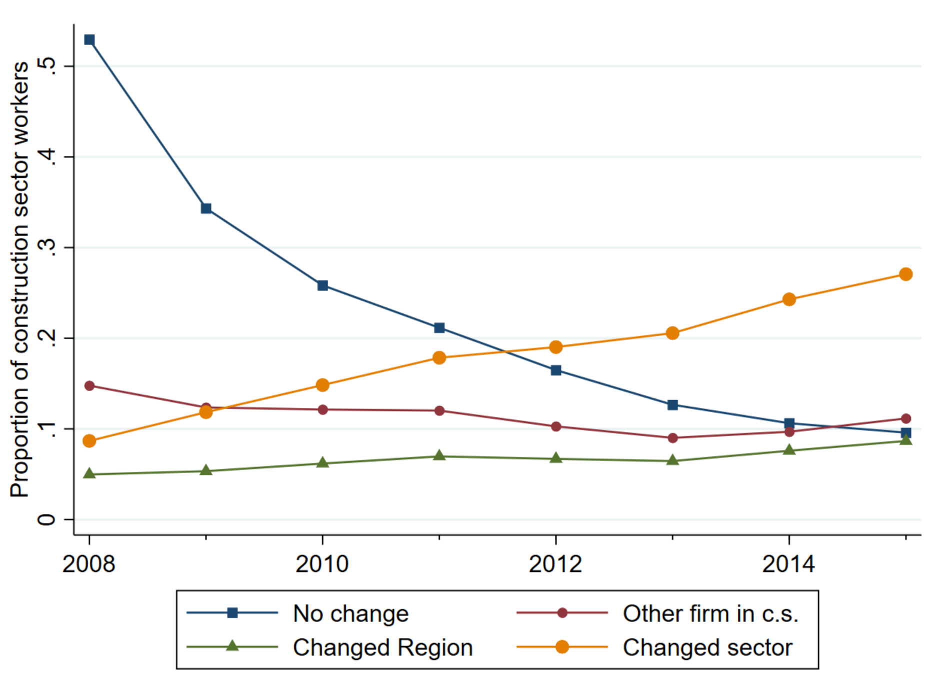


Figure 4: Working status of individuals employed in the construction sector in 2007
Notes: The shares are computed based on workers in the construction sector in 2007, and every year I tracked their working status up to 2015.
Source: CSWL 2006-2017

province; in 2008, 5.5% of workers lived in a different province than in 2007. After three years, however, this percentage does not change significantly, increasing by only three percentage points, while workers changing sectors increased from 9 to 30 percent during the same time.

In the construction sector, different factors are responsible for the employment decline. Highlighting the sector losing its place as a job creator. Still this analysis does not inform about welfare losses of workers previously employed in the construction sector. Job loss is widely documented to have negative and persistent effects on worker outcomes. The most vulnerable workers and how they adjust to economic shocks are crucial to understanding the effects of economic shocks. In light of this, it is natural to ask which workers are most likely to be found in each employment status after the crisis.

The Figure 5 shows the average age and foreign-born status of workers in the different categories of working status in 2013. As above, these results are based on the sample of workers employed in the construction sector in 2007. According to the results, workers who changed regions or sectors are younger than those who stayed in the construction sector or went unemployed. Over the past decade, a large fraction of workers has been employed in temporary contracts. The situation is much more prevalent among young workers who wait to be promoted into 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

(a) Mean age

(b) Share of foreign workers

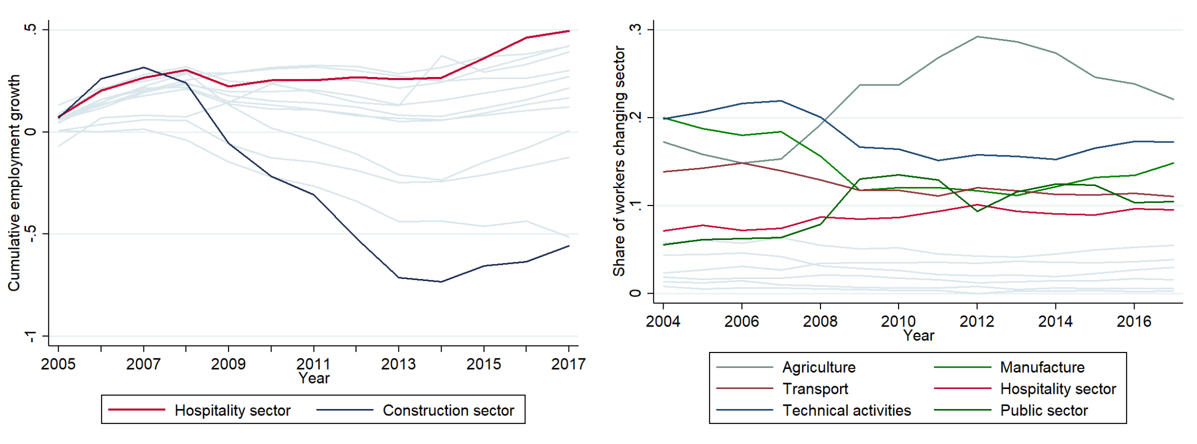
Figure 5: Descriptive statistics of workers in the construction sector in 2007
Notes: Panel (a) Average age in 2007 of workers in the construction sector by status in 2013. Panel (b) Share of foreign workers in the construction sector by status in 2012. Sample is restricted to workers in the construction sector in 2007 and aged 20-55 years old

Source: MCVL 2006-2017

cost than similar workers in permanent positions. Still, they also have more flexible human capital due to lower tenure and job-specific experience, which makes them find optimal to change sector or region as the opportunity cost to change is smaller compared to workers with more specific human capital as in Neal (1995) and Gathmann and Schönberg (2010); therefore attenuating the original impact. I test this in the following sections.

Foreign workers are over-represented in non-working conditions and among those individuals that migrate. It is consistent with the fact that foreign workers migrate more frequently (Cadena and Kovak (2016)). I also present evidence in the appendix A.5 that foreign workers in the most exposed regions are more likely to leave administrative records. Spain's data does not track workers who leave the country, which largely explains the higher propensity of unobserved foreign workers, justified by the return migration of this population. After returning to their home country, individuals may reduce their cumulative earnings, not necessarily because they worked less or received a lower wage, but because they are no longer observed. In order to avoid such bias, the estimation sample is restricted to native workers.

During that period, many workers reallocate to another sector. Where are they moving to? The period of economic expansion in Spain was characterized by many changes, including greater use of temporary contracts, substantial inflows of foreign workers, and increased availability of land, which implied a significant increase in construction employment. As a result of the Great Recession, the country went through a structural transformation, with the construction sector declining and the hospitality and other sectors growing. Figure 6 depicts these changes in Panel a.



(a) Cumulative employment growth

(b) Movers by sector

Figure 6: Cumulative employment growth and sector of change from the construction sector

Notes: Panel (a) Sector of destination as the proportion of total movers by year from the construction sector, 2004-2017. Panel (b) Cumulative yearly employment growth per sector, 2005-2017.
Source: MCVL 2006-2017

Is there a reallocation of workers from the shrinking sector to the hospitality sector? The short answer is no. All Spanish provinces were affected by the contraction in construction employment. Nevertheless, those provinces have a different sectoral composition, which makes exposed workers dependent on the local labor demand. Consequently, the adjustment depends not only on the cost of changing sectors or the likelihood of individual workers switching sectors. In addition, it is dependent on their skill set's relative demand. As an exploratory exercise, panel b) of Figure 6 shows how workers initially in the construction sector moved to very different sectors. Employment in agriculture, livestock, fishery, and related activities increased during the Great Recession and are the first activities receiving workers previously in the construction sector. Nevertheless, there is also an important mass of workers moving to manufacture, hospitality, technical activities, and even the public sector.

4.2 Province level impact

The initial employment share and the employment contraction of the construction sector during the Great Recession differed among the Spanish provinces. [24]. These exposure differences are the basis for my empirical analysis as it allows me to study the impact of the employment contraction of the construction sector on workers' career outcomes, and exploit the asymmetric regional decline of job opportunities.

The initial employment share of the construction sector by province ranges from 6.8

[24] I use March of 2006 as my initial period, this is a reasonable time as, at the moment, there are no signs of contraction, this started to be apparent in the fourth quarter of 2007 Figure 1

Figure 7: Change in share of workers in the c.s. during the GR by province
Notes: Change in the employment share of the construction sector by province between 2007 and 2012 against employment share in 2006. The computation of employment shares is based on yearly data. The sample uses 50 Spanish provinces and all workers employed in April of each year.
Source: MCVL 2006-2017

to 24.14 percent (Figure 7), such that the employment share is higher in the southern provinces [25]. For example, in Gipuzkoa, Araba, and Barcelona, the construction sector employed less than 10% of workers, while in the southern provinces of Ciudad Real, Huelva, and Malaga, it was more than 20%. The employment contraction ranged from 14.7% to 70.3%.

5 Worker level impact

This section examines how the shock to workers' employment opportunities affected their earnings and employment paths. The previous sections documented the changes experienced by the construction sector. Here I present evidence on how the decline of job opportunities due to the sector's decline impacts the worker's labor market outcomes. The impact of the employment decline on the construction sector is estimated for ex-ante observationally similar workers except for their province of residence before the Great Recession. The results are based on the estimation sample. I restrict to workers highly attached to the construction sector. I define those as individuals employed in this sector

[25] The same graph using labels for each province is in the appendix (Figure 14) and maps (Figure 19)

for at least one year during 2005-2006.

Table 2 presents descriptive statistics on cumulative earnings, average earnings, employment, and worker characteristics during the study period for construction workers and non-construction workers as a comparison group. The average non-construction worker earned positive earnings 4.6 out of a maximum of 6 years and earned cumulatively 61.56 times their pre-recession average monthly earnings. Workers initially employed in the construction sector had positive earnings 58% of the period between January 2007 to December 2012, about three-fourths the employment of the average non-construction worker. Finally, compared to their counterparts in other sectors, workers in the construction sector have lower educational attainment and are more likely to be male and foreign-born. I only consider native workers in the rest of the paper. During the Great Recession, outcomes of foreign workers were more likely to go unobserved, mainly due to return migration to the home country, which may cause a measurement bias of the effects.

The baseline specification in this section takes the form:

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

the normalized cumulative earnings of individual i are represented by y_i. Cumulative earnings are non-zero earnings from January 2007 through December 2012, divided by 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. [26]

X_i represent individual worker characteristics, such as gender, occupational skill level, tenure, experience, an indicator for fixed-term and part-time contracts, and interactions between age categories with educational attainment, all at the worker's 2007 values. Additionally, I consider regional controls, including the construction sector's employment share and the unemployment rate in the province of worker residence in 2006, a Bartik-type variable accounts for differential demand shocks in the other sectors, [27] and a Herfindahl-Hirschman Index for the employment concentration in the other sectors in order to capture for the overall diversity of the local sectoral composition.

In Table 3, I provide baseline estimates of equation (7) for a sample of highly attached workers to the construction sector. Column (1) includes the shock and a full set of age

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

[27] Bartik shock controls for trends on employment in non-construction sectors. It is constructed as $\sum_{j=1}^{12} ln\left(\frac{Employment_{2012}^j}{Employment_{2007}^j}\right) Share_r^j$ Where $Employment_t^j$ 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 2: Descriptive statistics of workers, 2007-2012

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

Notes: Workers in the construction and non-construction sectors are classified by their employment sector in 2007. An individual's cumulative earnings are calculated by dividing their non-zero earnings between 2007 and 2012 by their average monthly earnings between 2005 and 2006. Standard deviations are presented in parentheses
Source: MCVL 2006-2017

Table 3: Cumulative earnings and employment decline of the construction sector, 2007-2012

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

Standard errors in parentheses

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

Notes: Column (1) adds interactions of age categories with gender and education. Column (2) adds occupational skill group categories, indicators for part-time and fixed-term contracts, tenure, and experience fixed effects. Column (3) adds regional controls: local unemployment rate and employment share of the construction sector in 2006, a Bartik type shock, and HHI index. Column (4) considers as a shock the change in total workers in the construction sector between 2007 and 2012. Column (5) instruments the decline of the employment share of the construction sector with the cumulative growth rate of the construction sector between 2000 and 2006
Source: MCVL 2006-2017

dummies interacting with the worker's gender and educational attainment used to account for life cycle earnings variations. On average, workers in the construction sector accumulate fewer earnings between 2007 and 2012. I estimate that the decrease in cumulative earnings equates to 0.75 to 2.62 times their initial yearly earnings, for those who reside in the least and most affected provinces, respectively. In column (2), I also include variables associated with pre-shock labor market trajectory: occupation skill group, type of contract, tenure, and experience fixed effects. The main coefficient is attenuated by 35 percent, but it still suggests a significant impact.

Column (3) presents my preferred specification. I also include a Bartik-type shock and regional controls, which accounts for demand shocks in other sectors during the Great Recession. Other sectors may experience positive or negative shocks during the study period, which can be captured by the coefficient of the construction sector shock. The Bartik-type variable accounts for such source of variation, which limits the concern of correlated shocks to other sectors.

To interpret the coefficient estimates, consider a worker in a province in the 75th and 25th percentile of exposure: Valencia, where the employment decline in the construction sector was 59.34%, and Badajoz, where it was 45.53%. On average, workers have a greater impact due to higher exposure to the construction sector's employment decline.

A construction worker in Valencia accumulates 27% fewer earnings than a similar worker in Badajoz.

Finally, Columns (4) and (5) examine how possible sources of bias influence the results. The changes in the province's overall population may affect the estimated employment share in the construction sector, creating a measurement bias. Then, I kept the total employed workers by province constant between 2007 and 2012. Therefore, the shock only captures changes in the number of workers in the construction sector during that period. Column (4) presents the results of this estimated measure. As a result of this adjustment, the main coefficient is slightly attenuated, with a 3.7% change in the estimated coefficient.

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

The instrument is constructed using cumulative employment growth in the construction sector between 2000 and 2007 in the worker's province of residence. Figure 8 graphically illustrates that it satisfies the relevance condition. In addition, the construction sector's cumulative growth before the Great Recession is not related to earnings during the Great Recession, satisfying the exclusion restriction. Column (5) shows a 14.7% increase in the coefficient of interest. However, I keep the results from Column (3) as my preferred estimation since the results are very similar.

This effect may be explained by changes at the extensive margin (reduced years of work) or the intensive margin (reduced earnings per year). This point is explored in Table 4. All the specifications account for the same set of controls as in Column (3) of Table 3. Column (1) considers the normalized cumulative earnings between 2007 and 2012, and the results are similar to those in the previous table. [28] Column (2) of Table 4 consider as an outcome the cumulative days the worker was formally employed between 2007 and 2012, which is transformed into years just for the ease of interpretation. Column (3) explore the average yearly earnings between 2007 and 2012. In addition, Table 4 presents these results for a sample of workers employed in other sectors to compare the magnitude of the effects.

Column (2) of Panel (B) shows that workers not in the construction sector experienced a negative but small decline in working days between 2007 and 2012. In comparison, a

[28] These results require that the workers be employed in the construction sector during 2007, which imposes an additional restriction over the results presented above, explaining the small change in sample size.

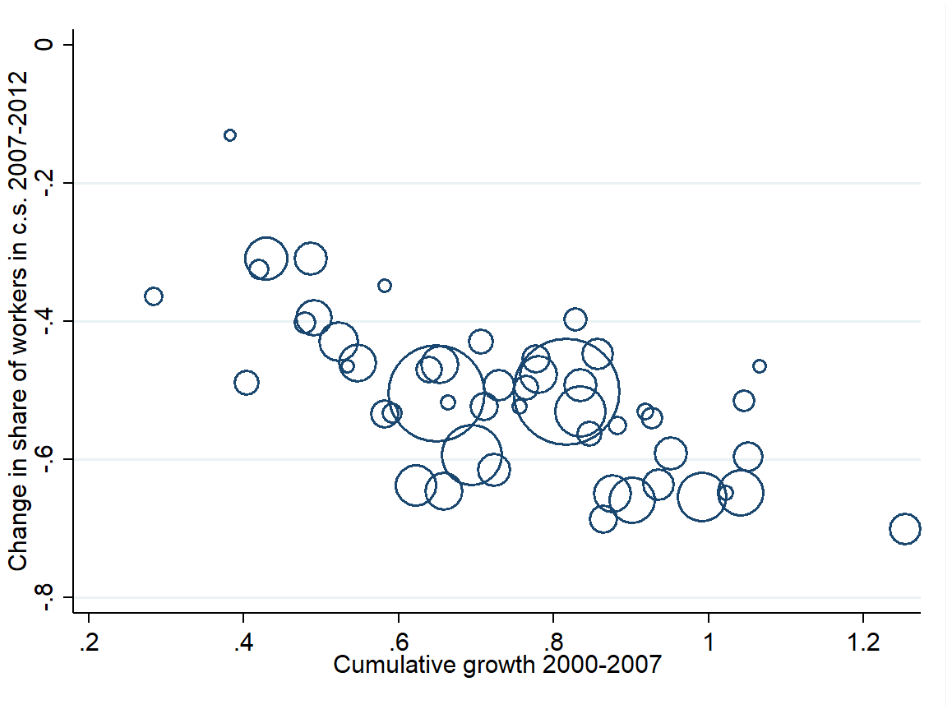


Figure 8: The cumulative growth in the construction sector and employment decline of the construction by province

Notes: Monthly share of construction workers, January 2004 to December 2017. The data is restricted to workers aged 20-60 employed during the reference period.
Source: MCVL 2006-2017

worker in the province with the median exposure accumulated 0.28 fewer years employed. In column (3), I present that the shock has no significant effect on average earnings for workers in the construction sector and those outside the sector. This evidence reveals that the impact on workers' earnings trajectories is explained by a combination of fewer days employed and a decline in the average earnings before the Great Recession. However, it shows that workers spend more time settling into another job than workers in other sectors.

5.1 Dynamic analysis

In this subsection, I examine the evolution of workers' impact on employment and earnings over time. Figure 9 shows a time series of the estimated effects of the construction sector's employment decline on employment and yearly earnings. Each year t's data point equals the coefficients from the following version of equation (7) on the estimation sample:

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

y_{it} is i's labor market outcome: binary employment status of year t and the yearly

Table 4: Labor market impact of the bust in the construction sector

	(1) Cumulative earnings	(2) Cumulative employment	(3) Average earnings
Panel A: Workers initially employed in the construction sector			
Shock	-1.948***	-1.672***	-0.00176
	(0.276)	(0.177)	(0.00364)
Constant	6.769***	5.235***	0.105***
	(0.226)	(0.0967)	(0.00332)
N	45296	45296	45296
R^2	.1998234	.2697646	.0266084
Controls	Yes	Yes	Yes
Panel B: Workers initially not employed in the construction sector			
Shock	-0.349	-0.557***	0.00597
	(0.183)	(0.148)	(0.00419)
Constant	5.605***	4.575***	0.0920***
	(0.135)	(0.0851)	(0.00366)
Controls	Yes	Yes	Yes

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) Odd columns present evidence for a sample of non-construction sector workers, (ii) even columns restrict to workers in the construction sector in 2007. I restrict to workers less than 50 years old in 2007 to avoid workers' early retirement before 2012. Shock measures the relative change in the share of workers in the construction sector by province. Bartik shock measures trends in employment growth in non-construction sectors.

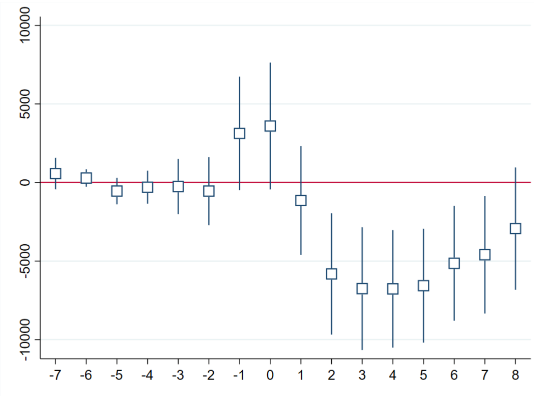
Source: CSWL 2006-2017

earnings at year t, $Shock_i^r$ denotes the local shock to the individual's i initial province of residence. $\mathbf{X}_i$ is a vector of individual's observable characteristics measured in 2007 and regional characteristics at their 2006 values. Comparing employment outcomes to pre-recession levels transparently allows a comparison of individual employment rate differentials. The identifying assumption is that local employment contraction of the construction sector is as good as randomly assigned, conditional on observables. The sample and independent variable values are fixed across annual regressions; only the outcome varies yearly. The 95 percent confidence intervals are based on standard errors clustered at the 2007 province of residence.

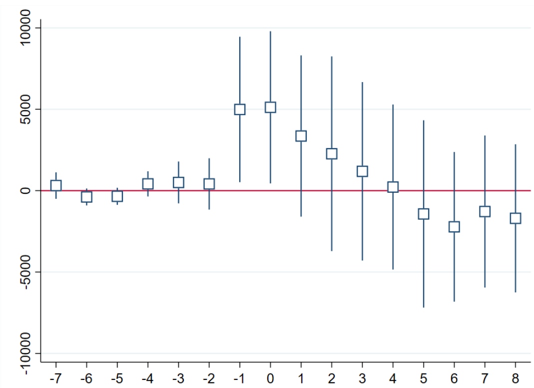
The estimating equations are identical to those in the baseline regression (Table 3, Column (3)) except that in place of workers' cumulative earnings over the entire period 2007–2012, each equation computes the yearly earnings and employment status. The estimation sample is restricted to workers aged 29–45 ("working age") in 2007 to confine the 2000–2015 analysis to those between typical schooling and retirement ages. The sample is restricted to Spanish citizens to minimize measurement bias caused by unobserved employment of foreign workers who migrate during the Great Recession.

The estimated coefficients are shown in Figure 9. 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 affects the worker's annual earnings. There was a negative impact on annual earnings during the Great Recession. It is consistent with previous evidence that workers in more exposed regions accumulated fewer earnings during the Great Recession. Nevertheless, earnings declines have slowed in the last years, with no significant differences between more and less exposed regions in 2015.

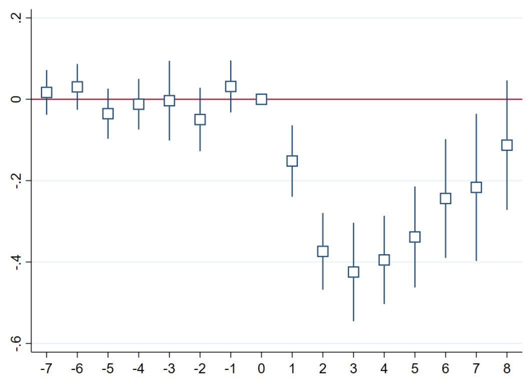
The previous consequences result from workers not being employed, which results in zero earnings and a reduction in their monthly earnings. In order to disentangle these two effects panels (b) and (c) examine how the shock affects employment probabilities and earnings of active workers. In panel (b), I explore how the shock affects the yearly earnings from a sample of workers with non-zero earnings. Lastly, panel (c) shows the shock's impact on the probability of being employed. Most of the effect can be attributed to decreased employment probabilities during the Great Recession. Panel (b) shows that there is a positive but insignificant effect on the yearly earnings, which is mainly driven by compositional effects, while panel (c) shows the same pattern as in panel (a), such that there is a negative impact of the shock on the probability of being employed which attenuates in the last years of the Great Recession. Therefore, their employment probability recovers with the overall economic activity for workers initially employed in the construction sector.



(a) Yearly earnings (Full sample)



(b) Yearly earnings (Only employed)



(c) Binary employment status

Figure 9: Impact of the constraction in the construction sector employment

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

Source: CSWL 2006-2017

5.2 Heterogeneity of the shock by individual characteristics

According to the previous section, local employment contraction in the construction sector significantly impacted workers' employment and earnings trajectory. In this section, I explore the heterogeneity of impact across individual characteristics. Figure 10 explores the consequences of the local shock on cumulative earnings across worker types. Based on the sample of workers initially employed in the construction sector, the figure plots point estimates and 95 percent confidence intervals based on separate regressions for each group of workers. I find that young, low-tenured, and low initial earners bore a proportionally larger incidence of the shock, suggesting that those shocks increased employment inequality across workers of different initial skill levels.

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

During the Great Recession, earnings inequality in Spain increased significantly. Bonhomme and Hospido (2017) argues that such an increase parallels the employment cyclicality in the lower middle part of the wage distribution. According to them, employment evolution in the construction sector played an important role in explaining this. As a contribution, Figure 10 presents that workers initially employed in the construction sector also exhibit considerable impact heterogeneity. Therefore, even within a defined group of workers, economic shocks have the potential to increase regional inequalities as workers across the wage distribution are differently affected.

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

Results are presented in Table 7. A test of equality for the four coefficients rejects the null hypothesis that they are equal to each other. According to the results, there is a

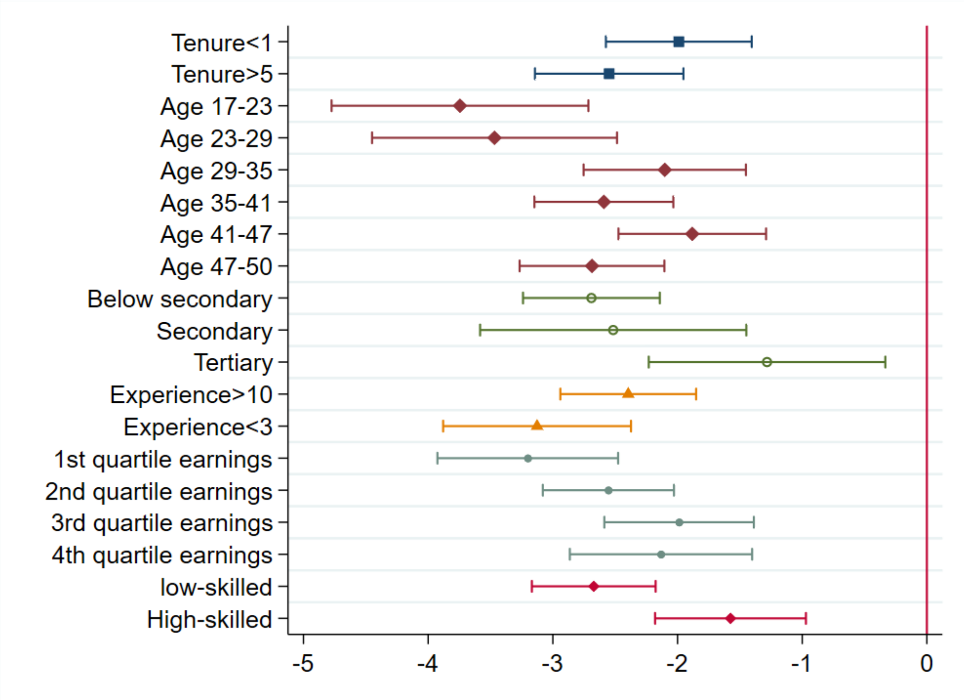


Figure 10: Cumulative earnings and local employment decline in the construction sector

Notes: Sample is restricted to native workers aged 20-50 years old in 2007 and working in the construction sector; cumulative variables are computed between 2007 and 2012. Wage is standardized by the average wage in 2006 of months with non-zero earnings. Every regression controls by: gender, age, education, skill group, and foreign status, and interactions between age and education. Bartik is computed without considering the construction sector. Each coefficient is obtained from separate regressions for each subgroup. Source: MCVL, 2006-2017 significant difference based on the worker's initial earnings. The shock is more severe for those with low initial earnings. As a result, national-wise earnings inequality increases, and regional disparities widen. Thus, workers in most affected regions are also differentially affected. There is a 20 percent difference in impact between beginning in the third quartile of the earnings distribution and the fourth quartile.

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

5.3 Worker's labor market adjustment

Transitions across sectors and geographical locations are mechanisms by which workers adapt to the effects of negative shocks. However, there are mixed results regarding how geographical mobility responds to negative shocks. Worker adjustment across regions appears slow and incomplete (Autor et al. (2014), Dix-Carneiro (2014)). This sluggishness is most pronounced among less-educated workers, a subset of workers who are overrepresented in the construction sector. In light of this fact, both geographical mobility and additional adjustment mechanisms should be studied.

This section examines the labor market adjustment of construction workers. Similarly to the previous section, the shock is the province's employment contraction in the construction sector between 2007 and 2012. Figure 11 examines how shocks affect the probability of changing province or sectors. The results are from separate regressions of a binary variable on changing sectors and regions conditional on the shock and a wide variety of individual and regional controls. A dynamic approach allows comparisons between coefficients before and during the Great Recession and tests for the absence of differential pre-trends.

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

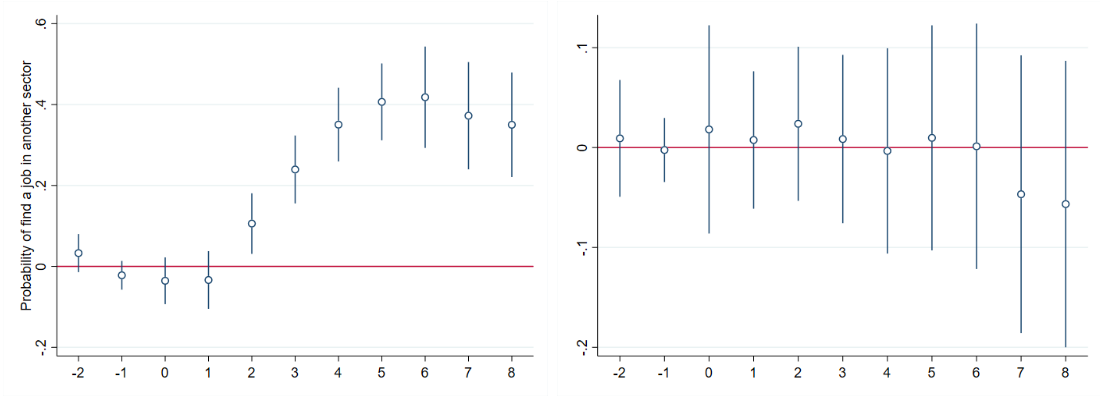
Table 5: Heterogeneity of the shock's impact

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

Standard errors in parentheses

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

Notes: Dependent variable: Standardized cumulative earnings, 2007–2012, cumulative days employed, 2007-2012, average monthly earnings, 2007-2012. All regressions include a constant and a full set of worker, job, and regional characteristics as additional controls. Demographic control interactions of age group, education, and gender. Initial occupational skill group, type of contract, tenure, experience, and experience squared. Regional characteristics: province-level unemployment rate at 2006, Bartik type shock, the employment share of the construction sector at 2006. All worker and job characteristics are measured in 2007, and regional controls were measured in 2006. The sample is restricted to workers in the construction sector before the shock, aged 20-50 years old.
Source: MCVL 2006-2017



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

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

Figure 11: Impact of contraction of the construction sector employment
Notes: Sample restricts to workers aged 29-42 and working in the construction sector in 2007. Coefficients of the shock using as outcome variable an indicator if the worker changed residence province or sector on a rolling basis. a) Out of the construction sector b) In a province different than the residence in 2007. Additional controls by initial share of construction sector employment, Bartik type variable, demographic characteristics and interactions
Source: CSWL 2006-2017

According to Borusyak et al. (2022), spatial correlation of demand shocks biases migration regressions. Workers consider local shocks and shocks to potential alternative locations, attenuating migration coefficients. An appropriate method is to account for the shock in connected locations. I construct an adjusted shock measure incorporating the strength of migration flows between provinces before the Great Recession.

The adjusted shock is shown in equation (9). $Shock_m$ represents the decline in construction employment from 2007 to 2012 in province m, and $\mu_{r/rightarrowk}$ represents the probability that a worker from province r migrates to province k conditional on the worker changing province. I construct the adjusted measure in two steps. I start by estimating transition probabilities between provinces using observed workers' migration from 2001 to 2006. I construct the shock variable that compares the local shock with the weighted average shock across provinces based on the transition probabilities. When determining the effect of a shock on a given province, it is compared against the shock experienced by all other provinces, with more weight placed on provinces that are usual migration destinations.

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

Table 6 shows the impact of the employment decline in the construction sector on the probability of changing sector and province. The first three columns analyze the likelihood that a person will work in a different province in 2012 than they did in 2007.

Table 6: Geographical vs sectoral reallocation to the economic shock

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

Standard errors in parentheses

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

Notes: Controls: interactions of age categories with gender and education 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 HHI index. The shock is the relative employment decline in the construction sector. Adjusted shock compares the shock in the province of residence to the shock in other provinces weighted by the migration strength between the province and all potential provinces.
Source: MCVL 2006-2017

The fourth to sixth columns examine the likelihood that they will work in a sector other than construction in 2012. As explained previously, Columns (3) and (6) adjust the shock measure to account for shocks in other provinces. The difference in shock between the province of residence and a weighted shock average is based on the likelihood of migrating to each province. I capture that workers are unlikely to migrate to regions that would receive them in the absence of the shock.

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

Column (4) indicates that workers originally employed in the construction sector were leaving the sector to adjust to the decline in employment opportunities. As shown in Column (5), adding individual and regional controls results in a small increase in the coefficient. Workers in the 75th percentile of exposure are more likely to move into another sector than workers in the 25th percentile.

6 Sectoral composition and the effect on worker's labor market adjustment

Availability of jobs and flexibility to move between sectors determine whether a worker switches sectors. Individuals with more relevant job options will, on average, be able to sort into better matches depending on their characteristics and region of residence. Since they find less time unemployed, these individuals may suffer a lower earnings penalty from job loss.

The reallocation index capture the relevant jobs options available to a given worker within their labor market. In most empirical studies, a local labor market refers to a defined geographic region. [29] Alternatively, they can be defined by exploiting worker flows within a region (Nimczik (2020)). Nevertheless, any binary labor market definition (i.e., which treats all jobs within a region as close substitutes and all jobs outside are ignored) ignores the fact that workers value jobs differently based on their characteristics. I apply a probabilistic definition of the labor market as in Schubert et al. (2020), recognizing that even similar jobs may be valued differently by the workers.

The next section incorporates the reallocation index into the analysis, considering how the sectoral composition impacts the labor market prospects of workers and easing their adjustment to negative shocks. The reallocation index is constructed by comparing sectors according to the similarity of their workforce. In this way, I follow a similar methodology to that used by Caldwell and Danieli (2018) and align with the framework outlined in Section 2. In the final section, I get similar results when I use transition probabilities between sectors instead of worker similarity to construct the reallocation index.

Sectoral composition and the contraction of the construction sector

This subsection expands the equation (7) by incorporating the reallocation index as an additional control. The probability that a worker with characteristics X_i in region r finds a job in another sector plays a role in attenuating the shock's impact. Then, to be consistent with that idea, having a larger reallocation index would attenuate the shock's impact on the earnings trajectories of the workers. I test and quantify this hypothesis by examining the adjustment to a large shock.

The results of this exercise are presented in Table 7. Working in the province at the

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

Table 7: Labor market impact of the employment contraction at the construction sector, 2007-2012

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

Standard errors in parentheses

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

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

Source: MCVL 2006-2017

25th and 75th percentiles of the shock, the average worker lost 1.19 (-2.35×0.5081) and 1.51 (-2.35×0.6463) times the initial average annual earnings. The initial average annual earnings impact in high-exposure provinces is almost 21 percent greater than in low-exposure provinces.

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

As described in the framework section, the interaction of reallocation index and shocks captures the attenuation of adverse conditions explained by having a better match between the worker's characteristics and the local sectoral composition. According to the results, an increase of one standard deviation on reallocation index results in a 17.9% attenuation of the shock's impact (0.432/2.420) . In other words, workers would be better off if a large shock occurred in a region where workers have highly valued characteristics.

Columns (3) and (4) present the impact that the shock and reallocation index had on the yearly employment of workers initially employed in the construction sector. The employment contraction in the construction sectors results in a statistically significant negative effect on workers' employment. By keeping good prospects in other sectors, workers in a region with good employment opportunities in other sectors may be able to offset the effects of such massive shocks by counterbalancing the decline in employment opportunities in the origin sector.

Column (3) shows that the average worker in the province at the 75 percentiles of exposure was employed 1.17 years less, while a worker at the 25th percentile was employed 0.92 years less due to the shock. It implies a differential exposure to employment for one-fourth of the year. The reallocation probabilities index shows a positive and statistically significant impact on cumulative employment. An increase by one standard deviation suggests a 4% increase in employment during the reference period. Additionally, column (4) shows that workers with a higher reallocation index attenuate shocks better, with importance increasing the larger the shock is on the initial province of residence.

Finally, Columns (5) and (6) demonstrate that workers in more exposed areas did not suffer a large impact on their average yearly earnings. The decline in average earnings between 2007 and 2012 for a worker in a province at the 75th percentile of exposure is 84 real euros compared to the initial annual earnings in 2009 [30]. It is statistically significant, but the economic magnitude is small.

6.0.1 Heterogeneous impact of the reallocation index

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

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

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

The results are presented in Table 8. Columns (1) and (3) show the impact of the shock without considering the reallocation index, which indicates that the decline in construction employment between 2007 and 2012 had a significant and statistically significant impact on the cumulative earnings and employment of workers initially employed there. Column (2) and (4) shows how those consequences vary with the degree of mismatch between their characteristics and the job opportunities in other sectors within the region. According to column (2), the workers experience a stronger shock on their earnings trajectories as they have a lower reallocation index, i.e., lower quality or better jobs are scarce in the region because of the sectoral composition. An equality test for the four coefficients is rejected at the 0.2% confidence level.

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

[30] 0.0857*0.6463*1596, the average monthly real earnings are 1596 real euros

Table 8: Sectoral composition and the consequences from the contraction of the construction sector

	(1)	(2)	(3)	(4)	(5)	(6)
	Cumulative wage		Cumulative employment		Average yearly earnings	
shock	-2.445***		-1.897***		-0.00810*	
	(0.245)		(0.177)		(0.00343)	
$Q_1 \cdot shock$		-2.892***		-2.336***		-0.0123*
		(0.377)		(0.293)		(0.00580)
$Q_2 \cdot shock$		-2.479***		-1.875***		-0.00738
		(0.409)		(0.273)		(0.00509)
$Q_3 \cdot shock$		-2.641***		-1.882***		-0.0115*
		(0.248)		(0.180)		(0.00443)
$Q_4 \cdot shock$		-1.840***		-1.569***		-0.00166
		(0.235)		(0.228)		(0.00487)
Constant	6.654***	6.367***	5.029***	4.868***	0.116***	0.113***
	(0.153)	(0.146)	(0.123)	(0.138)	(0.00264)	(0.00288)
Observations	46392	46392	46392	46392	46392	46392
R^2	.2338	.2341	.3231	.3233	.0315	.0316
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Notes: Dependent variable: Standardized cumulative earnings, 2007–2012, cumulative days employed, 2007-2012, average monthly earnings, 2007-2012. All regressions include a constant and a full set of worker, job, and regional characteristics as additional controls. Demographic control interactions of age group, education, and gender. Initial occupational skill group, type of contract, tenure, experience, and experience squared. Regional characteristics: province-level unemployment rate at 2006, Bartik type shock, the employment share of the construction sector at 2006. All worker and job characteristics are measured in 2007, and regional controls were measured in 2006. The sample is restricted to workers in the construction sector before the shock, aged 20-50 years old.
Source: CSWL 2006-2017

6.1 Residualized reallocation probabilities

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

Table 9 provides the results of adding the residualized reallocation index into the estimating equation. Column (1) presents the results of the 2007-2012 worker's cumulative earnings as a function of the reallocation index and the full set of controls. For ease of interpretation, I standardized the residualized reallocation index to have a zero mean and unitary standard deviation. As a result, an increase of one standard deviation in the reallocation index reduces the average shock's impact by 12.4%. Compared to the baseline results, the reallocation index coefficient is slightly attenuated, dropping by 9.8%. However, the magnitude remains statistically significant and economically relevant. Results in columns (3) and (4) indicate that a high reallocation probability positively affects workers' employment prospects during the Great Recession.

7 Are workers' responses to economic shocks affected by sectoral diversity?

This section assesses whether sectoral composition influences workers' willingness to change sector. The adaptation to economic shocks may occur by relocating to a less affected region or by changing sectors. In Section 5.3, I present evidence that workers adjusted mainly through sectoral reallocation. In line with that, I present suggestive evidence that sectoral composition influences the probability of changing sector, then affecting the worker's labor market adjustment. The composition of local economic activities shapes reemployment opportunities, affecting the worker's adjustment to economic shocks.

A relevant discussion is on how local economic performance is influenced by sectoral concentration, where two main theories arise. According to Marshall (1890), agglomeration forces improve local economic performance, the proximity of related industries facilitates intra-industry knowledge transfer, reduces the cost of transportation, and allows firms to benefit from more efficient labor markets. Jacobs and Jane (1969) argues that diversity fosters innovation and prosperity by promoting knowledge exchange. Related

Table 9: Residualized reallocation probabilities

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

Standard errors in parentheses

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

Notes: Dependent variable: Standardized cumulative earnings, 2007–2012, cumulative days employed, 2007-2012, average monthly earnings, 2007-2012. All regressions include a constant and a full set of worker, job, and regional characteristics as additional controls. Demographic control interactions of age group, education, and gender. Initial occupational skill group, type of contract, tenure, experience, and experience squared. Regional characteristics: province-level unemployment rate at 2006, Bartik type shock, the employment share of the construction sector at 2006. All worker and job characteristics are measured in 2007, and regional controls were measured in 2006. The sample is restricted to workers in the construction sector before the shock, aged 20-50 years old.
Source: CSWL 2006-2017

to that discussion, I focus on how the composition of local activities affects the worker's labor market adjustment, where a more diverse labor market benefits a broader group of workers who find themselves with a more diverse set of options in a case of a negative shock. My research contributes to that debate by examining how sectoral composition affects workers' adjustment.

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

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

Table 10 presents estimates of the probability of workers in the construction sector changing sectors between 2007 and 2012. There is a statistically significant positive relationship between the employment decline in the construction sector and the probability of leaving it. The HHI does not show a statistically significant relationship between sectoral mobility and sectoral concentration.

Column (2) in table 10 includes the reallocation index, which, as explained earlier, considers the distance between the worker's characteristics and the available options. The probability of changing sectors and the reallocation probabilities are positively related. Mobility into another sector is more likely in a province that matches worker characteristics and sectoral composition. Column (3) presents a decomposition of the into quartiles, enabling a more in-depth study of the heterogeneity and easing the interpretation of the coefficients. An equality test rejects the null hypothesis of equality among the three coefficients. Comparing the coefficients shows that the highest quartile accounts for the most variance.

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

Table 10: Sectoral composition and the probability of change sector

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

Standard errors in parentheses

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

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

Source: CSWL 2006-2017

Table 11: 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 yearly earnings
Shock	0.0737	-0.108	0.00188
	(0.206)	(0.147)	(0.00257)
Constant	4.410***	3.447***	0.106***
	(0.143)	(0.0729)	(0.00201)
N	25455	25455	25455
R^2	.0667	.1162	.0626
Controls	Yes	Yes	Yes

Standard errors in parentheses

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

Notes: The sample is restricted to native workers aged 20-50 in 2003 and working in the construction sector. I compute the cumulative variables between 2003 and 2007. Earnings are standardized by the worker's average earnings in 2002. Controls: gender, skill group, foreign status, and interactions of age categories and education attainment. Bartik is computed without considering the construction sector. The shock is the employment change in the construction sector between 2007 and 2012
Source: MCVL, 2006-2017

8 Basic robustness

8.1 Falsification of the decline in construction employment

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

Table 11 provides evidence neglecting that the shock is related to the pre-recession outcomes. Column (1) shows a positive but insignificant effect of the shock on both employment and earnings.

8.2 Reallocation index from transition probabilities

This section examines an alternative method to construct the reallocation index. It exploits the sector's transition probabilities instead of the similarity of their workforce. It uses the movement between similar workers to capture the likelihood that a worker would find it attractive to move to another sector from the construction sector.

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

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

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

The transition probabilities are constructed conditional on the individual leaving the construction sector and as a function of worker characteristics X_i. The vector X_i accounts for occupation skill group, gender, foreign-born status, and interactions of age categories with education attainment. [31]

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

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

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

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

Therefore, the final measure is:

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

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

Table 12: Reallocation probabilities from transition probabilities

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

Standard errors in parentheses

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

Notes: Sample workers aged 20-50 years old in 2007 and working in the construction sector before the crisis. Column (1) makes no additional restriction. Column (2) restricts native workers. The computation of the cumulative variables is from 2007 and 2012. Wage is standardized by the average wage in 2006 from months with non-zero earnings. Every regression controls gender, age, education, skill group, foreign status, and interactions between age and education. Bartik is computed without considering the construction sector, and predicted values for the outside option are from the first stage. **probit model**.
Source: MCVL, 2006-2017

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

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

Table 12 presents the results. Column (1) shows the impact on cumulative earnings from the shock, and column (2) decomposes the shock by quartiles of the reallocation probabilities. An equality test of the four coefficients is rejected, so the shock's impact heterogeneity is conditional on being more likely to move into another sector. The effect, however, is partially attenuated when compared to the reallocation probabilities in the baseline specification. As the labor market changed during the Great Recession, the flow of workers from the construction sector was less informative than during the expansion. However, there is still significant impact heterogeneity in columns (2) and (4) as a result of different transition probabilities.

8.3 Labor market adjustment and internal migration

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

According to figure 4, even though workers migrated from the exposed region during the Great Recession, the number of individuals who changed sectors surpassed those who changed provinces. This article has not studied these two forces simultaneously, given the focus on local sectoral composition and sectoral change. In this case, I will consider that some workers might move from one province to another to adjust, then consider the likelihood of them changing provinces and sectors.

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

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

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

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

Table 13: Labor market adjustment: Geographical and sectoral mobility

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

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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

Results are presented in table 13. Column (1) presents the baseline specification from section 6. The predicted probability of migration is added as a control in column (2). Interestingly, workers more likely to migrate have worse outcomes in the most affected regions. The migration probabilities were standardized to have a zero mean and unitary standard deviation. The increase of one standard deviation in migration probabilities is related to the decrease of 13.4 percent in the initial annual earnings between 2007 and 2012.

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

9 Conclusion

During the Great Recession, Spain was one of the most affected countries, both even within that, there is an important variability in the worker-level impact of this event. The construction sector was particularly affected, with the contraction unevenly distributed among Spanish provinces. This article exploits the employment contraction and the regional variation in this shock's depth to study how workers adjust after a negative shock. The results show that workers reallocate mainly from exposure to less exposed sectors rather than geographical reallocation, a secondary force for native Spanish workers.

To study sectoral reallocation systematically, this paper suggests the role of the sectoral composition as more diverse regions bring more opportunities to a wider set of workers. This reallocation index shows that opportunities vary among workers' characteristics and regions.

Regarding the persistence of the shock's impact, the province's sectoral composition is an important factor affecting the worker's outside options. Workers strongly exposed are not likely to change residence province compared to workers in the least exposed regions. However, workers in the same situation will change sectors, and the impact will depend directly on the moving cost, which also depends on the sectoral composition.

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

A Appendix

A.1 Definitions

A.1.1 Bartik

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

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

A.1.2 Outside option computation

Sample: Workers who changed contract, therefore with less than one month of tenure between 2003 and 2006. This sample over-represents young workers and those previously in a temporary contract, which is not an inadequate representation for the construction sector population most affected by the Great Recession. I don't take into account workers in the construction sector for the estimation of the probabilities. Below I comment on other possibilities.

Let:

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

Where y^j_i indicator that takes the value one if worker i is in sector j. Which is used to compute how likely a worker with characteristics X_i will work in sector j. Coefficients are estimated using a probit model.

Controls: Interactions of age dummies and gender, interactions of education and age dummies, occupation skill group and foreign born status.

Sectors used for the estimation:

- Agriculture, livestock, fishing
- Extractive activities
- Manufacture
- Energy, gas, and steem supply

Table 14: Descriptive statistics

	mean	sd
Share female workers	.545	.497
Age	31.2	9.0
Education:		
Below secondary	.560	.496
Secondary	.242	.428
Tertiary	.196	.397
Foreign	.184	.387
Contract fixed-term	.855	.351
Sectors:		
Agriculture, livestock, fishing	.104	.305
Extractive activities	.001	.039
Manufacture	.089	.285
Energy, gas, and steem supply	.006	.080
Commerce	.156	.363
Hospitality	.131	.337
Transport and storage, communication	.045	.209
Financial and insurance activities	.022	.148
Professional, scientific, technical activities	.106	.308
Other	.051	.220
Observations	544977	

Notes: Descriptive statistics from the first step
Source: CSWL, 2006-2017

- Commerce
- Hospitality
- Transport and storage, communication
- Financial and insurance activities
- Renting
- Professional, scientific, technical activities
- P.A. and defense, education, health services
- Other

Each equation is estimated separately, and the coefficients are used to get the predicted probabilities given the characteristics of my estimation sample. Therefore, capture for workers in the construction sector before the Great Recession what probability those workers move to each particular sector.

Then, 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 and the median wage in each sector.

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

Table 15: Descriptive evidence of new workers in construction sector

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

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

A.2 Tables

Table 16: Descriptive evidence of leavers from the construction sector

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

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

Source: MCVL, 2006-2017

Table 17: Impact of the employment contraction in the construction sector on worker's outcomes. By foreign born status.

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

Standard errors in parentheses

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

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

Source: CSWL 2006-2017.

Table 18: Impact of the employment contraction in the construction sector on worker's outcomes. By age group.

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

Standard errors in parentheses

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

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

Source: CSWL 2006-2017.

Table 19: Impact of the employment contraction on workers wage and employment trajectories

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

Standard errors in parentheses

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

Notes: Sample is restricted to native workers aged 20-50 years old in 2007, and working in the construction sector cumulative variables are computed between 2007 and 2012. Wage is standardized by the average wage in 2006 of months with non zero earnings. Every regression controls by: gender, age, education, skill group, and foreign status, and interactions between age and educations. Bartik is computed without considering the construction sector, and predicted values for the outside option are from a first stage **probit model**. The shock is the change in the construction sector employment share between 2007 and 2012 Source: CSWL, 2006-2017

Table 20: Province level sectoral composition and the impact of the contraction in the construction sector

	(1)	(2)	(3)	(4)	(5)	(6)
	Cumulative wage			Cumulative years		
shock	-27.01***	-26.76***	-70.06***	-1.598***	-1.595***	-4.139***
	(2.697)	(2.751)	(16.43)	(0.130)	(0.130)	(0.822)
Reallocation		4.147**	-20.96*		0.0484	-1.427**
		(1.451)	(9.218)		(0.0853)	(0.439)
Interaction			42.79**			2.515**
			(15.52)			(0.774)
Constant	78.97***	75.00***	100.1***	4.711***	4.664***	6.140***
	(4.879)	(4.788)	(10.65)	(0.254)	(0.269)	(0.503)
N	48079	48079	48079	48079	48079	48079
R^2	.1996151	.19978	.1999779	.3084236	.3084288	.3085861
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Notes: The sample is restricted to native workers aged 20-50 years old in 2007 and working in the construction sector. Cumulative variables are computed between 2007 and 2012. Wage is standardized by the average wage in 2006 of months with non zero earnings. Every regression controls by: gender, age, education, skill group, and foreign status, interactions of age and educational level, and interactions of age and if the last contract in 2007 was fixed-term. Additionally controls for initial experience and tenure before the Great Recession. At the local level controls for the initial size of the construction sector and unemployment rate per province in 2006, additionally a Bartik type variable which is computed without considering the construction sector and predicted values for the outside option are from a first stage **probit model**.

Source: CSWL, 2006-2017

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Change province	2008	2009	2010	2011	2012	2013	2014
shock	-0.00146	0.0103	0.00510	0.0183	0.0249	0.0349	0.0291	0.0159
	(0.0825)	(0.0352)	(0.0479)	(0.0581)	(0.0692)	(0.0741)	(0.0802)	(0.0862)
Outside	-0.00466	-0.00828	-0.00679	-0.00291	-0.00227	-0.00260	-0.00334	-0.00262
	(0.0176)	(0.00828)	(0.0125)	(0.0140)	(0.0153)	(0.0157)	(0.0178)	(0.0181)
$Outside \cdot shock$	-0.000960	0.0111	0.00724	0.000496	-0.0000116	-0.00259	-0.00351	-0.00454
	(0.0261)	(0.0124)	(0.0189)	(0.0209)	(0.0225)	(0.0230)	(0.0260)	(0.0268)
_cons	0.193***	0.0523**	0.0948***	0.117***	0.126***	0.152***	0.173***	0.189***
	(0.0334)	(0.0160)	(0.0194)	(0.0234)	(0.0268)	(0.0296)	(0.0307)	(0.0348)
N	39459	33429	35277	36204	36799	37131	37324	37516
R^2	.0371677	.0226586	.0297096	.0348221	.0374271	.0388521	.0393443	.0405042

Standard errors in parentheses

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

Notes: Sample restricts to workers aged 20-50 and working in the construction sector in 2007. Coefficients of the shock using as outcome variable an indicator if the worker has a valid spell a) Out of the construction sector b) In a province different than the residence in 2007. Additional controls by initial share of construction sector employment, Bartik type variable, demographic characteristics and interactions

Source: CSWL 2006-2017

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Change province	2008	2009	2010	2011	2012	2013	2014
Shock	0.283**	0.00956	0.0928*	0.150**	0.218***	0.296***	0.355***	0.361***
	(0.0856)	(0.0292)	(0.0365)	(0.0540)	(0.0595)	(0.0608)	(0.0654)	(0.0850)
Bartik	0.199	0.0617	0.178*	0.246*	0.232	0.285*	0.277*	0.173
	(0.185)	(0.0575)	(0.0702)	(0.118)	(0.121)	(0.123)	(0.136)	(0.179)
$ShareCS_{2006}$	-0.0551	-0.0736	-0.0810	0.0405	-0.0386	-0.122	-0.143	-0.0412
	(0.169)	(0.0685)	(0.0949)	(0.144)	(0.146)	(0.136)	(0.135)	(0.167)
Constant	0.401***	0.162***	0.241***	0.283***	0.288***	0.338***	0.358***	0.369***
	(0.0397)	(0.0209)	(0.0262)	(0.0368)	(0.0350)	(0.0370)	(0.0363)	(0.0378)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47056	38837	41288	42523	43300	43735	44001	44290
R^2	.0456326	.0205397	.0273154	.0340268	.0401488	.0472515	.0505823	.0546957

Standard errors in parentheses

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

Notes: Sample restricts to workers aged 20-50 and working in the construction sector in 2007. Coefficients of the shock using as outcome variable an indicator if the worker has a valid spell a) Out of the construction sector b) In a province different than the residence in 2007. Additional controls by initial share of construction sector employment, Bartik type variable, demographic characteristics and interactions
Source: CSWL 2006-2017

	(1)	(2)	(3)
	Cumulative wage	Cumulative years	Average yearly wage
		First tercile	
Shock	-24.80***	-1.442***	-0.175*
	(3.243)	(0.209)	(0.0747)
$ShareCS_{2006}$	-32.75*	-0.686	-0.616
	(16.11)	(0.497)	(0.351)
Constant	85.62***	4.773***	1.600***
	(4.203)	(0.217)	(0.0753)
		Third tercile	
Shock	-20.75***	-1.555***	-0.0954
	(4.824)	(0.266)	(0.0780)
$ShareCS_{2006}$	-36.03**	-0.570	-0.509
	(11.12)	(0.477)	(0.341)
Constant	61.50***	5.155***	0.980***
	(2.152)	(0.149)	(0.0325)

Standard errors in parentheses

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

Table 21: Impact of the employment contraction in the construction sector on worker's outcomes. By experience before the Great Recession.

	(1) Cumulative wage	(2) Cumulative years	(3) Average yearly wage
		Low experience (< 5 years)	
shock	-23.74***	-1.151***	-0.224***
	(3.304)	(0.229)	(0.0506)
$ShareCS_{2006}$	-19.97*	-1.573**	-0.0831
	(8.888)	(0.488)	(0.142)
Constant	87.58***	5.483***	1.465***
	(2.664)	(0.168)	(0.0304)
		High experience (> 10 years)	
shock	-26.98***	-1.816***	-0.0779
	(2.931)	(0.205)	(0.0423)
$ShareCS_{2006}$	7.616	0.383	0.154
	(6.661)	(0.423)	(0.107)
Constant	60.09***	4.555***	1.200***
	(2.456)	(0.150)	(0.0830)

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, foreign born status and a Bartik type variable to control for demand shocks in other sectors within the same province. I restrict to workers less than 50 years old in 2007 to avoid workers' early retirement before 2012. Shock measures the relative change of the employment share in the construction sector by province. Cumulative wage is the sum from 2007 to 2012 of non-zero earnings standardized by the average wage in 2006. Cumulative years is the accumulated days worked from 2007 to 2012 and converted into years. Average yearly wage is the average yearly wage from 2007 to 2012. *Source:* CSWL 2006-2017.

Table 22: Labor market outcomes depending on worker decisions

	(1)	(2)	(3)	(4)
	Change Province		Change sector	
main shock	-0.200	-0.460	0.582*	0.408
	(0.371)	(0.404)	(0.236)	(0.245)
Outside	0.0343	-0.386	-0.0144	-0.267***
	(0.0649)	(0.202)	(0.0271)	(0.0794)
Interaction		0.762*		0.458***
		(0.333)		(0.134)
Constant	-1.523**	-1.588**	-1.091***	-1.153***
	(0.510)	(0.565)	(0.298)	(0.277)
N	48111	48111	48111	48111
Controls	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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

Source: CSWL 2006-2017

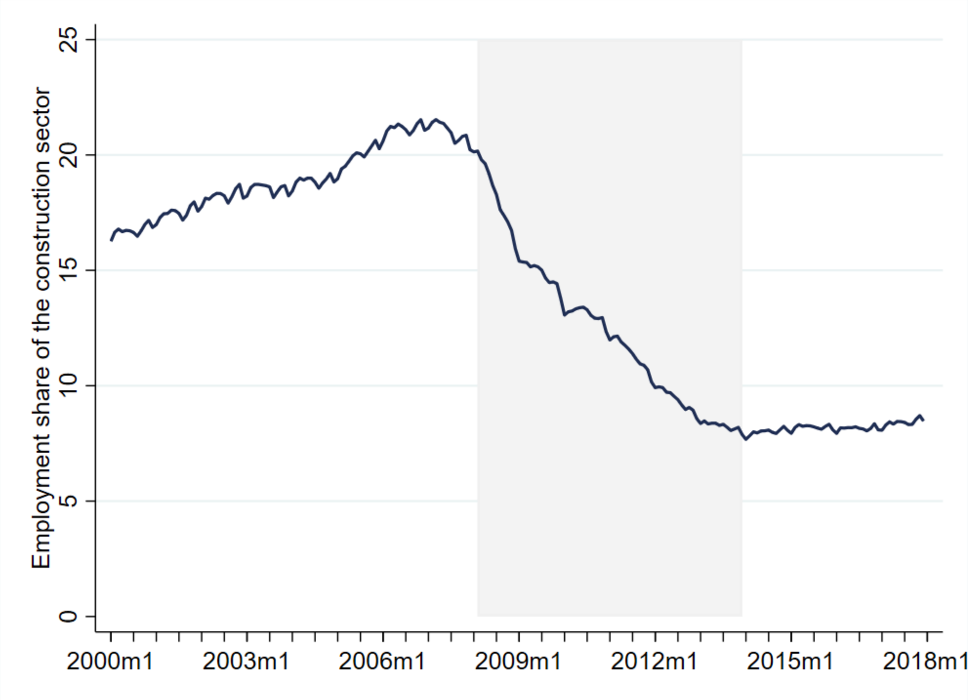


Figure 12: Employment share of the construction sector, 2004-2017

Notes: Monthly share of workers in the construction sector, January 2004 to December 2017. Data restricts to workers aged 20-60 years old, employed during the referenced period. Sample of male workers

Source: CSWL 2006-2017

A.3 Figures

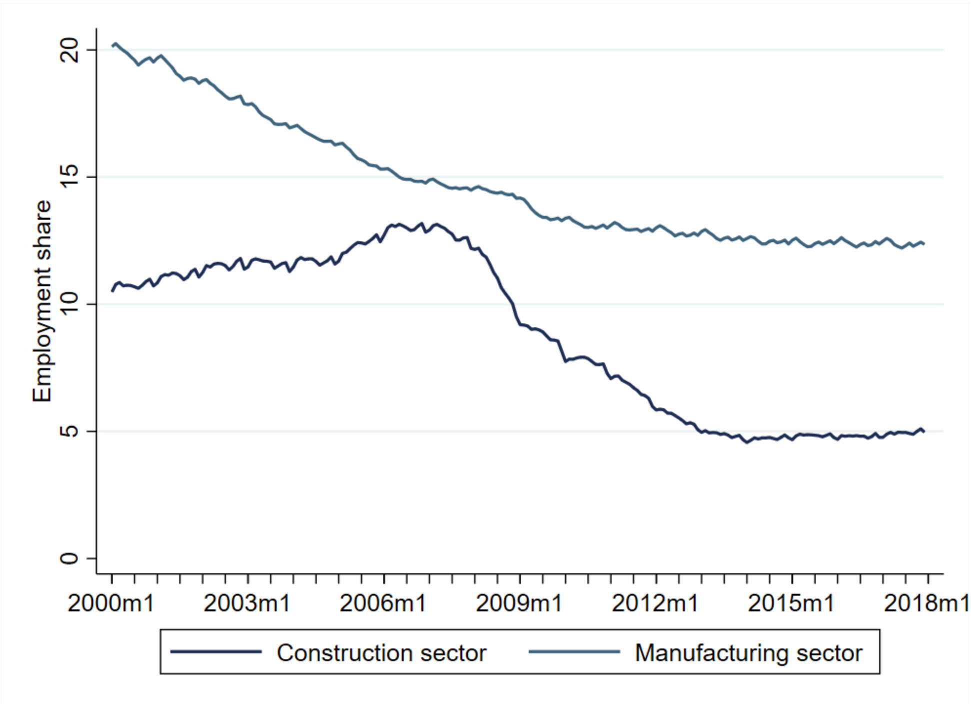


Figure 13: Employment share of the construction sector and manufacture, 2004-2017
Notes: Monthly share of workers in the construction sector and manufacture, January 2004 to December 2017. Data restricts to workers aged 20-60 years old, employed during the referenced period.
Source: CSWL 2006-2017

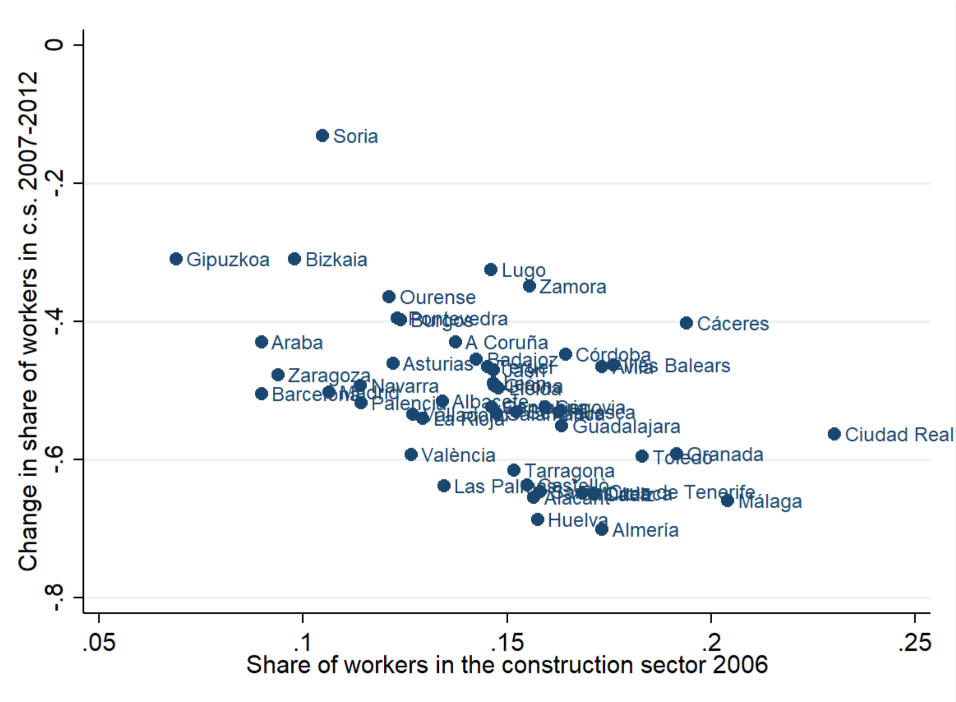
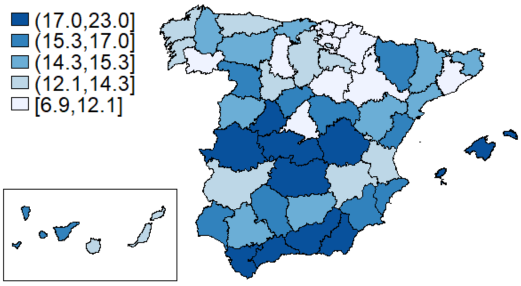
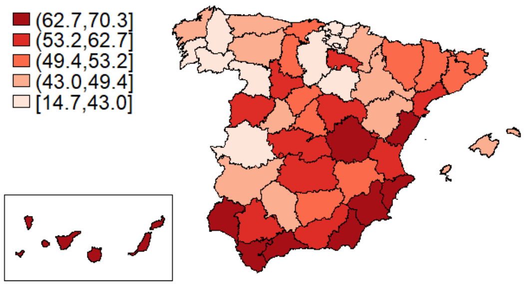


Figure 14: Change in share of workers in the c.s. during the GR by province
Notes: Change in the employment share of the construction sector by province between 2007 and 2012 against employment share in 2006 —computation of employment shares from yearly data in April of every year. Sample uses 50 Spanish provinces and data on all workers enrolled in the general regime of Social Security.
Source: MCVL 2006-2017



(a) Share of workers in the construction sector by province, 2006



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

Figure 15: Evolution of the construction sector by province

Notes: Panel a) Initial share of workers in the construction sector, shares are based on workers in the complete sample during March of 2006. Panel b) Relative decrease in share of workers in the construction sector by province between 2007 and 2012. The shares are calculated using annual data as of March of each year. Sample considers 50 Spanish provinces, and from the complete sample.

Source: MCVL 2006-2017

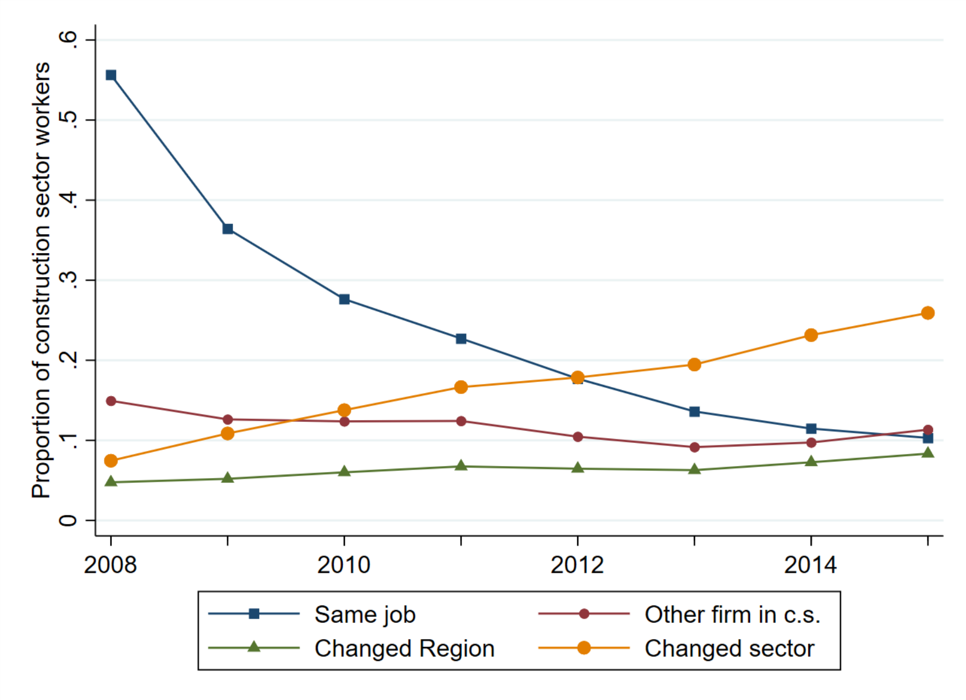


Figure 16: Working status of individuals employed in the construction sector in 2007

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.

Source: CSWL 2006-2017

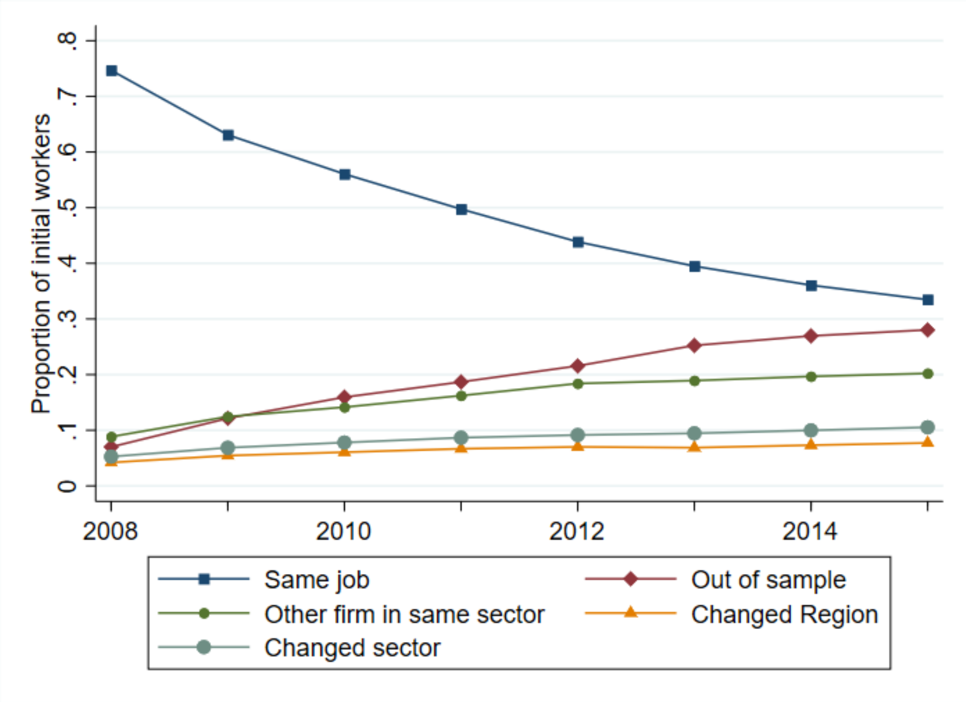
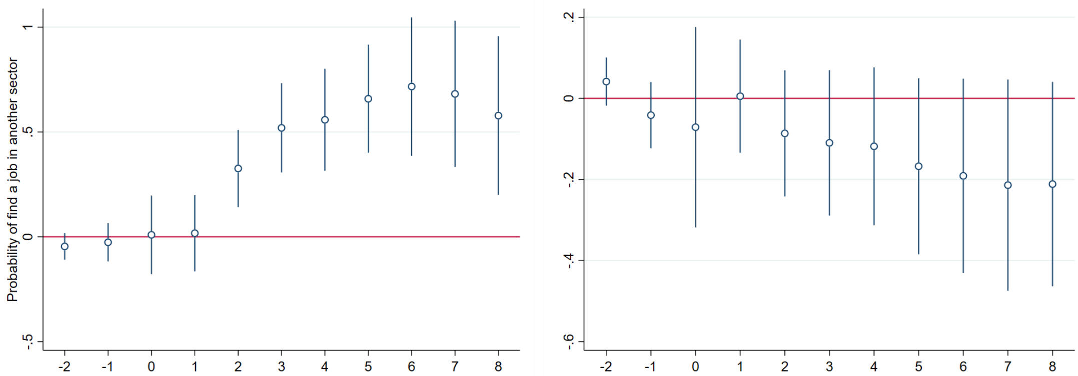


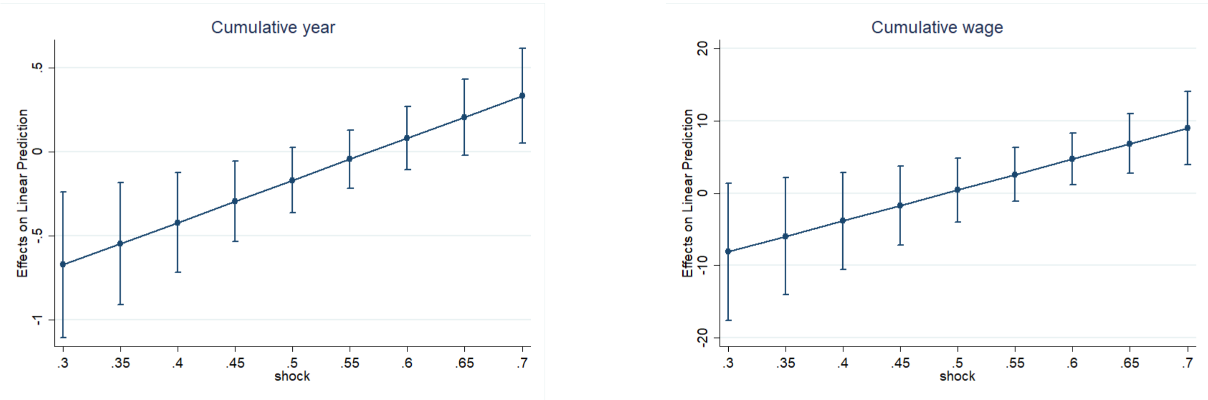
Figure 17: Working status of high skilled individuals in 2007
Notes: The shares are computed based on high skilled workers, and every year I tracked their working status up to 2015.
Source: CSWL 2006-2017



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

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

Figure 18: Impact of contraction of the construction sector employment. Weighted shock
Notes: Sample restricts to workers aged 29-42 and working in the construction sector in 2007. Coefficients of the shock using as outcome variable an indicator if the worker changed residence province or sector on a rolling basis. a) Out of the construction sector b) In a province different than the residence in 2007. Additional controls by initial share of construction sector employment, Bartik type variable, demographic characteristics and interactions
Source: CSWL 2006-2017

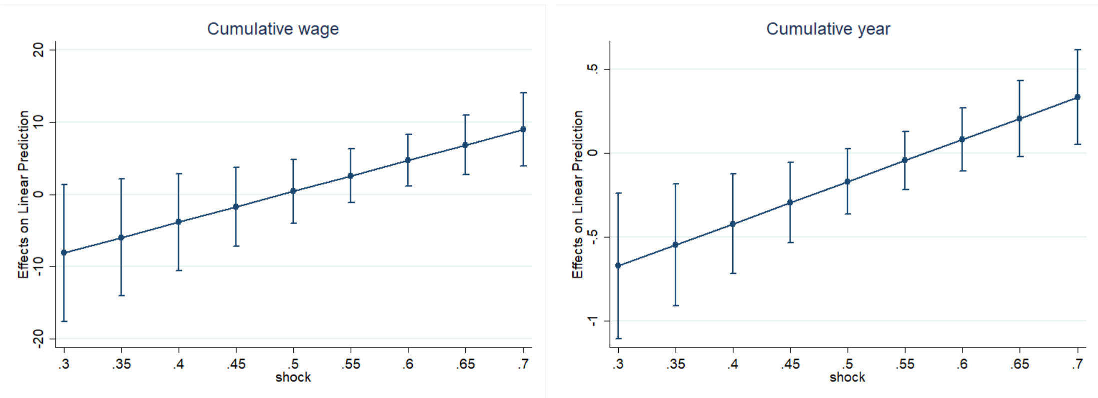


(a) Cumulative year (b) Cumulative wage

Figure 19: Marginal effect

Notes: Marginal effect.

Source: MCVL 2006-2017



(a) Cumulative wage, 2007-2012 (b) Cumulative years worked, 2007-2012

Figure 20: Marginal effects of the reallocation probabilities

Notes: The sample is restricted to native workers aged 20-50 years old in 2007 and working in the construction sector. Cumulative variables are computed between 2007 and 2012. Wage is standardized by the average wage in 2006 of months with non zero earnings. Every regression controls by: gender, age, education, skill group, and foreign status, interactions of age and educational level, and interactions of age and if the last contract in 2007 was fixed-term. Additionally controls for initial experience and tenure before the Great Recession. At the local level controls for the initial size of the construction sector and unemployment rate per province in 2006, additionally a Bartik type variable which is computed without considering the construction sector and predicted values for the outside option are from a first stage **probit model**.
Source: CSWL 2006-2017

A.4 Internal migration

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

Figure 21 shows that, on average, 3.25% workers changed job locations between 2000 and 2012. At the highest point, only 4.01% of individuals worked in a different province than the previous year. In comparison, Monras (2018) show that in the United States, the proportion of Americans working in a different metropolitan area compared to the previous year was 5.4 % before the Great Recession and 4.8% after 2007.

If workers move from more exposed to less exposed regions, outflows to other provinces should increase, even if this reaction takes some periods to appear. However, figure 21 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, in order to study this further, the following results change the scope to regional movements. There are two mechanisms through which workers' population in a specific region may change, interregional mobility and movements to and from unemployment or non-employment. This relationship is expressed as:

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

The sub-index m is applied for region, and t for period. The left-hand side represents the relative change in the worker's population between two periods, which is decomposed as inflows minus outflows from each region and inflows minus outflows from a non-working condition [32].

[32] 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

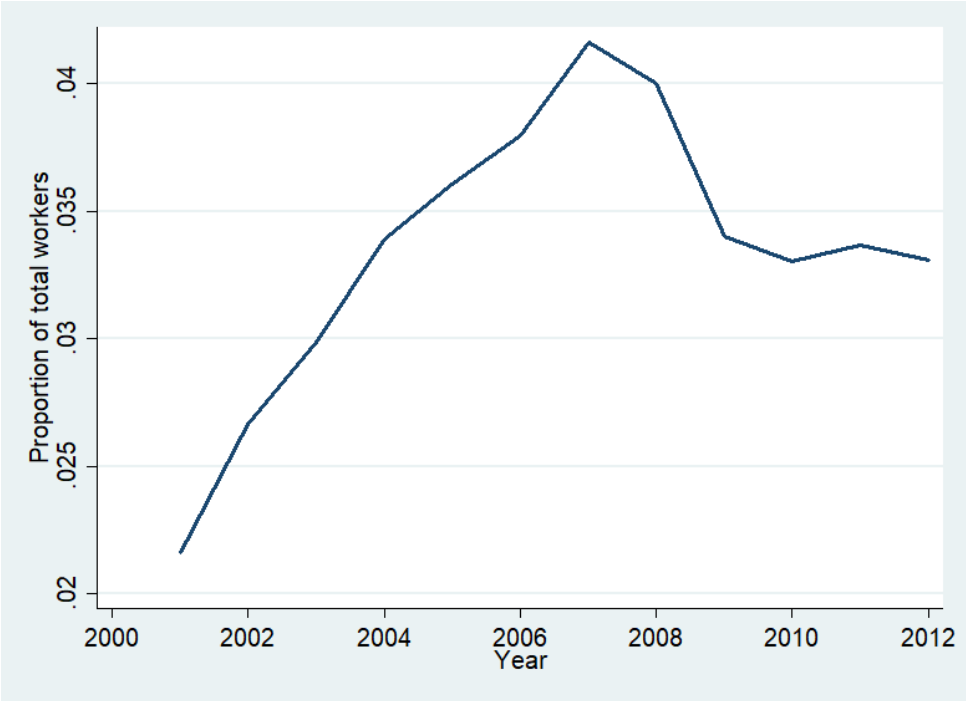


Figure 21: Share of workers change job's province
Notes: Share of individuals working in a different province with respect to the previous year, 2001-2012. The sample of workers between 2000-2012, based on sample of workers in MCVL Source: MCVL, 2006-2017

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

Given equation 10 is an exact decomposition, I can decompose the variance as how much of population growth rate in region m is explained by in-migration rates and how much by out-migration rates Monras (2018). [33] .

Consider the following regression:

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

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

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

Table 23: Decomposition variance of local population growth

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

Standard errors in parentheses

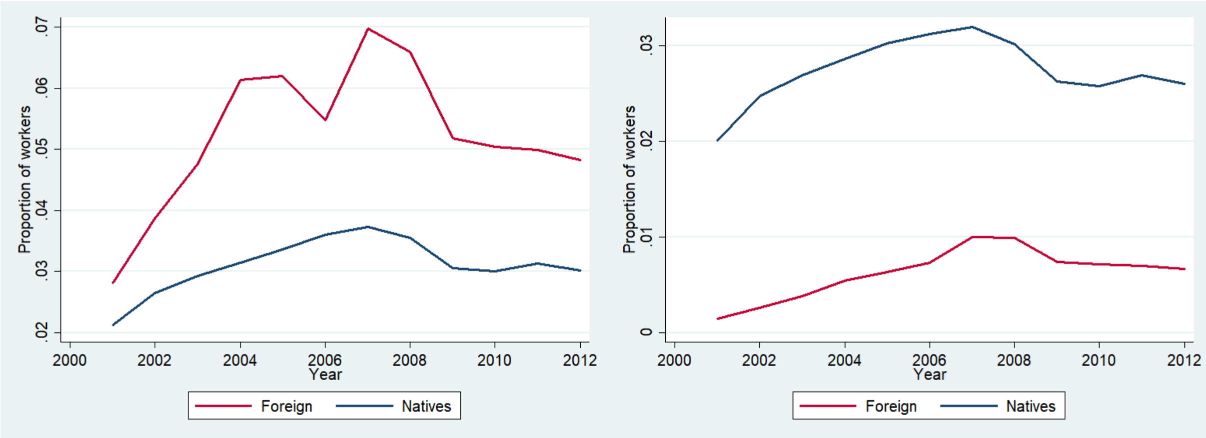
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Regression of in-migration and out-migration on region m worker's population change. Sample considers the 50 Spanish provinces between 2005 and 2008 in panel A, and after 2008 in panel B. Source: MCVL, 2006-2017

Table 23 shows worker flows from and to the non-working condition are relatively more important explaining local population growth. More than 50% of population growth variation is explained from non-employment flows, with a decrease in inflows' relative importance during the Great Recession, and an increase in outflows to non-employment. This fact is consistent with the drop in employment at the national level. Considering the local growth of workers in the construction sector, an equivalent picture is appreciated. There is a decrease in general with a decrease in outflows to non-employment.

The common idea is that foreign workers are more predisposed to migrate. This includes a more significant propensity to international and interregional migration. I will start by analyzing the proportion of foreign workers in the interregional flows. Figure **??** presents the share of movers as a proportion of all workers, divided by demographic group. Define $G \in \{F, N\}$ as the group-specific identifier, with F for foreign, and N for natives, in panel (a) I present the share $\frac{M_t^G}{P_t^G}$, where M_t^G accounts for the number of individuals in the group G working in a different province than the previous year, and P_t^G the total number of individuals from a group G at time t, while in panel (b) I present $\frac{M_t^G}{P_t^N + P_t^F}$.

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



(a) Movers by group

(b) Movers from total

Figure 22: Interregional movements

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

Source: MCVL 2006-2017

A.5 International migration

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

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

In native workers, there is a strong familiar link and wealth accumulation, which could maintain a long time of non-employment. In foreign workers, this force very likely is less critical than if an essential share of foreign workers disappears from the dataset. It is a consistent explanation to argue that they return to their home country.

Table 24 shows results from the probability a worker is not seen from sometime into the future, as assumed in the previous discussion, among them being a foreign worker implies a higher probability to disappear from the social security records, this proportion is robust on adding controls on the local conditions faced.

Also, during the first years of the Great Recession, the share of foreign workers that exit the social security records is higher than years before the Great Recession, and also during the recovery period (Figure 24)

Table 24: Probability a worker is non-employed during the Great Recession conditional con observables

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

Standard errors in parentheses

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

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

Source: MCVL 2006-2017

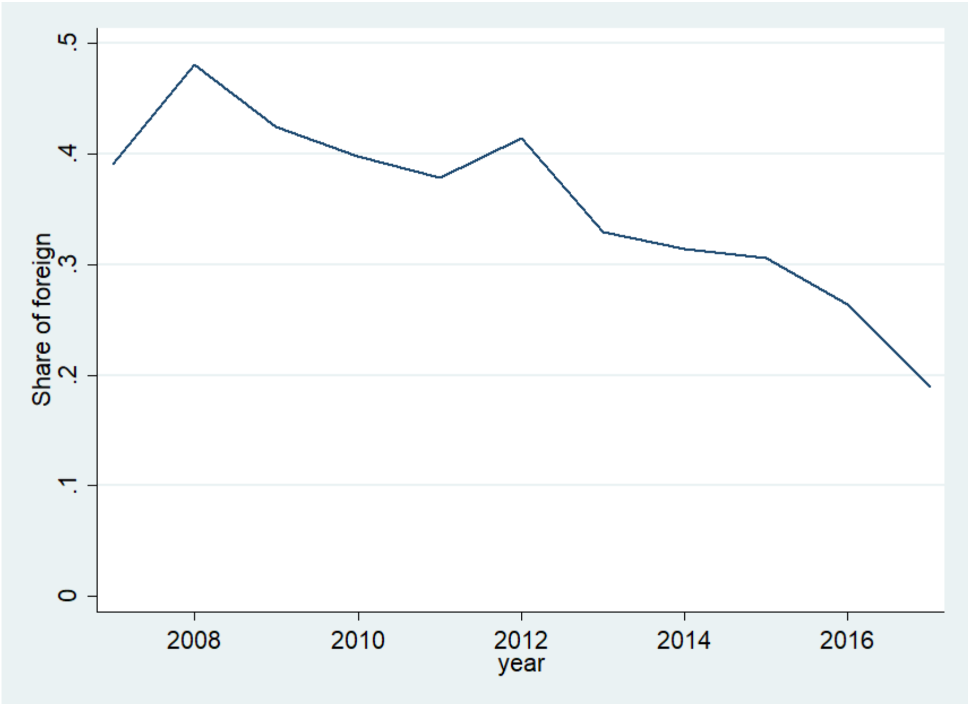


Figure 23: Share of foreign workers leaving the ss records
Notes: Share of foreign workers by year of exit from social security records of workers in the construction sector during 2007. Source: MCVL, 2006-2017

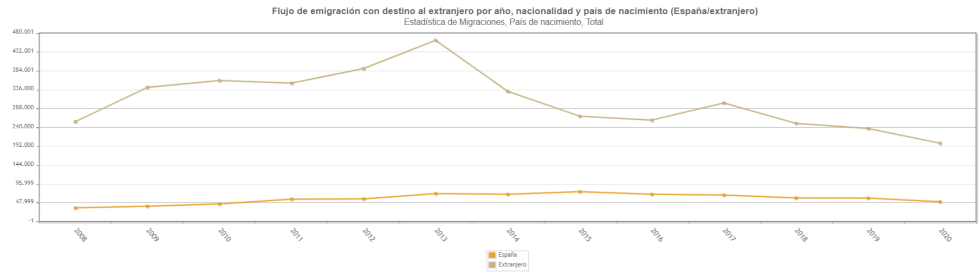


Figure 24: Emigration by country of birth
Notes: Share of foreign workers by year of exit from social security records of workers in the construction sector during 2007. Source: MCVL, 2006-2017

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