From bricklayers to waiters: labor market adjustment of Spanish workers during The Great Recession

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Abstract

This paper analyzes the Great Recession's shock on workers initially employed in the Spanish construction sector and the influence of local sectoral compositions in contributing to their subsequent labor market adjustment. The identification strategy exploits variation in the employment contraction of the construction sector across Spanish provinces and a rich set of worker characteristics available in administrative panel data (MCVL). I first show that construction sector workers in more heavily exposed areas to the employment contraction experienced a large and persistent decrease in their cumulative wages between 2007 and 2012. This impact resulted mainly from longer unemployment and non-employment spells rather than a decrease in the average wages of exposed workers. After documenting these causal impacts, I study the extent to which the local sectoral composition contributes to attenuate the shock's impact on workers' career outcomes. The results suggest that earnings losses are larger for workers in provinces where the sectoral composition provides fewer opportunities to change sectors. Furthermore, the estimated reallocation probabilities depend on the interaction of worker and regional characteristics. Workers whose characteristics are less concentrated among sectors are less affected as they are more likely to change the sector. One implication is that high sectoral concentrations in a region may impede worker's ability to adapt to economic shocks. Finally, these findings suggest that short-term labor market adjustments tend to be intersectoral rather than inter-regional, even under asymmetric regional exposure.

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1 Introduction

The Great Recession and the subsequent burst of the Spanish property bubble destroyed millions of jobs, including the most affected construction sector. According to reports from the Spanish Labor Force Survey, in the first quarter of 2008, the construction sector employed 2.7 million workers. Over the following four years, employment in the sector shrank by more than 50%, collapsing to 1.2 million employed workers by 2012. Figure 1 presents that the employment share of the construction sector declined from 13% to 6% of total employment in 2008 and 2012, respectively.

A crucial question for labor economists and policymakers is how do workers react to such negative demand shocks? In a classical contribution, Blanchard et al. (1992) find that the impact of labor demand shocks on wages and employment rates disappear in less than ten years, suggesting geographical mobility as the dominant adjustment mechanism. Contrary to the previous findings, recent studies find a much slower adjustment (Amior and Manning (2018) and Dao et al. (2017)) and that geographical mobility plays little importance on the worker's adjustment process (Autor et al. (2014) Dix-Carneiro and Kovak (2017)).

Because of this new evidence, alternative mechanisms should be studied. Workers' sectoral mobility allows workers to attenuate their labor impact by moving from an exposed sector to a growing or less affected one. Sectoral mobility has been studied more during recent years, the contribution by Yi et al. (2016), Artuç et al. (2010), Dix-Carneiro (2014), shows that even though mobility costs between sectors are relevant, labor mobility helps to attenuate the adverse effect of negative shocks on worker outcomes. Sectoral mobility has two possible effects on wages. First, the initial impact can be limited when workers leave the affected sector to a less affected or growing sector. Second, under entry barriers to other sectors due to human capital differences, the worker may receive a wage penalty or have a hard time finding a job in another sector Neal (1995). Therefore, if only a few sectors offer good opportunities to exposed workers in a given region, workers' adjustment will still be sluggish or incomplete.

This article examines sectoral mobility responses to geographic variation in the depth of the construction sector employment contraction. The first part of the paper follows Autor et al. (2014), and Yagan (2019) who study the impact of the Great Recession and the China shock, respectively, on the worker's earnings and employment trajectories. I define the worker's shock as the change in the construction sector employment share between 2007 and 2012 in the worker's province of residence. Categorize workers employed in the sector and by their province of residence at the time of the shock avoids selection problems arising from the post-shock resorting of workers among provinces and indus-

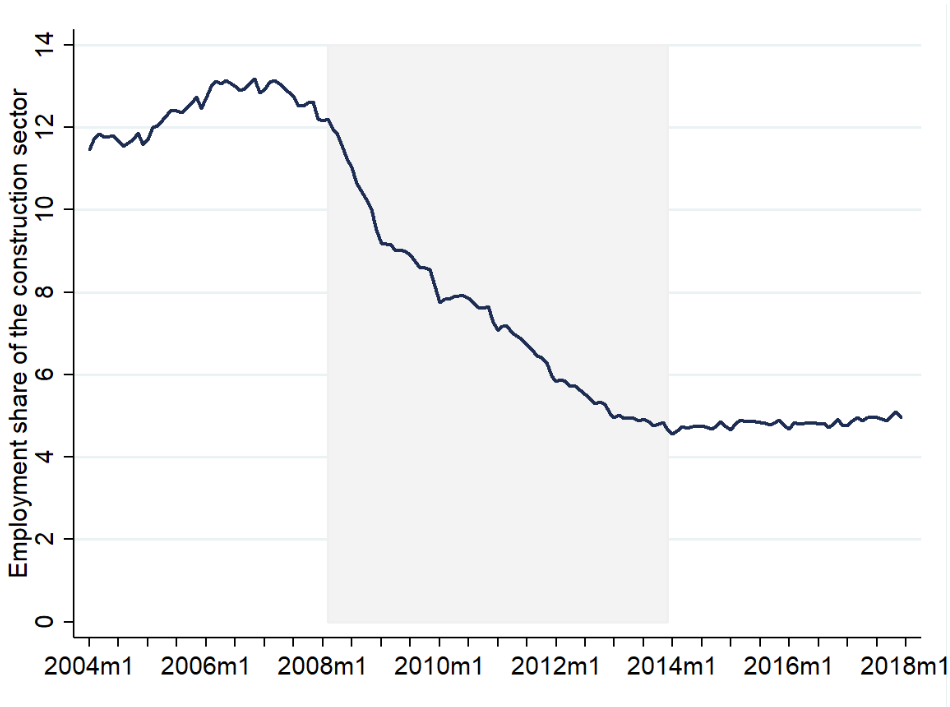


Figure 1: Employment share of workers in the Spanish construction sector, 2004-2017
Notes: Present the proportion of workers in the construction sector from January 2004 to December 2017. The data restricts to monthly observations of workers aged 20-60 years old and employed during the referenced period.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

tries. Similar workers may have very different prospects just by the size of the shock and the local characteristics of the province of residence. The second part of the paper address that question by exploit variation of the shock across provinces to investigate the contribution of the local sectoral compositions in attenuating the Great Recession's worker-level impact. To evaluate these costs, I construct an index that captures the likelihood of transitioning from the construction sector to any other sector (*reallocation index*). The measure is based on workers' characteristics and their province of residence before the shock and captures the extent to which workers may change sector to alleviate the shock's impact.

I rely on longitudinal data that tracks all the worker's labor market history and complete data on the worker's relevant characteristics to avoid potential biases arising from worker's characteristics which may correlate with the shock's severity on the earnings and employment trajectories. The Continuous Sample of Working Lives (MCVL) [2] includes the working history of a 4% of the workers affiliated to Spain's Social Security. The rich data source tracks wages and contract changes before and after the crisis, allowing the pre-shock period comparison.

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

The initial differences in employment and exposure to the employment contraction across provinces are the primary source of variation. Combined with the linked employer-employee component of the MCVL allows many interactions between worker and province-level characteristics to identify and quantify particular workers' impact and adjustment response.

The variation in incidence from the employment contraction arises from frictions to moving workers between jobs. In the absence of such frictions, wages would equalize for similar workers, and it would not be earnings differences among similar workers. The extent to which such frictions are more important to some workers is still an open question and helps understand the implications of job loss on workers' labor market outcomes.

This paper contributes to several strands of literature. First, as part of the literature on worker level adjustment to trade shocks Autor et al. (2014), Dix-Carneiro and Kovak (2017), and job displacement Jacobson et al. (1993), as there is enough evidence on the negative and persistent adverse effects of losing the job on worker's trajectories, but still less on the potential attenuation mechanisms used by workers. This article highlights how the interaction of local sectoral composition and workers' characteristics affects how workers attenuate the shock's impact. Moreover, it exploits a more sudden shock; the construction sector employment contraction, which was mainly unexpected, allows for easier identification of the impact and posterior labor market adjustment of exposed workers, mainly workers initially in the construction sector.

Additionally, relate to the literature on the estimation of worker's outside options Schubert et al. (2019), Beaudry et al. (2012), Caldwell and Danieli (2018). I contribute by studying how adjustment opportunities are closely related to the worker's outside option may explain the heterogeneity of the shock's impact on worker's outcomes. This article exploits demographic and occupational similarity by assuming workers with the same characteristics to be perfect substitutes for the same job, which follows the results by Caldwell and Danieli (2018) on the construction of the reallocation probabilities and apply in order to study the likelihood of similar workers to change sector within the same region.

During the Great Recession, the construction sector not only experiences a big change in size. The construction sector experienced a bigger employment decline than other comparable sectors. The composition of the sector changed, and I find that the share of workers under fixed-term contracts and the share of young workers decreased. These findings are complementary to Lacuesta et al. (2020) who report an increment in dropout rates during the expansionary period driven by youths moving into the construction sector, which temporarily increased the proportion of young workers in the sector.

Exposed workers adjusted mainly through inter-sectoral mobility rather than geographical mobility. By 2015, the number of workers initially employed in construction that changed sector is four times the number of workers in a different province compared to their residence in 2007.

The employment contraction in the construction sector caused that workers initially employed in the sector suffered a significant loss in cumulative wages. A worker in the province which suffered the average employment contraction accumulates 12.97 wages less, with heterogeneity on the impact of the shock. A worker in the 75th percentile compared to the 25th percentile of the employment contraction accumulate 3.4 less monthly wages. The decline was mainly due to decreased days worked rather than a decrease in average wages. On average, workers in the five least affected provinces accumulate 290 days more with positive earnings than workers in the five most affected provinces. Heterogeneity analysis reveals native workers and young workers suffered the biggest decline, consistent with the most considerable disruption. They have a steeper earnings trajectory than foreign and older workers, respectively.

However, conditional on the shock, an increase of one standard deviation in the reallocation probability reduces the wage loss by 0.54 standardized monthly wages, which is 17% of the previous impact. This fact highlights the size of the shock and that it varies both by worker and region, as the value of their skills is more or less valuable depending on the local sectoral composition.

Finally, the previous results are robust to several sensitivity tests. Importantly, falsification exercises using the Great Recession shock, but outcomes computed over years before the Great Recession show no statistically significant relationship between cumulative wages and the regional shock. The relevance of the reallocation probabilities at 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 during the expansionary years.

The rest of the paper is structured as follows: Section 2 presents the theoretical framework. Section 3 describes the data and presents relevant descriptive statistics. Section 4 describes construction sector workers before and after the crisis. Section 6 shows evidence of the impact of the crisis on labor market outcomes and study the reallocation probabilities. Section 7 presents several sensitivity analysis and finally Section 9 concludes.

1.1 Literature review

A growing literature documents large and long-lasting consequences of job loss in different contexts: mass layoffs Jacobson et al. (1993); Neal (1995); Farber (2017); Gulyas et al. (2019), the Great Recession Yagan (2019); Mian and Sufi (2014); Bachmann et al. (2015); Nagore García and van Soest (2017), and the growth on import competition from low-income countries Autor et al. (2014); Dix-Carneiro and Kovak (2017); Dauth et al. (2014). This literature consistently finds long-lasting effects on the worker's career trajectories. However, much less is known about how do workers react to such negative shocks.

Why is there evidence of the negative and persistent differences between exposed and less exposed workers to such economic shock? If labor market frictions are irrelevant, workers should reallocate to less-affected regions, mitigating the shock's impact on worker's labor market trajectories. Topel (1986), Blanchard et al. (1992) argues that local differences in exposure to adverse shocks trigger migration among regions, therefore equalizing local differences in employment and wages in a short time. However, recent evidence does not support that out-migration play a significant role in the labor market adjustment of exposed workers. Amior and Manning (2018) find that even though the migratory response is large, adjustment to shocks is incomplete within a decade. Dix-Carneiro and Kovak (2019) studying trade liberalization in Brazil emphasize the importance of geographic location determining the subsequent labor market career outcomes after a negative shock, implying that any worker adjustment occurs primarily within the region.

Different authors proposed different explanations for the minor role of geographical mobility in the adjustment process of exposed workers. Amior (2020) find that immigration crowds out the contribution from internal mobility into the adjustment process, and Huttunen et al. (2018) argue idiosyncratic life events. For example, fertility, divorce, and new relationships correlate with geographical mobility after a job loss, partly explaining the large income losses after a mass layoff.

The empirical evidence does not argue that geographical mobility plays no role in the labor market adjustment. The empirical evidence finds that groups of workers more geographically mobile contribute significantly to the region's adjustment, particularly important while studying labor market dynamics of foreign workers Cadena and Kovak (2016). However, the main response to a negative shock is a decrease in in-migration into the local area Dustmann et al. (2017); Gathmann et al. (2020); Monras (2018), and not as in classical references by a strong increase in out-migration from the exposed region.

Another strand of literature finds that workers affected by a sectoral shock, as in the manufacturing sector due to higher import competition from China, should reallocate to a less affected sector. Autor et al. (2014) obtains that those workers who leave manufacturing have a lower impact compared to workers who stayed in the sector. However, there is still much more to study about this mechanism.

Marinescu and Rathelot (2018) and Manning and Petrongolo (2017) observed that workers are discouraged by the distance between their residence and the opening vacancies, which is consistent with the low geographical mobility documented after a negative shock. Utar (2018) in Denmark, Dix-Carneiro (2014) in Brazil, and Walker (2013) in the US found that even though adjustment through sectoral mobility is still small compared to the number of workers hit by a shock, sectoral mobility plays a significant role in the labor market adjustment of workers. Then, workers who reallocate to another sector have an attenuated impact on their labor market outcomes. But why is it not seen for all the affected workers?

Yi et al. (2016) investigate the role that skill transferability and the local sectoral composition has on the movement between sectors and construct an index of labor market flexibility. This index captures how easily workers in manufacturing can transfer their skills into another sector within the same region. Therefore, it suggests that sectoral distances and local labor markets should be an important component in studying the distributional impact of negative shocks and the gains from trade in their setup.

In related literature, Beaudry et al. (2012) examines the relevance of the option value at determining the sectoral mobility of exposed workers and how changes in the sectoral composition impact the overall distribution of wages in a region as the outside option of the worker's changes. Following that idea, Caldwell and Danieli (2018) and Schubert et al. (2020) apply a more flexible definition of the relevant labor market workers face. They argue that the workers' options are not determined just by their location, as it is usually viewed in the literature of local labor markets Nimczik (2017). It also depends on the worker's characteristics and experience accumulated in the labor market.

If similar workers are concentrated in a specific industry or occupation, then the worker's options are more limited. However, the concentration of similar workers may have implications not only on workers' bargaining power. But also, workers with more options may adjust more easily after a negative shock. The idea used in Caldwell and Danieli (2018) and Schubert et al. (2020), their results exploit the concentration of similar workers in a particular labor market and study what is the impact on the wages as a way to approximate the impact of the outside option on the bargaining power of the workers.

2 Theoretical framework

In a standard model, workers hit by a negative shock leave the exposed sector or region to attenuate the disruption on their earnings and employment trajectories. In contrast, workers' wage losses depend on the type of worker and age in the absence of such adjustment. Empirical evidence reveals that workers adapt to economic shocks. However, this is not perfect, and in many cases, the workers never recover the earnings trajectory they have before the shock.

In the short term, geographical mobility costs are significantly higher than sectoral mobility costs, implying a slower adjustment through the first mechanism. In addition, recent empirical evidence finds geographical mobility is not the main response of workers exposed to negative shocks. [3] For these reasons, in what follows, I discuss the worker's adjustment through sectoral mobility. [4] With non-negligible sectoral mobility costs, the non-arbitrage condition is that the marginal worker must be indifferent between staying in the same sector and bear the sectoral mobility cost. These switching costs differ on the worker's characteristics, which affects the likelihood of moving. This section aims to provide a theoretical background for the worker's transition process after a shock and to what extent these costs vary by region and worker's 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, and workers are mobile across sectors but immobile across regions. The workers face a continuum of competitive firms, the total measure of workers and firms are 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 from worker's death or by opening new vacancies due to expected firm growth. Posted vacancies contain a take-it-or-leave-it wage offer, with the posted wage equal to the firm's wage to similar workers with characteristics X_i. The prior implies that in the absence of

[3]e.g. Autor et al. (2014) Yagan (2019) Dix-Carneiro and Kovak (2017)

[4]Appendix A.4 provides evidence that this is a plausible assumption in this context.

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 the other sector's are assumed to be all equal but vary the region $\tilde{w}(r)$. [5]

In the spirit of Burdett and Mortensen (1980) I assume job seekers randomly receive job offers within their labor market [6]. 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 understates 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 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 collect their wages. Unemployed workers get job offers randomly, in case they receive an offer they accept it [7]. 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}). 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

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

[6]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

[7]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.

of the wages in that sector $\tilde{W}(r)$ [8]. Additionally, workers may receive offers from firms in the construction sector, the probability is captured by the employment share of the sector in the region σ^r_{cs}. If the worker did not receive an offer from a firm in the construction sector, or a firm in another sector the worker remains unemployed and have a payoff equal to zero 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):

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

The worker's shock attenuation depends on the opportunities to reallocate exposed workers into another sector and partly from the reemployment into 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. In the other extreme, if workers cannot change sector workers alternate between employment and unemployment periods; the shock's impact is just the future earnings discounted by the probability that they would lose 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:

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

Then, for agent i we 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:

$$E_i = f(X_i, r) + \mu_r \theta^r_i + \mu_r \mathbb{P}(X_i, r)\delta^r_i$$

.

In the previous expression $f(x_i, r)$ is a function of the worker and regional character-

[8] 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

istics that define the earnings trajectory of worker i. The parameters of interest are θ_i^r, which measures the impact in terms of pre-shock earnings on the labor market trajectories, and δ_i^r, which accounts for the attenuation of the shock conditional on μ_r.

The term $\mathbb{P}(X_i, r)$ is key to study the interaction between worker's characteristics and the sectoral composition at the local level. In what follows, I introduce a brief discussion about 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 home, as revealed by Marinescu and Rathelot (2018). Next, I will propose the measure for reallocation probabilities which exploit the similarity between the worker's characteristics and the sectoral composition. This approach considers workers' opportunities are defined by the relative size of each sector, but also by the likelihood workers would move to each sector conditional on their characteristics.

Reallocation probabilities: Determine the set of relevant options of the workers hit by a negative shock required to define what is the proper labor market of the worker. Using the local area as the worker's labor market in practice captures most of the job mobility patterns of workers. However, it does not consider the possibility of workers changing sectors and occupations. Additionally not all the 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.[9]

The reallocation probabilities depend on the sector's employment size and the probability that workers with similar characteristics are employed in each sector. This implies determining the probability that workers with similar characteristics are matched to a firm in each sector. To simplify this comparison, 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 observing a worker with characteristics x and a firm in sector j matched in equilibrium. Which is defined as:

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

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

This measure is applied to determine 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 similar workers, implies that $P(f|i) = P(f|i')$, and exploiting that both the firms and workers have a unitary measure $P(f|i) = P(f,i)$ [10].

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, $P(j|i) = \frac{P(J=j,X=X_i)}{P(X=X_i)P(J=j)}$. [11] The equation 4 captures the likelihood that a worker i will receive an offer from a firm in sector j. The firms in the local area r are grouped in different sectors. Now, by adding over all the sectors and weigh each propensity by the sector's employment share. The previous captures the random matching feature of the framework, as the random offers to the worker depend on the sector's size and the likelihood to work in the sector conditional on their characteristics X_i.

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

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

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

The reallocation probabilities vary between and within regions depending on the characteristics of workers. The intuition behind this is that the set of available jobs may depend not only on the worker characteristics but also on the regional sectoral composition. In other words, conditional on the worker characteristics X_i sector j may be a better option if the sector is sufficiently big in that region.

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

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

2.1 Empirical predictions

1. In the absence of attenuation to the shock, how steep are the earnings trajectory of the worker. Larger is the shock's impact. From the framework, it is obtained that higher is $V_{t+1}(X_i)$, steeper is their earnings profile, and the shock causes a larger disruption on their earnings trajectory.

2. Even though workers have a large shock, if they have good prospects in other sectors, i.e., they have a large $\mathbb{P}(X_i, r)$ that makes workers follow a new trajectory in another sector and face a minor impact from the shock. The intuition behind this is that workers with a low sectoral reallocation probability spend more time looking for another job and have a larger burden on their earnings profile.

3. The shock's impact varies both by worker characteristics and by regions. Different reallocation probabilities explain this. Workers may have a different valuation to their characteristics which impacts the attenuation of the shock.

3 Data

The primary data source is the 2006 to 2017 editions of the Continuous Sample of Working Lives (CSWL) [12]. This rich dataset with a longitudinal design is built from Spanish administrative records matching social security, income tax, and census records.

The raw data constitutes a non-stratified random sample of 4% of Spain's Social Security records population. The observational unit is working status changes since the first employment spell or since 1962 for earlier entrants. Any individual present in a previous wave and still registered with the Social Security administration remain in the following waves. However, when some of these individuals are no longer affiliated with the Social Security Administration, they will be substituted with new members.

Earnings information from social security records is available from 1980 or since the beginning of a worker's working life for earlier entrants. This information is upper and lower bounded, and the limits are updated every year, depending on inflation and labor market conditions. In addition, earnings information from tax records is available. However, this starts from 2006 to 2017 only for sampled workers on each edition. As the earnings data from tax records is uncensored, if available for the individual, all the results will be constructed based on tax data earnings information. Otherwise, it will be used information from social media security records.

[12] In spanish Muestra Continua de vidas laborales

The advantage of using several waves of the CSWL is that expanding the sample with people affiliated with Social Security one year but not on previous editions allows increasing the number of tracked individuals and allowing additional years of income tax information.

From the CSWL, I built a monthly panel covering from 2000 to 2017. This data combines individual, firm, and job characteristics. It includes gender, educational level, date of birth, activity sector at the two-digit level, province of the establishment, occupational contribution group, and monthly wages or unemployment benefits.

The raw data has information on each spell's entry and exit date. I built individual experience based on the number of days between the beginning and end of each spell during their working life and later helped construct a proxy for the number of monthly days worked.

A disadvantage of the CSWL is the lack of information on hours worked. Having information on hours worked would allow the computation of hourly wages and study additional sources of adjustment. Therefore this article focuses on a variation in daily wages. The monthly days worked allowed to correct the monthly wages by a variation on days worked during each month; this exploits the number of days between each working spell's start and end. Also, when necessary, I control the type of contract (full-time or part-time contract).

3.1 Sample restrictions

I restrict 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 autonomous workers due to the lack of reliable information on wages and days worked. The regional information considers only the 50 Spanish provinces, excluding the two autonomous cities of Ceuta and Melilla, from which the sample would be small.

The earnings information from tax records in the Basque Country and Navarre are not included. These autonomous communities collect income taxes independently from the national government of Spain. Therefore, in such cases, the information relies on Social Security records.

Additionally, two sub-samples are constructed. The descriptive evidence is built from the complete monthly panel, labeled as the complete sample. This dataset is a monthly panel of observations from January 2000 to December 2017 for workers aged 20 to 60 years old, with at least one working spell during each month. If it is not explicit, this restricts to information from active workers. Depending on the objective, this sample is further restricted to workers in the construction sector or yearly observations, but this will be made explicit when necessary.

The complete data set comprises, on average, 509,856 individuals. Which varies as the unemployment rate and participation evolve during the study period. In particular, the Great Recession, which affected the number of individuals registered in the Social Security records. Additional to these changes, the proportion of young workers in the data decreased, from 27.94% between 2005 and 2007 to 17.05% in 2013-2017 [13] . The proportion of female workers in the sample went from 43% to 47,51%; the increase in female labor force participation is consistent with the increase experienced in the last decades in most western countries and, in particular, the increase in Spain, even though there is a deceleration to this trend during the Great Recession. Guner et al. (2014).

To estimate and describe the shock, the sample is restricted to workers with high attachment to the construction sector before the recession. These individuals are more likely to be affected by the employment contraction of the sector. This sample keeps native workers in the construction sector for at least 12 months between 2005 and 2006 and a valid spell in 2007. This data set is labeled as the estimation sample. The primary analysis computes the cumulative wages between 2007 and 2012. Then, further restricts individuals aged 20 to 55 years old in 2007 to avoid mechanical changes in cumulative wages due to workers' early retirement.

Earnings information is based on wages from tax records; if a worker has no information from tax records, then wages from social security records are used. Wages are deflated using the price index with 2009 as the base year.

4 Description of the Construction Sector

Table 1 presents descriptive statistics from the workers in the construction sector before and after the Great Recession. Workers in fixed-term contracts are overrepresented in the sector; they represented 64.1% of total employment in 2007, with a decrease of 28.6% in 2012. 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, and Spain, the OECD country with the highest share of workers under a fixed-term contract at the time. [14]. Bentolila et al. (2012) argue this flexibility promoted the expansion of the construction sector. Temporary contracts were a policy to decrease unemployment as it increases the flexibility of hiring employers. However, these

[13]Youth unemployment (ages 25-24) increased steadily during the Great Recession attaining more than 50%Verd et al. (2019)

[14]See https://www.eurofound.europa.eu/publications/blog/the-rise-of-temporary-contracts-in-europe

Table 1: Descriptive statistics of the construction sector employment

	2004	2007	2012	2017
Age				
24<	0.109	0.095	0.036	0.023
24-35	0.409	0.409	0.325	0.219
35-45	0.278	0.285	0.355	0.379
> 45	0.204	0.211	0.284	0.379
Mean age	35.968	36.295	39.274	41.859
Education				
Below secondary	0.779	0.768	0.689	0.703
Secondary	0.160	0.165	0.205	0.194
Tertiary	0.061	0.068	0.106	0.104
Type of contract				
Part-time	0.033	0.034	0.071	0.085
Fixed-term	0.709	0.650	0.476	0.515
Foreign born	0.144	0.249	0.173	0.185
Occupations				
Very-high skilled occupations	0.018	0.020	0.042	0.037
High skilled occupations	0.041	0.043	0.072	0.063
Medium-high skilled occupations	0.055	0.057	0.084	0.070
Medium-low skilled occupations	0.614	0.622	0.642	0.651
Low skilled occupations	0.272	0.258	0.160	0.179

Notes: Table reports characteristics of workers in the construction sector.

Source: CSWL, 2006-2017

contracts are more vulnerable to the business cycle. Evidence of this is the sharp decrease in the construction sector during the Great Recession.

Additionally, table 1 shows the proportion of young workers, low-skilled, and foreign workers decreased after the Great Recession. Nevertheless, do this evidence shows these workers were the most affected during the Great Recession? Not necessarily, workers with those characteristics were the most vulnerable, which is evident from the employment decline of each sub-group. However, the sector also experienced a change in the composition of newcomers (table 9) as well as leavers (table 10). Both tables reveal that fewer young workers enter the sector and the proportion of workers leaving shifts overtime. The following sections further study the changes experienced by the sector and which individuals suffered the most significant impact on their earnings and employment trajectories.

4.1 Employment decomposition

Spain registered a long period of economic growth between 1995 and 2008, which, combined with institutional changes and large migration inflows, led to the construction sector's employment growth followed by a strong decline during the Great Recession. The observed employment slump in the construction sector triggered fluctuations in the composition of worker flows. This subsection aims to disentangle which components were responsible for this contraction.

This subsection exploits shifts in employment from one year to the next of workers in the construction sector. The focus is on the sector's inflows and outflows towards non-employment, unemployment, and outside the construction sector between 2004 and 2017.

The results from this decomposition are presented in figure 2. Panel (a) and (b) show inflows and outflows, respectively, and the construction sector's yearly percentage change in employment.

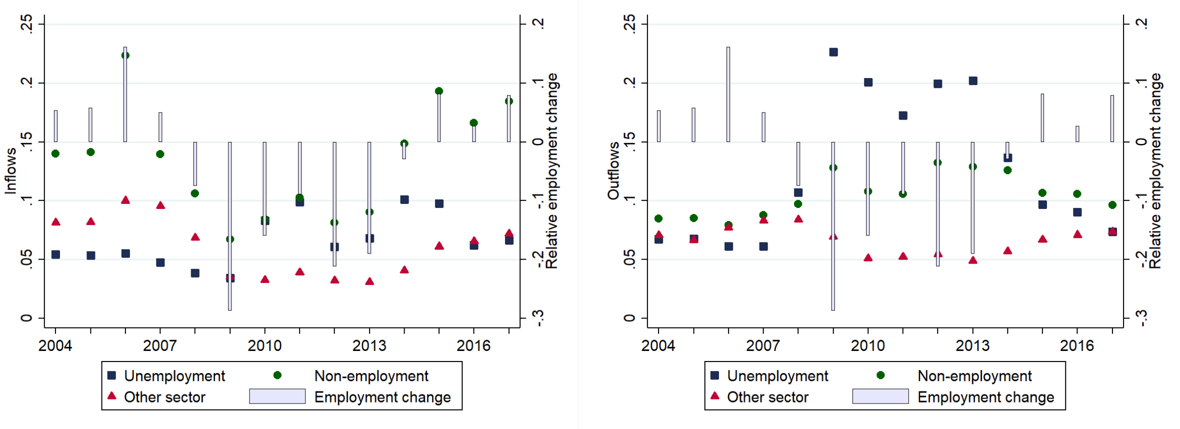
Panel (a) presents evidence of large inflows from unemployment, non-employment, and other sectors before the crisis, consistent with the changes mentioned above. Before the Great Recession, inflows from non-employment explain most of the employment growth. The inflow of foreign workers accelerated since 2000, stimulated this Moraga et al. (2019). As shown before in table 1 14.4% of workers were foreign in 2004, increasing to 24.9% before the Great Recession. The increase was a consequence of the relatively high salaries paid to low educated workers during the expansionary period Lacuesta et al. (2020).

Panel (b) shows that before the Great Recession, outflows from the construction sector into non-employment, unemployment, and other sectors exhibited a similar evolution, a situation that stopped in 2007. The moves to unemployment increased abruptly, mainly explaining the increase in overall outflows. The second is outflows to non-employment, consistent with an increase in international migration, workers moving to the informal sector, self-employment, or leaving the labor market.

The construction sector's employment contraction is similarly explained by decreased inflows and increased outflows to the sector. That establishes that the employment contraction of the sector implied a reduction of workers moving to the sector, which may not affect workers and an increase of workers losing their job. [15]

Figure 2 shows outflows into other sectors are not a major force explaining the employment decline. However, aggregate flows obscure compositional and dynamic decisions made by workers during this period. In the following exercise, I restrict my analysis to workers in the construction sector in 2007 and follow 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

[15] During the period 2008-2013 a 42.2% explains the change in employment change on the reduction of inflows and 57.7% from an increase in outflows



(a) Inflows to c.s.

(b) Outflows to c.s.

Figure 2: 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 with respect to population in $t-1$ Panel (b) Inflows to construction sector that one year before were in another sector, non employment or unemployment with respect to workers in $t-1$. Sample is restricted to yearly observations between 2003 and 2017 of workers aged 20-60 years old.

Source: CSWL 2006-2017

are unemployed/non-employed.

Results in figure 3 highlight three main facts [16]. First, most of the construction sector workers during the bust of the housing bubble lost their job. These workers remained out of the Social security administration records, including unemployed workers, international migration, work in the informal sector, or remain out of the labor market. Evidence presented in Bentolila et al. (2017) shows that actually, the increase in unemployment is one of the main forces, documenting a sharp increase in long-term unemployment during the years of the crisis. This is explained by shifts in the relative demand for skill and the distribution of employment by industry from the construction sector's employment contraction.

Second, movements to another sector are increasingly more important over time. Consistent with costly sectoral mobility, both as a decision to change sector is not immediate, and also it takes time for workers to find another job. In contrast, the number of workers remaining in the construction sector decreases; this is appreciated from the decline in the share of workers staying in their original job and the decrease in the percentage of workers moving to a different firm within the same sector.

Finally, interregional migration is a secondary adjustment mechanism. In 2008 5.5% were in a different province with respect to one year before. Nevertheless, between 2008

[16]The share of workers non-employed seems exceptionally high. To study this Figure, 17 tracks workers using a more restrictive sample; the sample considers native workers with ages between 20 and 45 years old and employed in the construction sector in 2007. Using this sample, the qualitative results are maintained

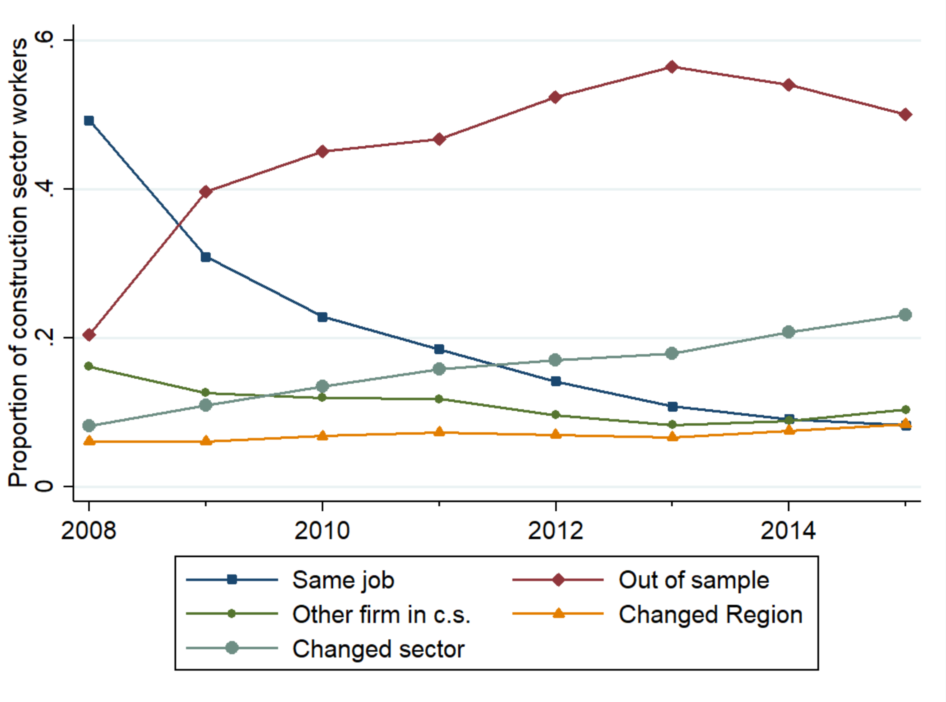


Figure 3: Working status of individuals employed in the construction sector in 2007
Notes: The shares are computed based on workers in the construction sector in 2007, and every year I tracked their working status up to 2015.
Source: CSWL 2006-2017

and 2012, this percentage does not increase much. But, it gets relatively less important over time, an expected result due to the low interregional migration documented historically in Spain.

The following sections focus on sectoral mobility as an adjustment mechanism, and studies this systematically, recent empirical evidence find geographical mobility as an adjustment mechanism is slow, therefore additional forces should be studied. The reduction of inflows from other regions is essential but cannot be considered the workers' primary adjustment mechanism. However, instead, a force contributing to the local labor market adjustment, This result is found not just in Spain, but also in Dix-Carneiro and Kovak (2017) in Brazil's case and Dustmann et al. (2017) in a supply shock to German regions. [17]

Different forces explain the decline of the construction sector employment. Previous results showed that both outflows from the sector increased and inflows into the sector decreased, highlighting the sector lost its place as a generator of jobs. The dynamics of this decline pointed to a sharp increase of workers leaving the sector between 2007 and 2008. But also an increasing proportion of workers previously in the construction sector

[17] Study interregional migration is out of the scope of this paper, but consistent with the evidence on this section it is not the main adjustment mechanism of workers during the Great Recession. Additional analysis on this topic is on the appendix in subsection A.5

(a) Mean age

(b) Share of foreign workers

Figure 4: 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

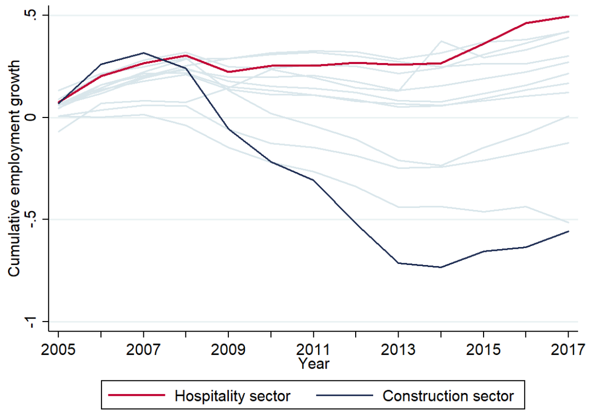
Source: MCVL 2006-2017

who found a job in another sector. However, which workers suffer the most significant welfare loss? And in particular, which workers are more likely to be found on each working status after the crisis?

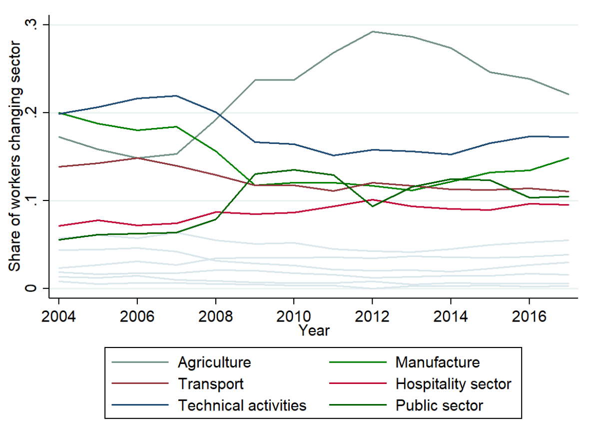
Figure 5 study the age and proportion of foreign-born workers on the different categories of working status in 2013. These results use the same sample of workers as above. Results show the workers who changed region or sector are younger than those who stayed in the construction sector or get non-employed. Young workers have been persistently in temporary work. For some of them, this is a stepping stone [18], but for some, they follow a concatenation of temporary jobs, never finding a stable job, which makes that these workers are more likely to lose their job. 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.

Foreign workers are over-represented among the workers that remained in a non-working condition or changed region. Consistent with a higher propensity of foreign workers to migrate. This evidence suggests that foreign workers in the construction sector are more likely to disappear from records in an exposed region. The data does not allow to track workers leaving Spain. Then, individuals returning to their home country may reduce their cumulative wage, not necessarily because they worked less or received

[18]Check: Are Temporary Jobs Stepping Stones or Dead Ends? A Meta-Analytical Review of the Literature



(a) Cumulative employment growth



(b) Movers by sector

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

Notes: Panel (a) Sector of destination as 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

a lower wage, but because they are no longer observed. Therefore, the estimation sample will be restricted to native workers to avoid such bias. [19]

Where are the affected workers going? Spain, as explained before, experience many changes during the period of economic expansion, institutional as the higher flexibilization on the utilization of temporary contracts, substantial inflows of foreign workers, and higher availability of land for construction. All those ingredients led to an important growth of the construction sector employment. After the Great Recession, Spain experienced a new change in its industrial composition, particularly the growth in the service sector. Among all the industries, the ones related to accommodation and restaurants experienced a significant increase. As presented in panel a) of figure 5, the construction sector experienced the biggest cumulative decline during the Great Recession with no signs of recovery to the pre-recession employment while at the same time employment in the hospitality sector spiked.

But does it imply workers reallocate from the shrinking sector into the hospitality sector? Not necessarily, the employment contraction in the construction sector was suffered differently in all the Spanish provinces. Still, those provinces have a different sectoral mix, which makes exposed workers depend on the local level's relative demand for their skills. Therefore, the adjustment depends not only on the cost of changing the sector or the likelihood of individual workers to change the sector. But also on the opportunities given by the sectoral composition and the relative demand for their skills. As an exploratory exercise panel b) of figure 5 shows how workers initially in the construction

[19] Check he appendix for discussion

sector moved to very different sectors. In the first place to agriculture, livestock, fishery, and related activities increased during the Great Recession and are placed as the first activities receiving workers previously in the construction sector. But, also there is an important mass of workers moving to manufacture, hospitality, technical activities and even to the public sector. Future sections explore how the interaction of regional and individual characteristics helps to the adjustment of exposed workers.

4.2 Province level impact

The employment expansion was not uniformly distributed among Spanish provinces, neither was the employment contraction in the construction sector; this creates disparities in how intense was the shock for the workers depending on the province of residence.

Before the Great Recession the initial employment share, and the employment contraction during the downturn varied among the Spanish provinces [20]. These differences in exposure are the basis for the empirical analysis as allows to study differences on exposure to the employment contraction of the construction sector on workers career outcomes.

The initial employment share of the construction sector by province ranges from 6.8 to 24.14 percent (figure 6), such that the employment share is higher in the southern provinces [21]. For example, in Gipuzkoa, Araba, and Barcelona, the construction sector employed less than 10% of workers, while in the south Ciudad Real, Huelva, and Malaga, it was more than 20%. Also, the employment contraction varied between 14.7% and 70.3%.

5 Worker level impact

This section extends the previous results by shifting the focus from aggregate market level reactions to adjustment at the worker level. I estimate the difference in outcomes among ex-ante observationally similar workers except for their province of residence before the Great Recession. Decomposing changes in earnings across different margins reveals where the adjustment process frictions arise and which types of workers face larger adjustment burdens.

The intuition in this section follows the presented theoretical framework. Workers in hard-hit regions are more likely to be dismissed. Besides, these regions experience an

[20] 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

[21] The same graph using labels for each province is in the appendix (Figure 15) and maps (Figure 19)

Figure 6: Change in share of workers in the c.s. during the GR by province
Notes: Change in the employment share of the construction sector by province between 2007 and 2012 against employment share in 2006 —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

increase in workers actively looking for another job. These two forces move in the same direction, affecting exposed workers' labor market prospects and limiting the availability of open positions for workers leaving the construction sector and for workers indirectly affected by a loose local labor market. The base year for comparison is 2007, as officially the contraction started in the last quarter of 2007.

I begin by examining the impact of the local employment decline of the construction sector on cumulative earnings and employment. This section study four outcomes over the sample period: total labor earnings, the number of years with positive labor market earnings, average earnings, and job turnover. Table 11 describes variation for these outcomes. For the sample of workers not employed in the construction sector before the Great Recession, the average worker had positive labor market earnings in 4.6 years of the 6 years, cumulatively earned 61.56 times their average monthly wage in 2007. In comparison, workers initially employed in the construction sector had positive earnings 58% of the period between January 2007 and December 2012, three-fourths of the time employed for workers, not in the construction sector. Both groups of workers are composed differently. In particular, workers in the construction sector are less educated, and male and foreign workers are overrepresented in the sample of construction sector workers.

The baseline specification takes the form:

$$y_i = Shock_i^r \beta_0 + \mathbf{X}_i' \Delta + \epsilon_i \tag{6}$$

The dependent variable y_i is the labor market outcome of individual i. In particular, the cumulative monthly wage, cumulative years worked, or the average monthly wage over 2007 to 2012. The cumulative wage embodies the sum of non-zero wages from January 2007 to December 2012 normalized by the average wage in 2006. The normalization by average earnings is equivalent to the applied by Autor et al. (2014) and Yagan (2019). Normalizing by worker's initial earnings provides a measure for assessing the shock's impact on earnings evolution. The advantage is that the future results have an interpretation in terms of pre-shock earnings. The cumulative working days is the aggregated number of days worked between the start and the end of the spell, a proxy for the number of days worked during 2007 and 2012. This is later expressed as cumulative years worked for ease of interpretation. Finally, the average yearly wage is computed for 2007 to 2012, as the worker's average non-zero earnings during that period.

The vector X_i contains pre-shock worker and regional characteristics, accounting for gender, age, education, occupational skill, all measured for worker i in 2007. Additionally, a Bartik-type variable to account for differential demand shocks in other sectors within the same province. [22].To control for regional components, which may be related to the initial employment size of the construction sector, the main specification also controls by the employment share of the construction sector by the province in 2006 and the regional unemployment rate in 2006.

This exercise compare workers with similar demographic and regional characteristics, some of are not directly affected by the employment decline in the construction sector and some of whom directly lost their job due to that reason. If labor markets are frictionless, such that workers can costlessly change industries and obtain identical compensation in alternative lines of work, we will see no earnings or employment impacts from exposure to the local shock, and at best the impact on earnings and employment will be similar for workers in the construction sector and not in the sector.

Table 2 presents baseline estimates of equation (6) for the impact on cumulative earnings, cumulative years worked, and average wage between 2007 and 2012 on highly attached workers to the construction sector and workers in the rest of sectors. Odd columns study the sample of non-construction sector workers and even columns to workers initially in the construction sector. Column (1) finds a negative but not statistically significant

[22]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: Labor market impact of the bust in the construction sector

	Cumulative wage		Cumulative years		Mean wage	
	(1)	(2)	(3)	(4)	(5)	(6)
shock	-2.003	-24.89***	-0.0911	-1.440***	-0.0207	-0.145***
	(2.553)	(2.957)	(0.210)	(0.183)	(0.0380)	(0.0329)
$Empl.ShareCS_{2006}$	-34.22***	-23.61*	-2.290***	-2.066**	-0.0906	-0.0323
	(6.283)	(11.00)	(0.496)	(0.603)	(0.106)	(0.110)
Constant	77.05***	87.38***	5.147***	6.101***	1.285***	1.282***
	(1.403)	(1.883)	(0.0989)	(0.111)	(0.0200)	(0.0313)
N	304085	52671	304085	52671	304085	52671
R^2	.1027581	.1354508	.1821107	.1730574	.0328091	.0191908
Controls	Yes	Yes	Yes	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 of 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

relationship between the change in share of the construction sector by province and cumulative earnings over 2007 and 2012. While column (2) shows that, on average, workers initially employed in the construction sector accumulate fewer monthly wages than a situation in the absence of the shock. The shock ranges from 0.2 to 0.7, implying that workers accumulate 4 to 17.4 monthly wages less due to the shock. This evidence is important as it shows that the impact of the shock's exposure was higher for workers directly affected by the contraction. The impact is not explained from region-specific characteristics, as in that case, workers who were not in the construction sector would be equally affected.

To interpret the coefficient estimates, consider a worker in a province in the 25th and 75th percentile of exposure, Valencia, where the employment contraction of the construction sector was 59.34%, and Badajoz, where the decline was 45.53%. In Valencia, workers who were not in the construction sector accumulate 3.44 [23] monthly wages less than a similar worker in Badajoz. Which implies that everything else equal on average workers have a 23.29% larger impact by a larger exposure to the employment decline of the construction sector. [24]

Do this reduction stem from changes at the extensive margin (reduced years of work), the intensive margin (reduced earnings per year) or both? This question is studied in

[23] Operation: ((0.5934-0.4553)*-24.89)

[24] For a graphical representation of this comparison check figure 14 in the appendix

columns(3)-(6). Columns (3) and (4) present the impact on cumulative years with non-zero earnings, and columns (5) and (6) on the average wage over 2007 and 2012.

Column (3) shows that workers that were not in the construction sector experienced a negative but small decline in the days worked between 2007 and 2012. In comparison, a worker in the province in the median of exposure to the shock accumulated 0.76 fewer years with non-zero earnings. Finally, Column (5) shows no significant effect on average wages, and Column (6) decreases the average wage of workers initially employed in the construction 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 wage before the Great Recession. The last is not necessarily surprising as the construction sector offered high wages, which helped to attract many workers into the sector at times of boom before the Great Recession. But, it shows that workers spend more time settling into another job. [25]

Table 2 shows a negative effect both on cumulative wage and cumulative employment conditional on the initial employment size of the construction sector at the province level. This effect is appreciated both on construction sector workers and non-construction sector workers. The initial share of the construction sector controls for region-specific characteristics; among them, the ones imply that the construction sector expanded more in some regions before the crisis. Therefore, the shock's impact analyzed in the table found that areas with high initial shares of construction are worse hit over and above, which can be explained by the drop in the construction itself.

5.1 Dynamic analysis

Figure 7 plots the time series of estimated effects of the employment decline of the construction sector on employment and yearly average wages. Each year t's data point equals the coefficients from the following version of equation 6 on the estimation sample:

$$y_{it} = Shock_i^r \beta_0 + \mathbf{X}_i' \Delta + \epsilon_{it} \tag{7}$$

y_{it} is i's change in mean binary employment status from pre-recession years to year t, $Shock_i^r$ denotes the local shock to i's 2007 province of residence, and $\mathbf{X}_i$ denotes 2007 worker observable characteristics. Measuring employment outcomes relative to each individual's pre-recession mean transparently allows for baseline employment rate differences,

[25]Additional to the decrease in days worked, workers in the construction sector experience more job to job movements, consistent with workers losing their match quality after a lay-off, then they must take some job to job transitions until they find a good match, explaining part of the cumulative earnings loss (Table 12)

similar to the relative cumulative earnings outcome of Autor et al. (2014) and the relative employment by Yagan (2019). The identifying assumption is that local employment contraction of the construction sector are as good as randomly assigned, conditional on observables. The sample and independent variable values are fixed across annual regressions; only the outcome varies from year to year. The 95 percent confidence intervals are based on standard errors clustered by 2007 province.

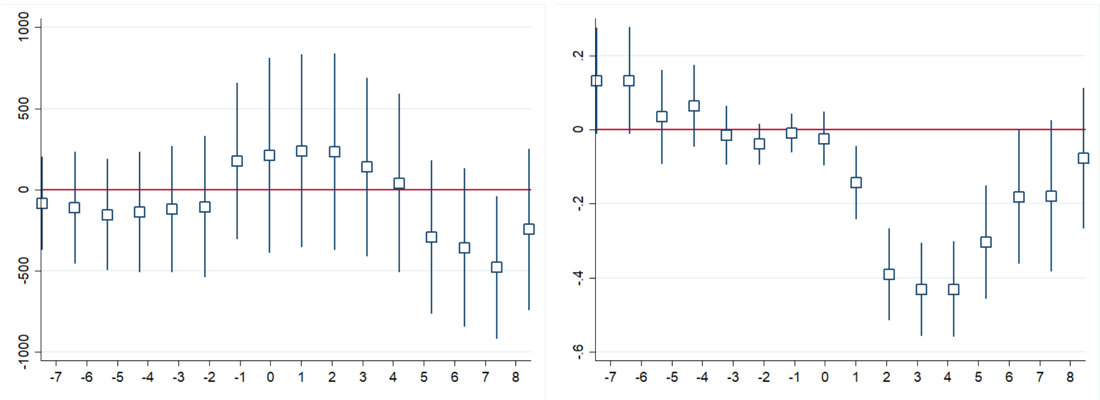
The estimating equations are identical to those in the baseline regression (Table 16, column (5)) except that in place of workers' cumulative earnings over the entire period 2007–2012, each regression computes the cumulative earnings up through the year indicated on the horizontal axis. The estimation sample is restricted to those aged 29–45 ("working age") in 2007 to confine the 2000–2015 employment analysis to those between typical schooling and retirement ages. It is restricted to Spanish citizens to minimize unobserved employment in foreign countries, which are more likely to migrate during the Great Recession.

The shock is as in the previous section, the employment contraction over the 2007–2012 period, such that the figure depicts how the impact of the shock amasses over time. The figure reveals a significant adverse effect on the probability of working during the Great Recession and a positive but insignificant effect on average wages. The impact coefficients become progressively more negative during the first years of the Great Recession, which grows rapidly up to attain the peak in 2010; the impact starts attenuating up to 2015, where there is no statistically significant relationship between the shock and the probability of having a job. The last is in contrast to the evidence on job displacement. For workers initially employed in the construction sector, their probability of being employed recovers with the overall economic activity.

The yearly average wage path in Panel (a) of Figure 7 shows a positive but insignificant effect on the exposure to the construction sector employment contraction. This effect is appreciated before the Great Recession's start encompasses a positive selection of workers in the construction sector, even in 2007, which increases during the Great Recession and rapidly attenuates. Then Panel (b) shows worker's in more exposed regions are less likely to work during the Great Recession. This result is consistent with previous evidence on fewer days worked and the lower accumulation of monthly wages for workers in hard-hit regions.

5.2 Heterogeneity of the shock by characteristics

This section analyzes impact heterogeneity across individuals. The previous section found that local employment contraction in the construction sector caused a significant impact



(a) Yearly average wage

(b) Binary employment status

Figure 7: 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

on the employment and earnings trajectories of workers employed in the construction sector. Figure 8 explores effects of the local shock on cumulative earnings across worker types. The figure's plot point estimates and 95 percent confidence intervals of the impact of local shock overall in the sample of workers initially employed in the construction sector. I find that young, low-tenured, and low initial earners bore more of the earnings incidence of the employment contraction, 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 wage 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 at widening inequalities in the labor market as the most vulnerable individuals are the ones experiencing the highest impact from economic shocks. A particularity of this exercise is that there is not a clear pattern among age groups. If any, the youngest individuals are the ones most affected by this shock. In opposition to evidence in the US presented by Yagan (2019), young workers are not more resilient to economic downturns, which could be expected from the large increase in youth inequality during the Great Recession in Spain. In more than 90% of the cases, young workers in Spain begin their careers in temporary jobs that are more easily dismissed in economic downturns than permanent and even older workers. In case of dismissal, the employer must pay higher costs.

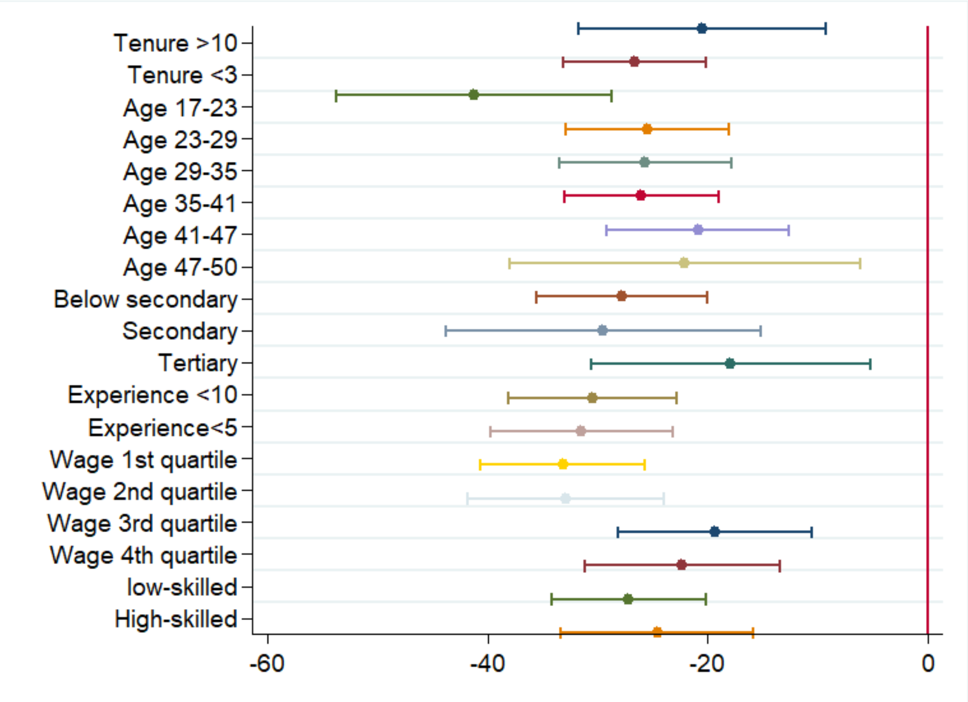
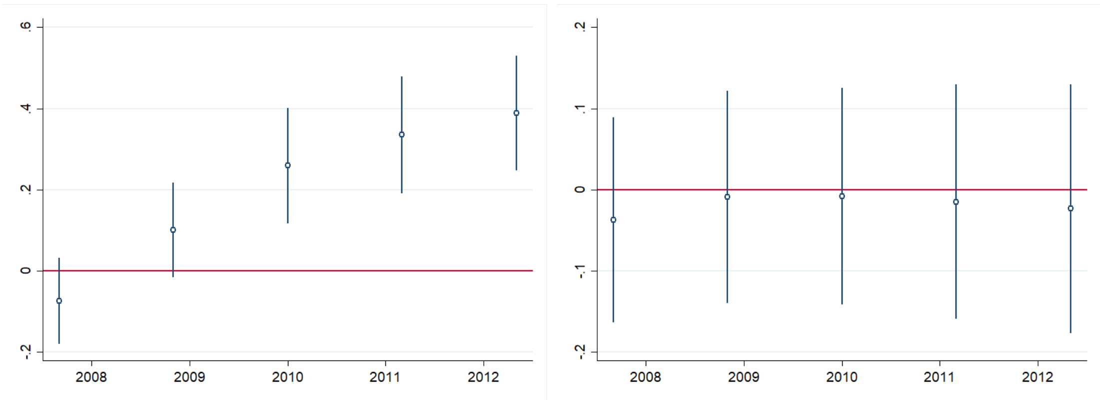


Figure 8: Impact heterogeneity

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, each coefficient is obtained from separate regressions for each subgroup. 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 9: 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

5.3 Adjustment

Transitions across sectors and geographic locations are mechanisms by which workers may adapt to the consequences of negative demand shocks. The literature provides mixed evidence on mobility responses to labor market shocks. The flow of workers across regions following changes in local labor demand appears to be sluggish and incomplete Autor et al. (2014), Dix-Carneiro (2014). This sluggishness is most pronounced among less educated workers, a subset of workers which is overrepresented in the construction sector.

As in the previous section, the shock is the employment contraction over the 2007–2012 period. The figure depicts how the impact of the shock affects the probability of change in location or sector. The figure reveals that workers in the most affected regions are also more likely to change sector, consistent with a decrease in construction sector opportunities. Within that region, the construction sector suffers a larger decline; workers reallocate into another sector. On the other side, there is not a statistically significant relationship between the probability of change province.

6 Sectoral composition and labor market adjustment

As presented in the section 2, workers' impact from the shock depends on two terms, on one side, how steep is their earnings trajectories, but on the other, on the opportunities workers have to attenuate the shock's impact. Recent literature tries to measure the outside option opportunities of workers and estimate their influence on wages. Schubert et al. (2020) mention that there are three main approaches to estimate occupational similarity, which are the basis for estimating the outside option measure: i) Worker transitions, ii) skill and task similarity, and iii) demographic and qualification similarity between occupations.

The first approach exploits the worker flows between occupations, which can exploit that transition probabilities are not symmetric but depend on how stable the transitions between those occupations are. The second approach defines two occupations as close, the more similar the skills and tasks they require. This approach exploits each occupation's task content but relies on a correct approximation of skills for each occupation. The information in the CSWL makes this approach unfeasible. In this dataset, the information on occupations is too aggregate; however, this approach also has the disadvantage of not capturing non-skill-related aspects of the feasibility and desirability of moving between occupations. The last approach defines two occupations as more similar. The more similar are their workers' characteristics. It has similar disadvantages to the previous approach, but given that it is constructed based on observed characteristics, a given job's desirability is somehow controlled.

This study follows the third approach, which is close to the methodology followed by Caldwell and Danieli (2018) and is consistent with the framework exposed in section 2. However, the last section presents evidence using the transition probabilities from which I get similar results.

6.1 Computation of the reallocation probabilities

This section describes the estimation of the reallocation probabilities. As explained before, this approach exploits the cross-sectional allocation of observably similar workers to estimate each worker's relevant options. This allocation capture the worker's ability to commute, the set of jobs within each industry suitable to the worker's skills, and the worker's demand for specific workplace amenities, all conditional on their observable characteristics.

The estimation of a given worker's option requires estimating their probability of working in each industry conditional on their characteristics. As shown in equation 5 the index depends on the likelihood of finding a worker in each sector conditional on their observable characteristics and the employment share of each sector on the province which is used as a proxy for the size of each industry.

The MCVL comprise pairs of matches between workers and firms in each sector; then, the first step is to estimate the probability of observing a match between a worker with characteristics X_i and a firm in sector j. The second step is to weigh the prior probability by the employment share of sector j in the residence's province.

$$Reallocation(X_i, r) = \sum_{j=1}^{J} \frac{\mathbb{P}(X = X_i, J_f = j)}{\mathbb{P}(X = X_i) \cdot \mathbb{P}(J_f = j)} EmplShare_j^r \tag{8}$$

$$= \sum_{j=1}^{J} \mathbb{P}(J_f = j | X_i) \frac{EmplShare_j^r}{EmplShare_j} \tag{9}$$

The estimation follows a two-step approach. The computation of probabilities from a probit model of an indicator of worker i's sector on controls for age, occupational skill group, education, gender, foreign-born status, and interactions of education and age of the worker, and gender with age. The estimated coefficients from this first stage are used to compute the predicted probabilities on the estimation sample. It represents the conditional probability of finding a worker with characteristics X_i in a given sector. Finally, I add up these predicted values using as weights the ratio between the employment share of sector j in the province r, over the employment share of sector j in the whole economy, both employment share measured at 2006 in order to avoid employment changes triggered by the Great Recession.

The first stage computes the probabilities on the complete sample of workers between 2005 and 2006 and then predicts the likelihood of finding a worker with given characteristics on each sector using the estimation sample. The employment share of each sector is computed using 2006 as base period. The reallocation probabilities are standardized to have an interpretation based on standard deviations. The histogram of the estimated measure is shown in figure 10

First, there is quite a large variation in the reallocation probabilities. To have a sense of magnitude, consider an environment where all the provinces have the same sectoral composition; in such a case, the employment share of each province is the same as the national sectoral composition. Then, all workers have the same valuation for their characteristics irrespective of the province of residence, which implies an equal valuation for their skills. In this extreme scenario, the reallocation probabilities would be equal to one for each worker, as the probabilities a worker receive an offer from each sector depends solely on the size of each sector which is the same on all the country. Now, workers who are more suitable to be matched to a firm in a given sector located in a province where such sector is big will have more opportunities to find a job in that sector. In this situation, the reallocation probabilities increase, and the workers have more opportunities. In

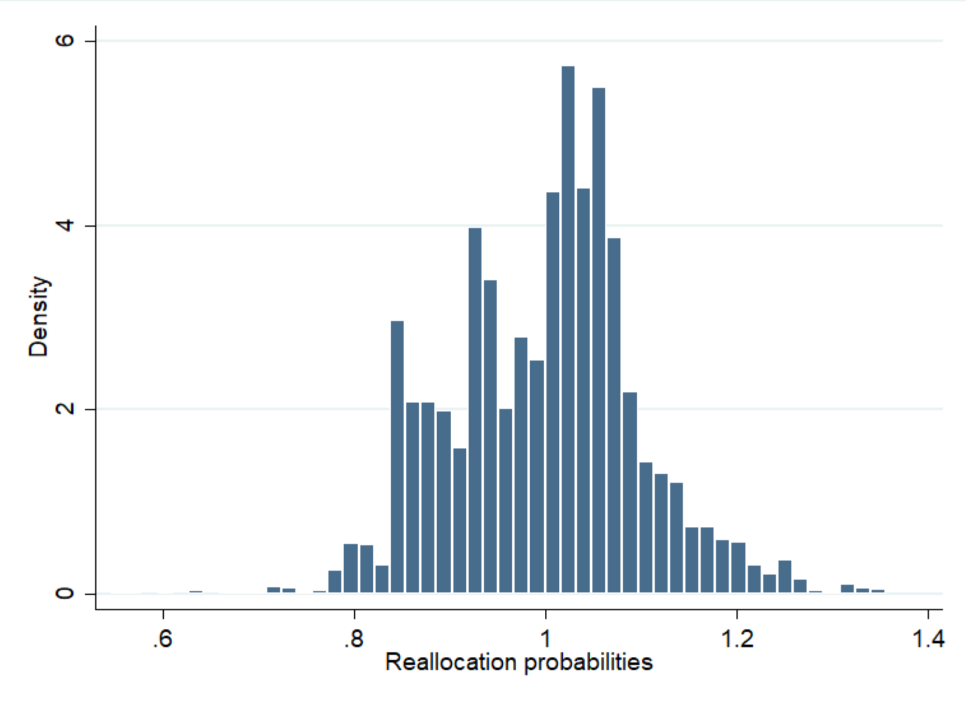


Figure 10: Histogram of the reallocation probabilities
Notes: Reallocation probabilities of workers employed in the construction sector in the year 2007.
Source: CSWL, 2006-2017

contrast, if the sector which is the best match for the worker is relatively small, the local opportunities for the worker will be smaller.

To exemplify this variation, by restricting to a similar population of workers. In particular, male workers aged 29 to 34, with secondary education a 20.7%, 32.9%, 25.1%, and 21.2% are in the first, second, third, and fourth quartile of the reallocation probabilities distribution, respectively. Therefore, even within very narrow groups of workers, there is a significant variation explained by the interaction of workers and regional sectoral composition.

Sectoral composition and the contraction of the construction sector

This subsection expands equation 6 by incorporating the reallocation probabilities, as expressed in equation 10. Following the intuition presented in section 2, the probability a worker with characteristics X_i in the region r finds a job in another sector of the same province plays a role in attenuating the shock's impact. Then, to be consistent with that idea, having a larger reallocation probabilities would imply a smaller shock's impact. How a worker in a hard-hit region alleviate the shock's impact depends on the value of their reallocation probabilities which capture the opportunities a worker has to reallocate into another sector.

$$E_i = \beta_0 + \sum_{k=1}^{4} Q_i^k shock_i^r \beta^k + \beta X_i + \epsilon_i \qquad (10)$$

Foreign workers, who are more likely to return to their home country, and workers older than 50 years old who are more likely to retire during a recession would mechanically decrease their cumulative earnings and employment. Therefore, results in this section restrict the sample to Spanish workers aged 20-50 years.

The intuition of a high reallocation probability on the workers' adjustment is that workers who face a smaller cost of entry into another sector will find it easier to change sectors, leave the exposed sector, and experience a smaller earnings loss.

Table 16 shows that workers in a province with a stronger employment contraction experienced a larger decline in cumulative wages. This impact is robust to control for observable worker and regional characteristics. Workers in a region such that other big sectors do well during the Great Recession experienced a smaller impact.

Column (2) shows a worker with higher reallocation probabilities experience a lower cumulative wage impact. As revealed in previous sections, workers in a more affected regions by the employment contraction experience a more substantial decrease in cumulative earnings explained from less days employed, wage cuts, or a downgrade from the job ladder. However, workers with a higher reallocation probability do better. In particular, workers which pass from the first to the second quatile of the reallocation probabilities experience a 8.8% smaller shock, and this difference is statistically significant at the 1%.

Similar results are found in Column (4) while studying the impact on cumulative employment. It shows that workers which move from the first to the second quartile of the reallocation probabilities showed to have a 7% smaller shock's impact.

6.2 Worker level adjustment mechanisms

This section employs the reallocation probabilities to study the role of the sectoral composition in the labour market adjustment of workers affected by the employment contraction of the construction sector.

Table 18 shows estimates on the probability of change province, change sector, and change firm within the same sector between 2007 and 2013 for workers in the construction sector in 2007. The estimated probability comes from a linear probability model, and

Table 3: Province level sectoral composition and the impact of the contraction in the construction sector

	(1)	(2)	(3)	(4)
	Cumulative wage		Cumulative year	
shock	-26.60***		-1.573***	
	(2.943)		(0.150)	
$Q_1 \cdot shock$		-28.39***		-1.636***
		(2.973)		(0.154)
$Q_2 \cdot shock$		-25.90***		-1.524***
		(3.100)		(0.164)
$Q_3 \cdot shock$		-24.92***		-1.519***
		(3.286)		(0.176)
$Q_4 \cdot shock$		-24.94***		-1.516***
		(3.069)		(0.152)
Constant	75.71***	73.66***	4.433***	4.357***
	(4.940)	(4.786)	(0.255)	(0.254)
N	48079	48079	48079	48079
R^2	.1892996	.1899767	.2922757	.2924818
Controls	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Notes: The sample is restricted to native workers aged 20-50 years old in 2007 and working in the construction sector. Cumulative variables are computed between 2007 and 2012. Wage is standardized by the average wage in 2006 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

each specification used as additional controls interactions between education and age of the worker. First, column (1) shows no statistically significant relationship between the employment contraction of the construction sector and the probability of migrating, consistent with focusing on sectoral change instead of the migration decision of exposed workers.

Column (2) of table 18 shows that everything else constant an increase in the size of the shock is related with a higher propensity to change sector. Then, an increase by one standard deviation in the exposure to the shock makes the worker 2.61 p.p. more likely to change sector. Also, consistent with the exposition in the section 2, an increase by one standard deviation in the outside option measure makes the worker more likely to change sector by 1.31 p.p. This is a 4% of the conditional probability a worker changes sector during the Great Recession. So, during the Great Recession, it is less likely that a worker finds a job in the construction sector living in a hard-hit region. In such cases, sector change costs outweigh the waiting time cost from being re-employed in the construction sector. This relationship is robust to controlling by worker's characteristics, the construction sector's initial size, and a controls for the overall performance in other sectors.

6.3 Heterogeneity

There is a possible source of concern in case particular observable characteristics drive the results from the reallocation probabilities attenuating the shock's impact. Then, this section employs two exercises to approach this. The first one controls for interactions of observable worker characteristics and the shock, in addition to the quartiles of the reallocation probabilities and the shock, analyzed in the previous section. The second exercise studies residualized reallocation probabilities, subtracting the part of the variation explained by the worker characteristics.

Table 13 and 6 shows the results.

Second exercise using a residualized reallocation probabilities

Table 4: Labor market outcomes depending on worker decisions

	(1)	(2)	(3)	(4)
	Change province		Change sector	
main				
shock	-0.255		0.622*	
	(0.396)		(0.246)	
$Q_1\cdot$ shock		-0.942		0.651
		(0.567)		(0.336)
$Q_1\cdot$ shock		-0.114		0.309
		(0.480)		(0.448)
$Q_1\cdot$ shock		-0.461		0.212
		(0.441)		(0.384)
$Q_1\cdot$ shock		0.530		1.127***
		(0.405)		(0.208)
Constant	-1.616***	-2.191***	-1.077***	-1.489***
	(0.484)	(0.587)	(0.308)	(0.256)
Observations	48078	48078	48078	48078
Controls	Yes	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 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

Table 5: Heterogeneity on the shock's impact: Cumulative wages

	(1)	(2)	(3)	(4)	(5)
	Cumulative wage				
$Q_1\cdot$ shock	-28.39***	-22.64***	-19.05***	-29.15***	-23.78***
	(2.973)	(5.585)	(4.857)	(3.020)	(5.688)
$Q_2\cdot$ shock	-25.90***	-20.20***	-16.57**	-26.71***	-21.30***
	(3.100)	(5.707)	(4.899)	(3.051)	(5.734)
$Q_3\cdot$ shock	-24.92***	-19.05**	-15.51**	-25.64***	-20.31**
	(3.286)	(5.603)	(5.146)	(3.275)	(5.892)
$Q_4\cdot$ shock	-24.94***	-18.75**	-15.52**	-25.66***	-20.33***
	(3.069)	(5.688)	(5.068)	(3.045)	(5.647)
Constant	73.66***	85.98***	74.39***	60.38***	73.95***
	(4.786)	(4.905)	(4.891)	(6.588)	(4.766)
N	48079	48079	48079	48079	48079
R^2	.1899767	.1912715	.1900769	.1902031	.190008
Controls	Yes	Yes	Yes	Yes	Yes
Additional	No	Age	Education	Skill	Gender

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 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. Each column considers an additional interaction between the shock and a worker's characteristic.
Source: CSWL 2006-2017

Table 6: Heterogeneity on the shock's impact: Cumulative employment

	(1)	(2)	(3)	(4)	(5)
	Cumulative employment				
$Q_1 \cdot$ shock	-1.636***	-1.592***	-1.174***	-1.539***	-1.218**
	(0.154)	(0.335)	(0.265)	(0.160)	(0.366)
$Q_1 \cdot$ shock	-1.524***	-1.483***	-1.063***	-1.431***	-1.109**
	(0.164)	(0.346)	(0.270)	(0.168)	(0.374)
$Q_1 \cdot$ shock	-1.519***	-1.472***	-1.053***	-1.419***	-1.102**
	(0.176)	(0.329)	(0.283)	(0.183)	(0.383)
$Q_1 \cdot$ shock	-1.516***	-1.458***	-1.049***	-1.421***	-1.100**
	(0.152)	(0.331)	(0.269)	(0.160)	(0.370)
Constant	4.357***	4.777***	4.424***	3.654***	4.383***
	(0.254)	(0.280)	(0.258)	(0.335)	(0.254)
N	48079	48079	48079	48079	48079
R^2	.2924818	.2928623	.2925795	.292676	.2925406
Controls	Yes	Yes	Yes	Yes	Yes
Additional	No	Age	Education	Skill	Gender

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 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. Each column considers an additional interaction between the shock and a worker's characteristic.

Source: CSWL 2006-2017

	(1) cumulative_wage	(2) cumulative_year
$Q_1\cdot$ shock	-29.18***	-1.671***
	(2.583)	(0.131)
$Q_2\cdot$ shock	-27.21***	-1.603***
	(2.650)	(0.136)
$Q_3\cdot$ shock	-26.46***	-1.601***
	(2.557)	(0.136)
$Q_4\cdot$ shock	-26.35***	-1.593***
	(2.521)	(0.117)
Constant	78.02***	4.688***
	(4.468)	(0.240)
N	48090	48090
R^2	.2001472	.3083475
Controls	Yes	Yes

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

7 Additional estimates

7.1 Placebo

Could the contraction's impact on the construction sector employment reflect a reallocation of employment opportunities in regions that experienced a more robust increase during the expansion and a stronger decline during the Great Recession? In such a case, the impact studied before at the worker level would present an inter-temporal reallocation from a steeper wage trajectory during the expansion to a sluggish increase during the recession. Following that argument, the shock's effect on the cumulative wages during the last years of expansion would be positive. This hypothesis is tested by exploring whether the construction sector's employment contraction between 2007 and 2012 predicts earnings and employment outcomes before the Great Recession. To this end, I constructed a sample of workers in the construction sector in 2003 and compute their cumulative wages over the 2003 to 2007 period.

Table 7 provides evidence neglecting that possibility. Column (1) shows a negative but insignificant effect of the shock on construction sector employment and the cumulative wage, which change sign and magnitude as additional controls are applied, on the preferred specification in the main analysis, which is shown in Column (5) finds a small positive, and insignificant relationship between the cumulative wages and exposure to the construction

Table 7: Falsification test of the impact of the employment contraction in the construction sector on cumulative days worked from 2003-2007

	(1)	(2)	(3)	(4)	(5)	(6)
	cumulative_wage			cumulative_year		
shock	9.607	10.13	9.753	-0.131	-0.0962	-0.0971
	(11.65)	(11.48)	(11.05)	(0.597)	(0.584)	(0.594)
Outside		-1.404	0.0545		-0.0941	-0.0908
		(0.812)	(3.193)		(0.0595)	(0.189)
Interaction			-2.652			-0.00602
			(5.957)			(0.382)
Constant	63.46***	62.37***	62.86***	3.570***	3.497***	3.498***
	(17.57)	(17.54)	(16.92)	(0.958)	(0.949)	(0.952)
N	68807	68807	68807	68807	68807	68807
R^2	.1627439	.1642891	.1644231	.219097	.2211343	.2211345
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Notes: Sample is restricted to native workers aged 20-50 years old in 2003, and working in the construction sector cumulative variables are computed between 2003 and 2007. 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

sector employment contraction. Therefore, the future impact is a poor predictor for past earnings. By moving the spotlight from the cumulative wages to the cumulative days worked over 2003 to 2007, the results add additional evidence neglecting a relationship between the shock and past outcomes.

7.2 Additional outside option measure

This section considers an alternative outside option measure. This measure exploits the labour market flows between sectors, conditional on the characteristics of the workers. In other words, it exploits 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.

Then, reestimate the regressions for cumulative earnings, cumulative days worked, and average yearly wage.

As explained in section 6, the outside option's computation could be categorized into three groups depending on the available data and the definition of relevant options for the worker. The main results in the previous part rely directly on worker similarity. Two occupations are close substitutes as a closer are their observable characteristics between their characteristics with the share of workers with their characteristics in another sector. This subsection expands the previous analysis by considering an additional outside option measure. In spirit follows Schubert et al. (2019) while exploits the actual mobility responses of workers leaving the construction sector over the 2000-2006 period.

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

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

This measure does not exploit the individual characteristics that make it more likely that a worker moves from the construction sector into another sector. To this end, the transition probabilities will be constructed based not only conditional on leaving the construction sector but also on additional worker characteristics X_i. The vector X_i accounts for education, occupational skill group, gender, foreign-born status, age, and month [26]

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

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

The computation of transition probabilities follows a probit model on the set of leavers from the construction sector over the 2000-2006 period. 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[27], This specification controls for observable characteristics and monthly fixed effects. From this first step, the predicted probabilities are obtained, and in order to get rid of transitory variation on the predicted probabilities, I take the average for each group X_i over the months, which is named as :

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

[26] The probabilities control by month as workers may move from one sector to another just by seasonal variation throughout the year, which may be transitory in some cases

[27] Therefore if worker i is in the construction sector in period t and in another sector in $t+1$

	(1)	(2)	(3)	(4)
	Cumulative wage		Cumulative year	
shock	-27.68***		-1.629***	
	(2.452)		(0.122)	
$Q_1\cdot$ shock		-28.32***		-1.651***
		(2.523)		(0.122)
$Q_2\cdot$ shock		-27.29***		-1.594***
		(2.558)		(0.128)
$Q_3\cdot$ shock		-25.89***		-1.554***
		(2.659)		(0.135)
$Q_4\cdot$ shock		-25.85***		-1.589***
		(2.566)		(0.127)
Constant	79.55***	79.03***	4.730***	4.663***
	(4.568)	(4.565)	(0.236)	(0.228)
N	48090	48090	48090	48090
R^2	.1997067	.2000565	.3082664	.3083605
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) restrict 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: CSWL, 2006-2017

Similar to the measure constructed before, the second step use the weighted average of the transition probabilities by the size of each sector at the province level. Therefore, the final measure is:

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

The main analysis finds that workers who were employed in the construction sector and live in a hard-hit province before the Great Recession accumulate substantially lower earnings during the economic downturn than comparable workers is a less affected region, a result consistent with labor market frictions preventing workers from smoothly adjusting. This paper in particular exploits the frictions a particular worker may have at the time of change sector. The movement depends on the worker characteristics and the particular match with the sectoral composition in the province, the idea is not only that their profile is attractive for a hiring firm, but also 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 **??** follows Table 16 by analyzing the impact of the employment contraction of the construction sector on cumulative earnings and cumulative days worked during the economic downturn period of 2007 to 2013. Column (1) shows the impact on cumulative days worked, column (2) regresses the cumulative wages and controls for demographic and regional characteristics. Column (1) shows a negative and significant effect of the shock's exposure on the number of days worked during the Great Recession of workers in the construction sector before the crisis. This result is consistent with all the previous evidence but particularly important is that as in the table **??** there is a positive and significant relationship between the Outside option and the alleviation of the shock's impact. In comparison with the previous results, using the transition probabilities shows a higher predictive power, this is comparing the R^2 in both specifications, and also finds a larger relevance of the local sectoral composition while studying the alleviation of the shock; however, this evidence is consistent with the one explained before.

Column (2) in table **??** shows the results from the regression of the cumulative wage between 2007 and 2013 of workers in the estimation sample. The coefficient of interest is the interaction of the shock and the Outside option. Consistent with evidence in table **??** live in a province such that the sectoral composition brings opportunities to a wide range of workers helps to alleviate the impact of the shock.

7.3 Instrumental variables

A natural concern is that the shock is not driven by demand-side factors but a combination of supply and demand, which may exacerbate the shock's impact. For that reason, this section follows an instrumental variables approach to clean the estimation from such factors. To capture the demand-side component of the contraction in construction sector employment, this section instrumented the construction sector employment contraction by the cumulative growth of the construction sector between 2000 and 2007 at the local level.

In particular, consider the main specification, which studies the impact of the employ-

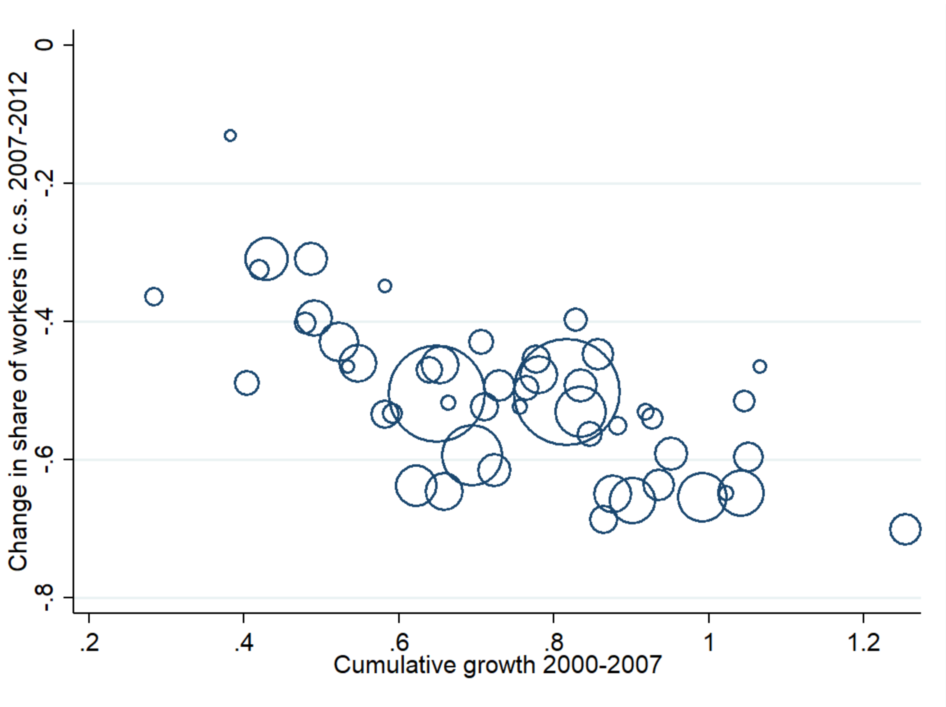


Figure 11: Relevance

Notes: Monthly share of workers in the construction sector, January 2004 to December 2017. Data restricted to workers aged 20-60 years old, employed during the reference period. Data restricted to male workers show similar patterns.
Source: CSWL 2006-2017

ment sector's contraction on the cumulative wage between 2007 and 2012.

$$y_i = \alpha_0 + \alpha_2 Shock^r + \beta X_i + \epsilon$$

Assume the error term is composed by an idiosyncratic term and a supply-side shifter W_i^r such that:

$$E[Shock_i\ \epsilon_i] \neq 0 \text{ because } E[Shock_i W_i] \neq 0.$$

The following results instrument the shock by the province employment's cumulative growth in the construction sector between 2000 and 2007. This is related to the change in the employment share of the construction sector during the Great Recession. It satisfies the relevance condition as it is graphically shown in figure 11. Additionally, the construction sector's cumulative growth before the Great Recession is not related to wages during the Great Recession. Then it satisfies the exclusion restriction:

$$E[Shock_i\ Z_i] \neq 0 \text{ and } E[\varepsilon_i\ Z_i] = 0.$$

Assuming the shock's impact is not independent of the error term, the construction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Cumulative wage				Cumulative year		
shock	-25.22***	-27.26***	-31.41***	-37.07***	-1.414***	-1.523***	-1.527***	-1.857***
	(3.557)	(3.586)	(7.412)	(8.241)	(0.207)	(0.202)	(0.449)	(0.482)
Outside	0.551	-2.608*	0.446	-4.658*	0.0156	-0.154*	0.0137	-0.283*
	(0.289)	(1.008)	(0.290)	(1.814)	(0.0193)	(0.0625)	(0.0200)	(0.114)
Interaction		5.712**		9.156**		0.307**		0.533**
		(1.664)		(3.142)		(0.107)		(0.204)
Constant	87.88***	87.08***	91.99***	92.30***	5.743***	5.700***	5.819***	5.837***
	(4.048)	(4.152)	(6.450)	(6.235)	(0.280)	(0.285)	(0.403)	(0.386)
N	48125	48125	48125	48125	48125	48125	48125	48125
R^2	.1329619	.1332778	.1327335	.1327231	.1656305	.1658405	.1656126	.1656383

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,cumulative variables are computed between 2007 and 2012. Cumulative days measures the number of days with non-zero earnings between 2007 and 2012. Every regression controls by: gender, age, education, skill group, and foreign status. 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 instrumented by the cumulative employment growth of the construction sector between 2000 and 2007

Source: CSWL, 2006-2017

sector's employment contraction coefficient will be biased, and the interaction between the shock and the Outside option. For this reason, the following specification also uses as an instrument the interaction between the cumulative growth of the construction sector employment and the Outside option as instruments for the shock and the interaction of the shock with the Outside option. Results from this estimation are in figur

7.4 Labor market adjustment and internal migration

As argued in Section 4.1, given the nature of the shock, which was highly unexpected, and the Spanish labor market institutions, 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.

Figure 3 shows that during the Great Recession and early in the recovery period, even though there is a set of workers who migrate from the exposed region, the number of individuals who changed sector exceeds the ones who changed province. These two forces have not been studied simultaneously in this article.

This subsection tries to shed light on the importance of sectoral and regional mobility for workers exposed to the employment contraction of the construction sector. In order to do so, this section applied a similar two-step approach as the one for sectoral mobility to study the contribution of sectoral mobility to the alleviation of the shock's impact.

This section aims to capture the likelihood that a worker would migrate due to the impact of the shock. In order to do so, I estimate the conditional probability that a worker would change province for the period 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:

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

Where σ_r is a province fixed effect, ψ_t is a month fixed-effect used to capture the seasonal component of change province, and X_i is a vector of worker characteristics which includes: occupational skill groups, indicators for part-time and fixed-term contracts, labor market experience, interactions of age and gender, and interactions of age and education. Following this estimation, the second step predicts the conditional probability a worker would change the region on the set of workers in the estimation sample.

Additional to the probability a worker would change province, using the worker's labor market history, I construct an indicator if the worker changed province before the Great Recession to capture that the propensity to migrate would depend on an individual-specific component.

	(1)	(2)	(3)	(4)	(5)	(6)
	Cumulative wage			Cumulative year		
shock	-27.26***	-40.66***	-41.12***	-1.523***	-2.764***	-2.809***
	(3.586)	(4.744)	(4.413)	(0.202)	(0.409)	(0.385)
Outside	-2.608*	-4.617***	-5.104***	-0.154*	-0.340***	-0.388***
	(1.008)	(1.211)	(1.167)	(0.0625)	(0.0945)	(0.0881)
Interaction	5.712**	9.850***	10.73***	0.307**	0.690***	0.777***
	(1.664)	(2.210)	(2.145)	(0.107)	(0.182)	(0.170)
Mov. Probability		-6.682***	-9.469***		-0.619***	-0.893***
		(0.475)	(2.015)		(0.0432)	(0.176)
$Prob. \cdot shock$			4.994			0.491
			(3.679)			(0.316)
Constant	87.08***	74.60***	74.40***	5.700***	4.544***	4.524***
	(4.152)	(5.024)	(4.972)	(0.285)	(0.463)	(0.461)
N	48125	48125	48125	48125	48125	48125
R^2	.1332778	.1756405	.1758474	.1658405	.2496371	.2500979

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

8 Discussion and policy implications

9 Conclusion

During the Great Recession, Spain was one of the most affected countries, both even within that, there is an important variability on the worker level impact of this event. Among that, 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 exposed sectors to less exposed sectors, rather than geographical reallocation was a secondary force for native Spanish workers.

To study the 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 both among worker's 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 option. 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 on years before the Great Recession show no statistically significant relationship. The relevance of the reallocation probabilities at alleviating the impact of the bust 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 8: 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.

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

Different possibilities:

1. First step calculated in full sample. The construction sector counts as an option.
2. First step calculated in full sample. The construction sector does not count as an option.
3. First step calculated in sample of workers who changed to a new contract. The construction sector counts as an option.
4. First step calculated in sample of workers who changed to a new contract. The construction sector does not count as an option.
5. First step calculated in sample of native male workers who changed to a new contract. The construction sector counts as an option.
6. First step calculated in sample of native male workers who changed to a new contract. The construction sector does not count as an option.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Change sector			
shock	1.315***	0.868**	1.382***	1.384***	1.462***	1.348***	1.484***
	(0.264)	(0.319)	(0.223)	(0.245)	(0.182)	(0.250)	(0.237)
outside1	-1.237						
	(1.399)						
outside2		-6.774***					
		(1.332)					
outside3			3.990***				
			(0.784)				
outside4				0.0364			
				(1.135)			
outside5					3.643***		
					(1.076)		
outside6						-1.536	
						(1.211)	
outside7							1.448
							(0.786)
Constant	-0.548	0.269	-1.366***	-0.770***	-1.288***	-0.615**	-1.015***
	(0.307)	(0.303)	(0.151)	(0.207)	(0.130)	(0.198)	(0.189)
N	39881	39881	39881	39881	39881	39881	39881
R^2							
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Table 9: Descriptive evidence of new workers in construction sector

	2004	2007	2012	2017
Age				
<24	0.347	0.306	0.259	0.229
24-35	0.393	0.404	0.341	0.416
35-45	0.176	0.193	0.238	0.195
<45	0.085	0.098	0.161	0.161
Mean age	29.92	30.75	33.19	32.81
Education				
Below secondary	0.705	0.708	0.673	0.676
Secondary	0.197	0.199	0.208	0.205
Tertiary	0.098	0.094	0.120	0.118
Type of contract				
Part-time	0.088	0.085	0.210	0.188
Fixed-term	0.878	0.836	0.850	0.827
Foreign born	0.285	0.417	0.233	0.280
Occupations				
Very-high skilled occupations	0.016	0.018	0.026	0.026
High skilled occupations	0.028	0.028	0.031	0.039
Medium-high skilled occupations	0.042	0.046	0.062	0.051
Medium-low skilled occupations	0.403	0.439	0.410	0.454
Low skilled occupations	0.511	0.469	0.471	0.430

Notes: Table reports characteristics of new workers in construction sector per year.

Source: MCVL, 2006-2017

A.2 Tables

A.3 Figures

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

Table 10: Descriptive evidence of leavers from the construction sector

	2004	2007	2012	2017
Age				
<24	0.183	0.149	0.098	0.118
24-35	0.419	0.359	0.319	0.328
35-45	0.235	0.225	0.252	0.278
>45	0.163	0.267	0.331	0.276
Mean age	33.92	34.85	36.98	37.41
Education				
Below secondary	0.641	0.656	0.651	0.658
Secondary	0.209	0.199	0.198	0.202
Tertiary	0.150	0.145	0.151	0.140
Type of contract				
Part-time	0.191	0.191	0.254	0.278
Fixed-term	0.809	0.783	0.764	0.823
Foreign born	0.141	0.224	0.200	0.196
Occupations				
Very-high skilled occupations	0.022	0.020	0.026	0.026
High skilled occupations	0.044	0.040	0.048	0.053
Medium-high skilled occupations	0.112	0.103	0.110	0.115
Medium-low skilled occupations	0.450	0.415	0.388	0.407
Low skilled occupations	0.372	0.325	0.315	0.399

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 11: Descriptive statistics of workers, 2007-2012

	(1) Non-construction	(2) Construction
Cumulative wage	61.56	45.80
	(29.07)	(26.37)
Cumulative year	4.55	3.48
	(1.804)	(1.779)
shock	0.54	0.56
	(0.0897)	(0.0887)
tenure	3.57	2.06
	(4.579)	(3.033)
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)
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)
N	304085	52671

mean coefficients; sd in parentheses

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

	(1)	(2)	(3)	(4)
	Cumulative wage			
Shock	-15.30*	-26.60***	-23.39***	-33.48***
	(7.032)	(5.906)	(3.775)	(2.739)
$ShareCS_{2006}$	-3.088	8.692	-25.99*	-6.345
	(21.19)	(15.68)	(11.86)	(7.117)
Constant	72.38***	78.80***	79.51***	78.65***
	(4.032)	(5.860)	(2.883)	(1.747)
N	4308	2723	13745	22636
R^2	.1216983	.2098462	.1507534	.2420899
Controls	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Column (1) Change province and sector (2) Change province but no sector (3) Change sector but no province (4) No change. I keep just native workers

Source: MCVL, 2006-2017

Table 12: Job-to-job transitions and exposure to contraction of employment share

	Firm Movements	
	(1)	(2)
$ShareCS_{2006}$	3.071**	7.422***
	(1.109)	(2.063)
Shock	-0.0534	2.179*
	(0.473)	(1.068)
Bartik shock	-0.0416	1.282
	(1.171)	(2.014)
Observations	497622	76568
Controls	Yes	Yes

Standard errors in parentheses

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

(1) non CS (2) CS

Table 13: Impact of the employment contraction in the construction sector on worker's outcomes. By foreign born status.

	(1)	(2)	(3)
	Cumulative wage	Cumulative years	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 14: 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 15: 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

	(1) cumulative_wage	(2) cumulative_wage	(3) cumulative_wage	(4) cumulative_year	cumu
shock	-25.88***			-1.420***	
	(3.280)			(0.189)	
First_outside		-32.79***	-24.96*		
		(4.501)	(12.40)		
Second_outside		-25.38***	-18.40		
		(4.892)	(14.08)		
Third_outside		-26.25***	-21.62		
		(5.919)	(13.70)		
Fourth_outside		-18.06***	-13.39		
		(3.966)	(12.78)		
_cons	85.97***	81.92***	81.78***	5.653***	
	(4.236)	(4.240)	(7.201)	(0.263)	
N	48083	48083	48083	48083	
R^2	.1321234	.1327021	.133475	.1659352	
Controls	Yes	Yes	Yes	Yes	

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

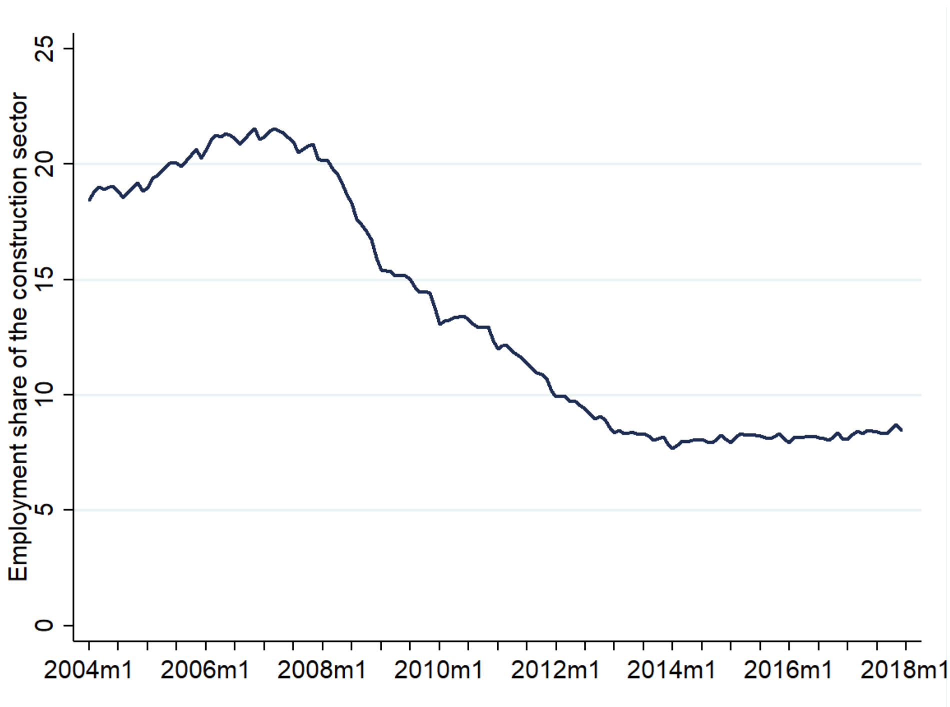


Figure 12: Employment share of the construction sector, 2004-2017
Notes: Monthly share of workers in the construction sector, January 2004 to December 2017. Data restricts to workers aged 20-60 years old, employed during the referenced period. Sample of male workers
Source: CSWL 2006-2017

Table 16: 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) Change province	(2) 2008	(3) 2009	(4) 2010	(5) 2011	(6) 2012	(7) 2013	(8) 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) Cumulative wage	(2) Cumulative years	(3) 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 17: 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 18: 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

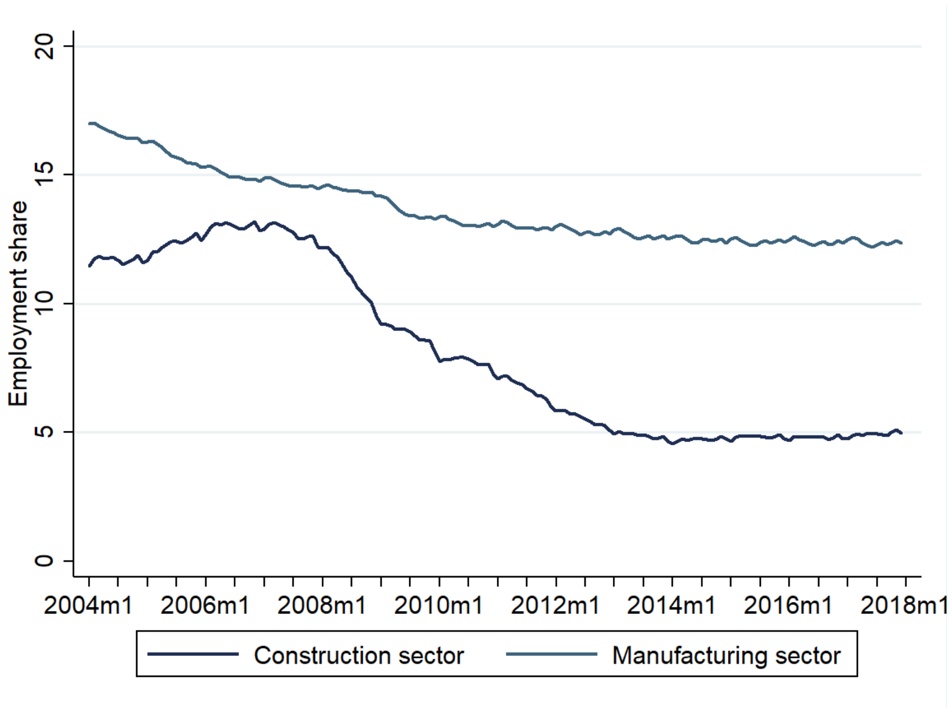


Figure 13: Employment share of the construction sector and manufacture, 2004-2017

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

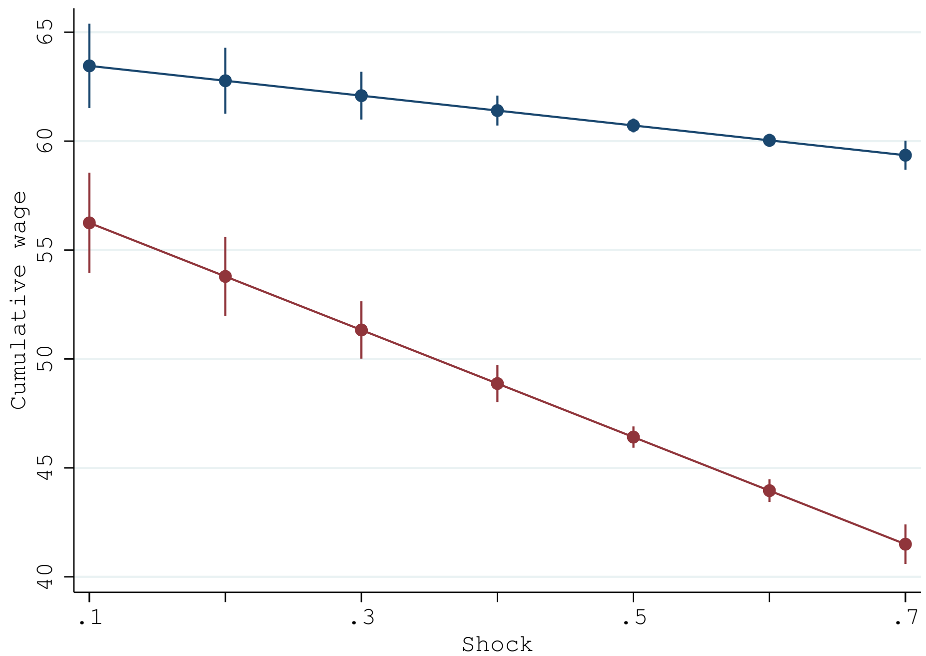


Figure 14: Impact of the employment contraction on workers initially employed in the construction sector and in other sectors

Notes: Predicted cumulative wage impact from the contraction of the construction sector. Coefficients are estimated in column (1) and (2) of Table 2
Source: CSWL 2006-2017.

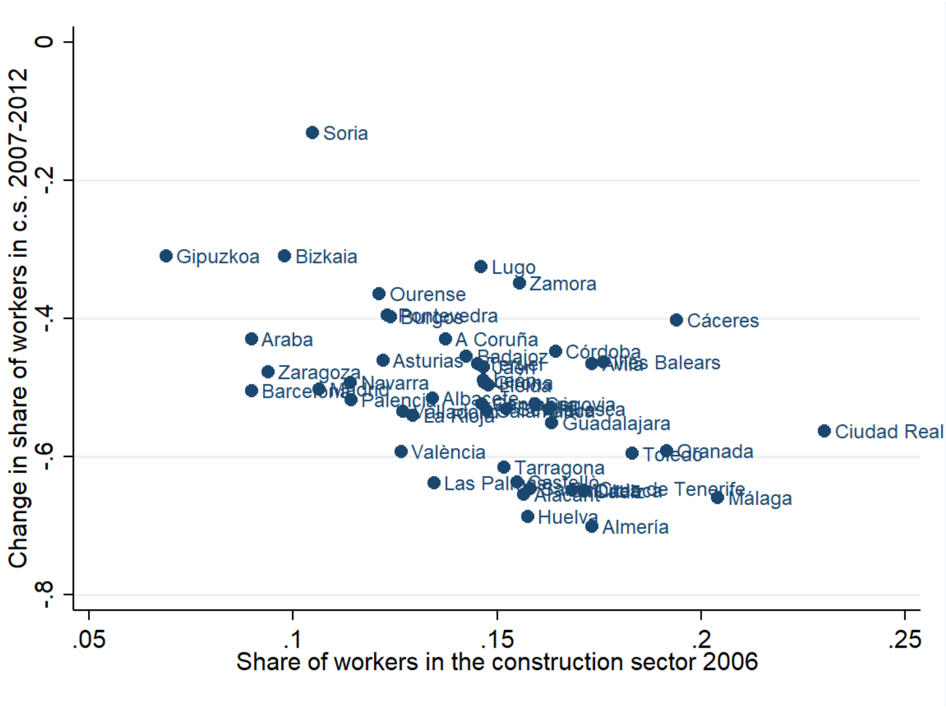
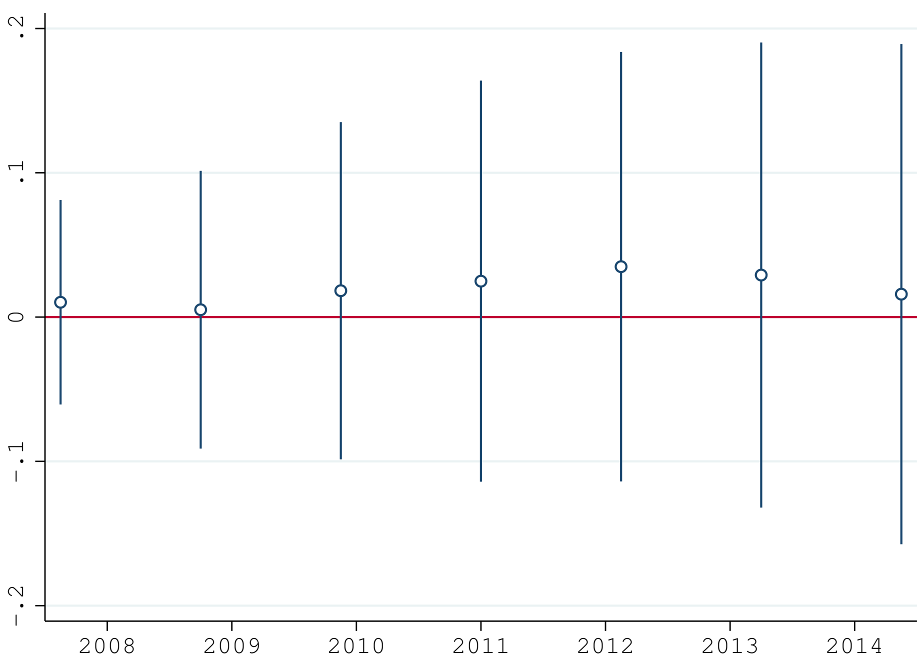
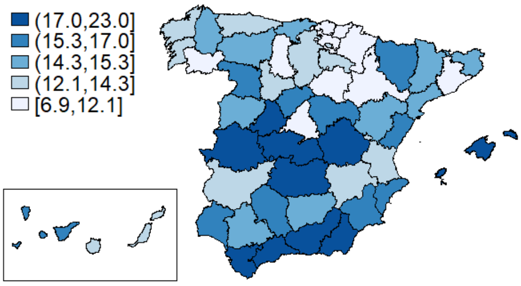


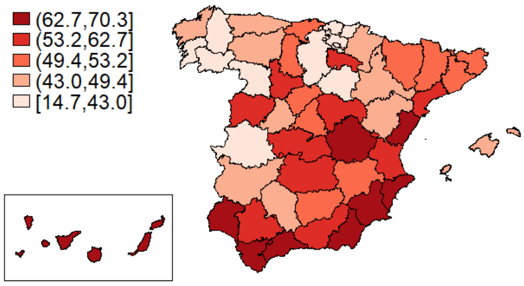
Figure 15: Change in share of workers in the c.s. during the GR by province
Notes: Change in the employment share of the construction sector by province between 2007 and 2012 against employment share in 2006 —computation of employment shares from yearly data in April of every year. Sample uses 50 Spanish provinces and data on all workers enrolled in the general regime of Social Security.
Source: MCVL 2006-2017



Notes: From do-file 9 line 137
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 16: 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

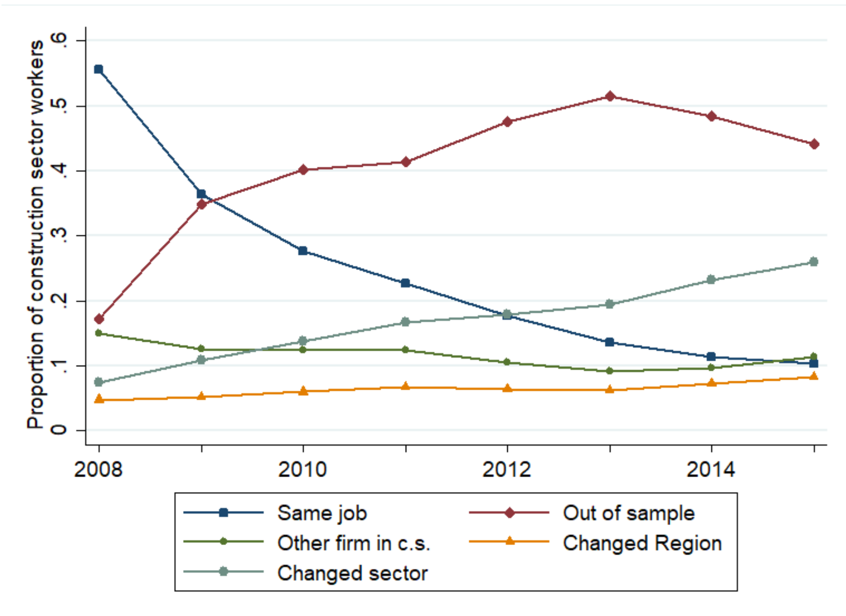


Figure 17: Working status of individuals employed in the construction sector in 2007

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

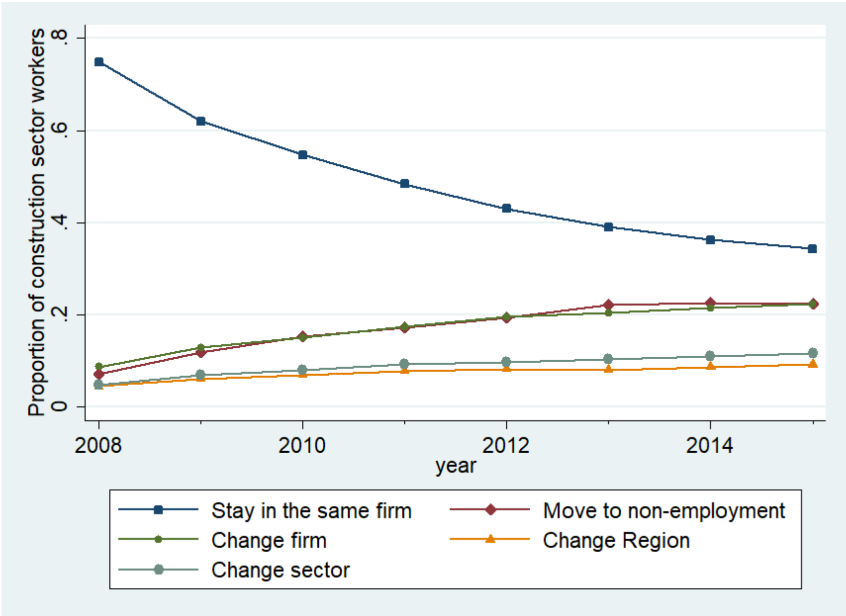
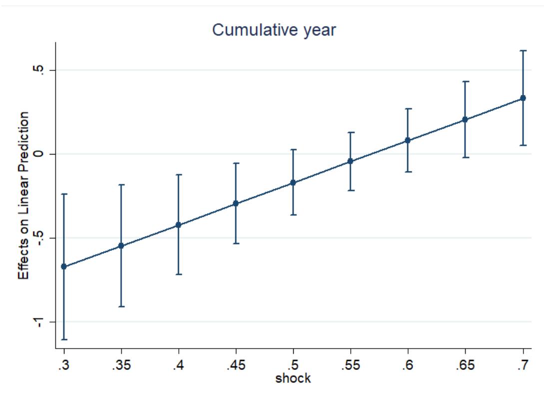


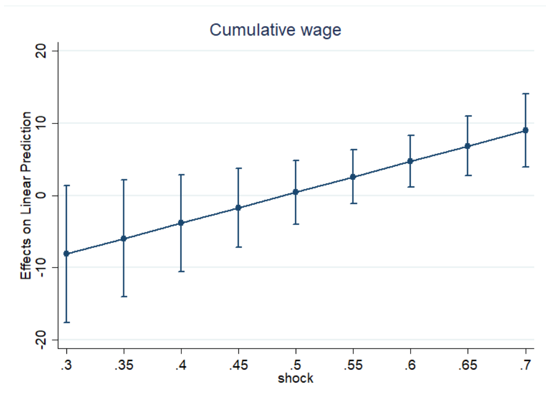
Figure 18: Working status of high skilled individuals in 2007

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) Cumulative year

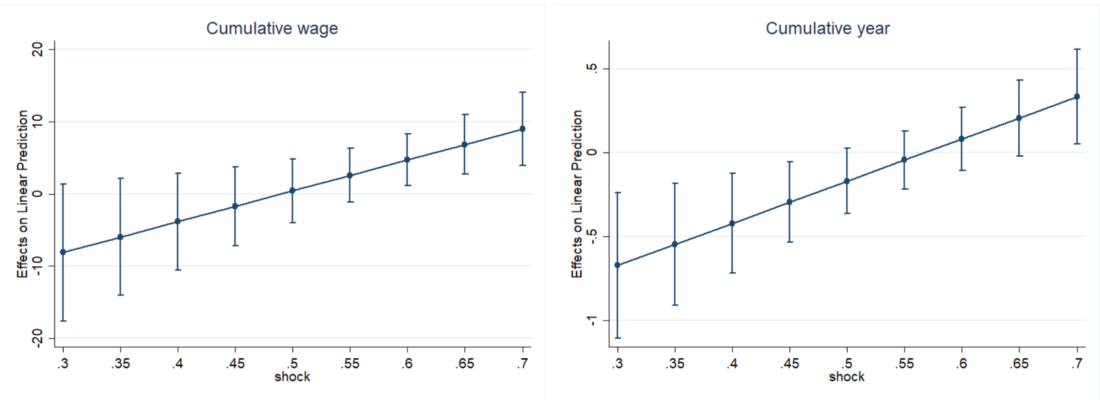


(b) Cumulative wage

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

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:

$$\frac{L_{m,t} - L_{m,t-1}}{L_{m,t-1}} = \Big[\frac{I^r_{m,t}}{L_{m,t-1}} - \frac{O^r_{m,t}}{L_{m,t-1}}\Big] + \Big[\frac{I^u_{m,t}}{L_{m,t-1}} - \frac{O^u_{m,t}}{L_{m,t-1}}\Big] \tag{11}$$

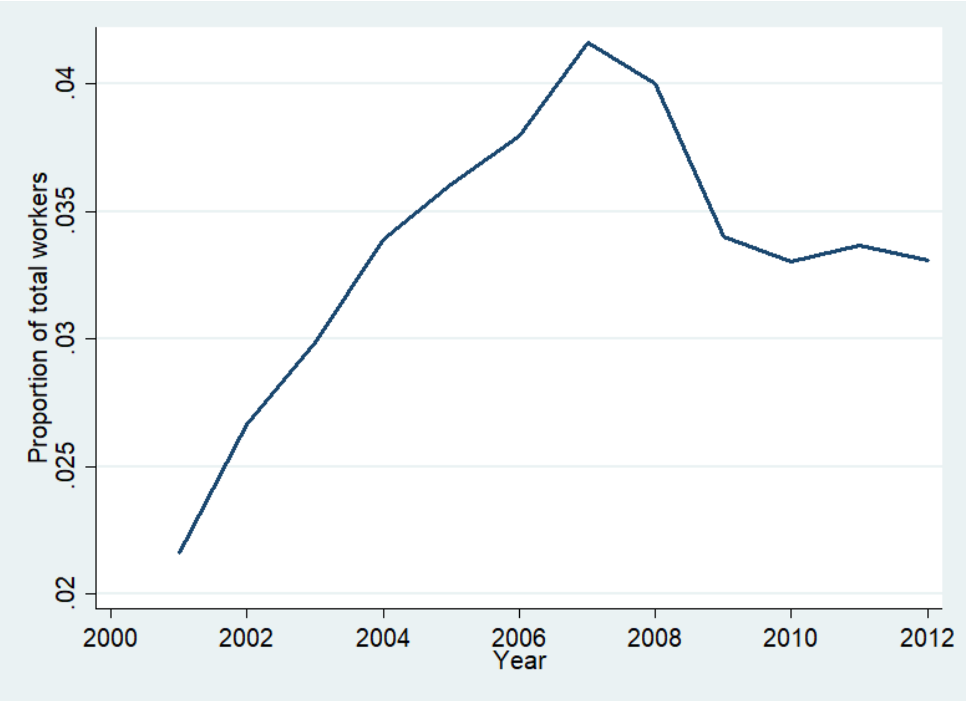


Figure 21: Share of workers change job's province
Notes: Share of individuals working in a different province with respect to the previous year, 2001-2012. The sample of workers between 2000-2012, based on sample of workers in MCVL Source: MCVL, 2006-2017

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 [28].

$I^r_{m,t}$ 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 11 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). [29] .

Consider the following regression:

[28] 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

[29] 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 19: 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

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

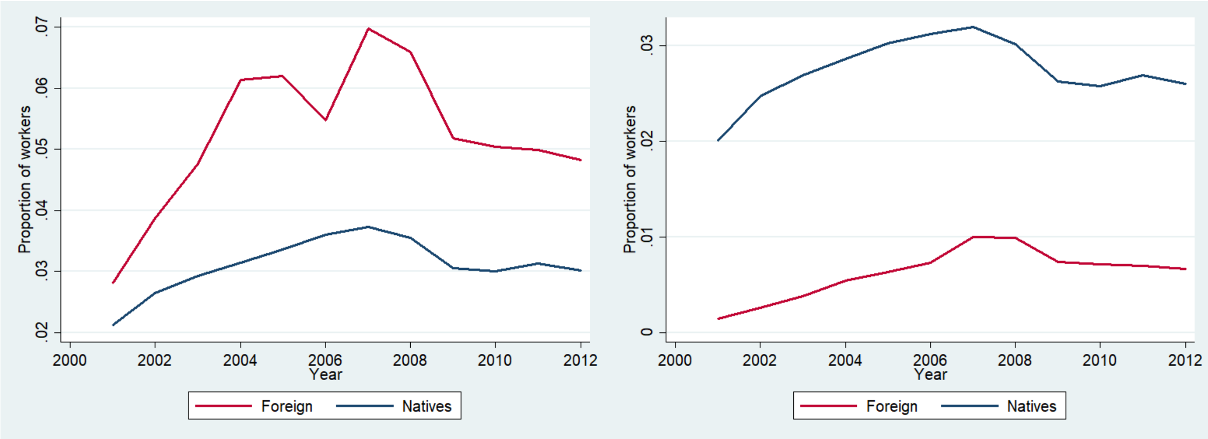
Notes: Regression of in-migration and out-migration on region m worker's population change. Sample considers the 50 Spanish provinces between 2005 and 2008 in panel A, and after 2008 in panel B. Source: MCVL, 2006-2017

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

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

Table 19 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 $\frac{M_t^G}{P_t^N + P_t^F}$.



(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

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.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 20 shows results from the probability a worker is not seen from sometime into

Table 20: 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

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)

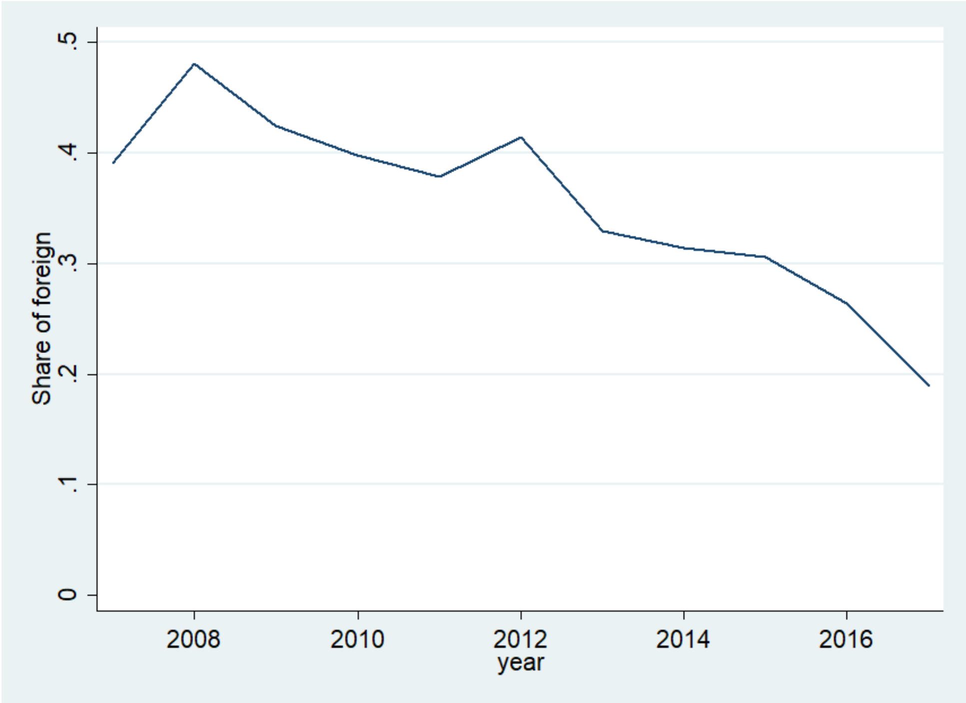


Figure 23: Share of foreign workers leaving the ss records
Notes: Share of foreign workers by year of exit from social security records of workers in the construction sector during 2007. Source: MCVL, 2006-2017

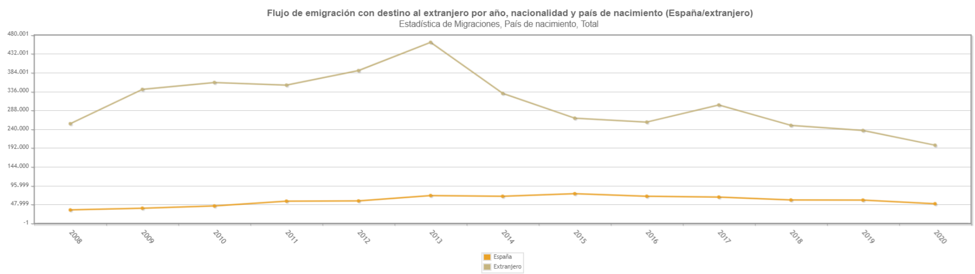


Figure 24: Emigration by country of birth
Notes: Share of foreign workers by year of exit from social security records of workers in the construction sector during 2007. Source: MCVL, 2006-2017

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