Journal of Economic Geography (2017) pp. 163–186 doi:10.1093/jeg/lbx026

Big plant closures and local employment

*Jordi Jofre-Monseny**, *Maria Sánchez-Vidal***,† *and Elisabet Viladecans-Marsal****

* Department of Economics and Institut d'Economia de Barcelona, Universitat de Barcelona, Barcelona 08034, Spain
** Centre for Economic Performance (LSE) and Institut d'Economia de Barcelona, London WC2A 3PH, UK
***Department of Economics, Institut d'Economia de Barcelona and CEPR, Universitat de Barcelona, Barcelona 08034, Spain
† Corresponding author: Maria Sánchez-Vidal, Centre for Economic Performance (LSE) and Institut d'Economia de Barcelona, London WC2A 3PH, UK. *email* <M.Sanchez-Vidal@lse.ac.uk>

Abstract

This paper estimates the impact of large plant closures on the local employment in the affected industry. Specifically, we examine the closure of 45 large manufacturing plants in Spain which relocated abroad between 2001 and 2006. We run differences-in-differences specifications in which locations that experience a closure are matched to locations with similar pre-treatment employment levels and trends. The results show that when a plant closes, for each job directly lost in the plant closure, only between 0.6 and 0.7 jobs are actually lost in the local affected industry. These effects are driven by employment expansions in local incumbent firms and, to a lesser extent, by the creation of new firms in the local industry.

Keywords: Local employment, plant closures, input–output
JEL classifications: R34, R12, R23, J23
Date submitted: 18 January 2016 **Editorial decision:** 6 July 2017 **Date accepted:** 16 July 2017

1. Introduction

Local and regional governments around the world provide large plants with generous subsidies, often in the form of tax breaks. According to the *New York Times*, each year US local and state governments spend more than $80 billion on incentives targeted to individual firms.[1] In Europe, although government aid to firms is generally forbidden by EU legislation, national and regional governments do subsidize large plants by exploiting certain exemptions, including funds used to promote research and development, environmental protection, and economic activities in lagging regions. Subsidies are frequently offered to attract new plants. For instance, Tesla Motors recently decided to locate an electric-car battery 'gigafactory' in Nevada (partly) because of a $1.25 billion tax deal. However, once a plant is operational, subsidies to avoid its relocation (or that of some of its activities) are also common. In fact, the $8.7 billion tax break that Boeing was recently offered to produce a new jet in Seattle is the largest incentive received by an individual firm in US history. In Spain, the Seat and Ford plants in Barcelona and Valencia have regularly held regional governments to 'ransom' under the threat of relocating production.

1 http://www.nytimes.com/interactive/2012/12/01/us/government-incentives.html.

The welfare effects of subsidies targeted to individual firms are unclear (Wilson, 1999). Subsidies might cause inefficiencies if they shift plant locations to low productivity areas. However, as emphasized by Glaeser (2001) and Greenstone and Moretti (2004), subsidies can also be welfare enhancing. If the local labor supply curve slopes upward, inframarginal resident workers will gain by the presence of a large plant. In this context, subsidies can be seen as bids offered by different locations reflecting local welfare gains. A similar argument applies if large plants create significant (positive) local production externalities. Then, a subsidy will be efficient if it induces a plant to locate in an area in which the resulting local externality is especially large.

In the policy arena, the desirability of subsidies targeted to individual firms is often evaluated on a cost per job basis. An argument often made in justification of such subsidies is that large plants create positive employment in the local industry as they purchase inputs from local firms and/or raise the productivity of local firms due to agglomeration economies. However, the opening of a large plant might also tighten the local labor market driving up wages and, thus, reduce local industry employment. The objective of this paper is to estimate empirically the net industry employment effects of large manufacturing plant closures.

Specifically, we estimate the net impact on the local industry of the closure of 45 large manufacturing plants (median layoff of 264 jobs), which relocated abroad between 2001 and 2006. We match each municipality experiencing a closure to a small set of municipalities (four in the baseline analysis) that are very similar in terms of their employment levels of the year 2000. We also find that treatments and the selected controls do not differ in their pre-treatment employment trends, either. This lends empirical support to the hypothesis that the plant relocations examined here were the result of international strategies adopted by parent companies and did not respond to declining, area-specific employment trends. We run differences-in-differences specifications in which each treatment is matched to its controls by including case-specific fixed effects. The results show that when a plant closes, for each job directly lost in the layoff, only between 0.6 and 0.7 jobs are actually lost in the local industry affected by the closure. This is explained because, for each job affected by a closure, local incumbent plants expand employment by around 0.2 jobs while new plants create about another 0.1 jobs.

The effects of a plant closure might not be restricted to the directly affected industry.[2] Indeed, the employment in other manufacturing industries might be reduced if the plant to close also purchases inputs from local firms in other industries. Similarly, the plant closure reduces local income which might negatively impact the demand for local (non-tradable) services (Moretti, 2010). These effects might be offset by the decline in wages caused by the negative labor demand shock. In turn, the shock might trigger an outflow of workers. Since mobility is costly and workers might have idiosyncratic preferences for locations, less jobs can also increase unemployment and decrease labor force participation (Blanchard and Katz, 1992). We do not find employment effects outside the affected industry, nor effects along the migration, participation or unemployment margins. In this respect we note that while the closure that we examine constitutes an important shock to the affected local industry (the mass layoff represents around 30%

2 Several studies including Moretti (2011), Notowidigdo (2013) and Diamond (2016) study labor demand shocks in a spatial equilibrium setting with integrated labor and housing markets.

of the industry employment), the average shock to the local economy as a whole is substantially smaller (about 3% of total employment).[3] Hence, it is not obvious that our results carry over to instances where a negative labor demand shock affects a sizable part of the local economy as a whole.

The fact that a significant fraction of fired workers are reemployed in local incumbent firms in the industry that suffered the closure suggests that a substantial part of workers' skills are industry-specific. This result is consistent with two findings from the literature analyzing the individual consequences of mass layoffs. On the one hand, using worker-level data on collective dismissals in Spain, Garda (2013) documents that, of those workers finding a job after the layoff, more than half of them do so in the same industry.[4] On the other hand, several studies including Jacobson et al. (1993), Couch and Placzek (2010) and von Wachter et al. (2011) have found that workers affected by a mass layoff experience a substantial drop in earnings in the short-run which narrows but does not disappear in the long-run. Neal (1995) finds that these earning losses are substantially lower for workers not switching across industries, suggesting again that human capital is to some degree industry-specific.

Fox and Murray (2004) and Edmiston (2004) study the employment effects of large plant openings in the USA. Both studies conclude that such openings largely fail to create indirect jobs in the local economy. Here, our study seeks to complement these earlier reports by quantifying the effects of large plant closures. Note that the effects of openings and closures need not necessarily coincide if, for instance, a closure provides an opportunity for local incumbents to hire trained workers who have recently been laid off. Our study shows that plant closures do not, in fact, destroy indirect jobs and, moreover, that they actually generate jobs in local incumbent firms. As a consequence, the net employment effects of closures are smaller than the initial layoff itself. Greenstone et al. (2010) also study large plant openings in the USA but focus on the impact on local productivity. In a unique empirical design, the authors use data on the subsidies offered to new plants by different local and state governments to define 'winning' counties (those attracting a plant) and 'losing' counties (those left as runners-up in the choice process). They find that the opening of a large plant increases the productivity of incumbent plants in the winning county relative to that of plants in the losing county. In line with our study, Hooker and Knetter (2001) and Poppert and Herzog (2003) estimate the local employment effects of closures but focus their attention on US military bases as opposed to manufacturing plants. They report that net employment effects are very similar to the number of jobs directly destroyed by the closure. Finally, Moretti (2010) develops a framework to estimate empirically the local impact of creating an additional job in a tradable industry on employment levels in the rest of local industries.[5] His estimates indicate that additional jobs in one part of the tradable sector have a negligible impact on jobs in other parts of the tradable sector but

3 Moreover, our results imply that about a third of the mass layoff is actually offset by employment increases in other firms of the industry in which the closure occurs.

4 Garda (2013) does not exploit the geography of mass layoffs. In fact, the worker's level database that she uses (*Muestra Continua de Vidas Laborales*) only discloses the municipality of the layoff for municipalities exceeding 40,000 inhabitants. This implies that we are not able to identify the location of most plants that we consider, implying that we are not able to study the individual-level histories of the workers affected by our plant closures.

5 Using this same framework, Faggio and Overman (2014) estimate the local labor market effects of public sector employment.

a large positive effect on those in the non-tradable sector, especially if these newly created positions are for skilled occupations that command higher wages.

Following on from this introduction, the rest of the paper is organized as follows. Section 2 describes the data used throughout the paper with particular emphasis on individual plant closures. In Section 3, we explain how we select the control locations to match the areas experiencing a plant closure in terms of their respective pre-treatment employment levels. Section 4 introduces the empirical specifications used and presents the results. Finally, Section 5 concludes.

2. Data

Our study examines the impact of 45 large plant closures in the manufacturing sector resulting from international relocations. In this section, we first describe the characteristics and circumstances of these closures. Then, we turn our attention to the employment data sources that constitute our outcome of interest.

2.1. (International relocation) plant closures

Information on plant closures (and their corresponding job losses) is obtained by combining various data sources. Thus, we draw on information from the firms' international relocation dataset built by Myro and Fernández-Otheo (2008) and combine this with balance sheet data extracted from the *Sistema de Análisis de Balances Ibéricos* (SABI) and information obtained from newspapers and the trade unions. We restrict our attention to the 45 plant closures resulting from international relocations that occurred between 2001 and 2006 and which involved, at least, 100 job losses.[6] We exclude closures in the five largest Spanish municipalities (Madrid, Barcelona, Valencia, Seville, and Zaragoza) as layoffs here are unlikely to represent a relevant shock to local employment. However, by so doing, only three closures are excluded.

For each closure, we collected the following information: firm's name, year of closure, number of workers laid off, activity (three-digit CNAE-93 classification), municipality of origin and the new country of destination.[7] Table A1, deferred to the Appendix, reports these plant-level data. Half of the closures in our dataset (49%) correspond to what the OECD classifies as medium-technology industries. The number of workers laid off ranges between 105 and 1600, with a median of 264. In Spain, firms are among the smallest in OECD countries.[8] In fact, the average manufacturing plant employs 14 workers and, therefore, all the closures in our sample can be considered as being big.[9] In terms of their impact on the local economy, the layoffs represent, on average, 30% of local employment in the industry suffering the plant closure. Hence, the average plant closure that we study is co-located with other firms in the same industry.[10]

6 Greenstone et al. (2010) examine evidence from 47 large plant openings in the USA.
7 CNAE-93 is the Spanish equivalent to the NACE classification.
8 Entrepreneurship at a Glance 2012 (OECD).
9 Spanish Social Security for the year 2000.
10 See Crozet et al. (2004) for evidence that FDI investments are attracted to areas with concentrations of same-industry firms.

The plant closures we analyze form part of international relocation processes. As Table A1 shows, most plants relocated to China or Eastern Europe. Using international relocation closures to estimate the effect of large layoffs on the local economy is helpful in terms of identification to the extent that these closures can be attributed directly to the parent companies' international strategy rather than the effects of declining local employment. As is shown below, we find no evidence that the areas experiencing closures present differential employment trends prior to the closure. Two other factors need to be borne in mind when interpreting the effects of these plant closures. First, the study period was characterized by economic growth. Between 2000 and 2008, the Spanish economy experienced an average annual growth rate of 3.1%; however, in the manufacturing sector, growth was much less vigorous with employment rising at an annual rate of 0.77%. Second, among the countries of the OECD, Spain's employment protection regulations represent some of the strictest. This holds also for collective dismissals.[11] In Spain, plant closures are accompanied by a bargaining process between the firm and trade unions mediated by the (regional) government. Anecdotal evidence suggests that deals generally involve severance payments above the (already very high) statutory level, early retirement packages and attempts by local and regional governments to re-locate workers within the local economy.

2.2. Employment outcomes

The main outcome we examine is local employment at the industry level. We draw primarily on Social Security employment counts by industry and municipality. The data cover the universe of employees in Spanish municipalities at the two-digit industry level. One caveat of this dataset is that it does not cover self-employed workers.[12] We follow employment outcomes in the period 2000–2008. Since we will study the impact of plant closures taking place between 2001 and 2006, this gives us a minimum of one pre-treatment year (2000) and two post-treatment years (2007 and 2008). Additionally, we use employment data from the 1990 Census of Establishments, which enables us to measure (and control for) local (pre-treatment) employment trends. We end the period of analysis in 2008 for two reasons. First, in 2009 the industry classification underwent a major overhaul and, second, 2008 was the last year of economic growth in Spain with output growing at 0.9%.[13,14]

3. Matching procedure

Most of the 8122 municipalities in Spain are quite small, which suggests the impact of a plant closure might extend beyond a municipality's borders. Therefore, we construct a 10-km ring around each municipality in order to capture a municipality's immediate neighbors. This ring is built by calculating air distances between municipality centroids and the resulting area serves as our baseline geographical unit. We define a treated area as one suffering a plant closure between 2001 and 2006 and we select four appropriate

11 OECD Employment Outcome 2004.

12 The data, in fact, exclude all workers in specific social security regimes which, in addition to the self-employed, include agricultural workers, and civil servants.

13 From 2009, the industry classification adopted was CNAE-2009.

14 In 2009, there was a sharp drop in output of 3.8% (EUROSTAT).

controls using a matching procedure based on employment characteristics measured in 2000. Since we are especially interested in the effects of closures on local employment in the affected industry, we will match treatments and controls based on total employment as well as on employment in the closure industry, as overall size and own-industry employment are the two main variables that characterize the relevant local economic environment for firms (Rosenthal and Strange, 2004). Each treatment and its corresponding controls constitute what we label here as a case.

The matching procedure applied operates in two steps. First, for each municipality in Spain, we compute its total level of employment in 2000 by adding to its own employment level that of its neighbors. Then, we rank the 8122 Spanish municipalities and create six categories (<5, 5–10, 10–20, 20–50, 50–100 and >100 thousand employees). We restrict the matching procedure to municipalities within the same total employment category. In the second step, the target is to make treated and control areas similar in terms of employment levels in 2000 in the specific industry affected by the closure. To do so, we compute the distance for this industry between the level of employment in each potential control and each treated area. This is done in two dimensions: first, we only consider employment at the level of the municipality and, second, we add to this figure the jobs in the neighboring municipalities. Then, we compute the following Euclidean distance $\sqrt{(I_m)^2+(I_a)^2}$, where I_m and I_a are the employment percentage deviations in the industry affected by the plant closure at the municipality and area (municipality and neighbors) levels, respectively.[15] Among the control municipalities whose employment level in this industry is higher than that of the treated municipality, i.e., $I_m > 0$, we select the two controls with the smallest Euclidean distance. We apply the same procedure to the control municipalities whose employment level in the affected industry is lower, i.e., $I_m < 0$.

We improve the matching strategy by further trimming controls that are too distant from the treated units (Imbens and Wooldridge, 2009). Specifically, we drop every matched control that differs from its treated municipality by more than 100% in any of the matching variables used.[16] While we allow municipalities to be the controls for more than one treatment, we do not find four controls for all 45 cases. As a result, we have 197 (as opposed to 225) case-municipality observations. Note that we have encountered the curse-of-dimensionality problem despite the small number of controls considered, implying that matching on more variables is unfeasible.[17] However, we will combine matching and regression analysis to improve our estimation strategy (Imbens and

15 The employment percentage deviation at the municipality level is defined as $I_m = (\text{emp}_{\text{treat}} - \text{emp}_{\text{contr}})/\text{emp}_{\text{contr}}$ where $\text{emp}_{\text{treat}}$ is the employment in the municipality and industry affected by the closure, while $\text{emp}_{\text{contr}}$ is the employment in the same industry in a potential control municipality. I_a is built with the exact same logic replacing municipality by area employment.

16 That is, if I_m, I_a or the equivalent metric for total employment at the area level is above 1 or below 0.5.

17 Alternatively, we could use propensity score matching that can naturally deal with many covariates without encountering the 'curse-of-dimensionality' problem. However, the plant closures that we study are, to a very large extent, unexpected and it is hard to come by with variables that can predict where plant closures will occur. A second alternative to matching, which is closer to the approach taken here, is the synthetic control algorithm, which matches pre-treatment trends in the dependent variable (see Abadie and Gardeazabal, 2003). However, this method is more appropriate for cases in which the treatment affects a large aggregate, such as a region or a country. In our case, we are able to choose our counterfactuals from a pool of more than 8000 municipalities and so building a synthetic control is unnecessary.

Wooldridge, 2009). Specifically, in the regressions we will include as controls all variables directly used in the matching as well as other pre-treatment covariates that we will detail below.

Figure 1 illustrates the case of *La Cellophane Española*, a rubber and plastics plant in *Burgos* that closed in 2001. Panel (a) shows the geographical location of treatment and controls (*Llinars del Vallès*, *Logroño*, *Alcalá de Henares* and *Silla*). Panel (b) zooms in to show that the five areas are in fact the sum of the municipality itself (dark gray) and its neighbors lying within a 10-km ring (light gray). These five municipalities have an employment level of between 50 and 100 thousand jobs if we consider the municipality itself together with the neighboring municipalities. *Llinars del Vallès* and *Silla* are the two closest matches having higher levels of employment than Burgos in the rubber and plastics industry in 2000. Analogously, *Logroño* and *Alcalá de Henares* are the two closest matches with lower levels of employment in this industry.

In order to validate the matching procedure, in Figure 2 we show the distributions of employment in the closing industry and of total employment for treatments and controls in 2000. Panels a) and c) refer to employment at the municipality level whereas panels b) and d) correspond to area levels. The distributions of treatment and control samples seem reasonably similar, suggesting that the matching strategy works. To complement this analysis, in Columns 2, 4, 6 and 8 in Table 1 we report the results of regressions in which each one of these pre-treatment employment levels is regressed on the treatment indicator variable, while controlling for case-fixed effects. The results validate the matching insofar as the treated and the controls do not present statistically significant differences for any of the variables used to perform the matching.[18]

In Columns 1, 3, 5 and 7 in Table 1 we run the same regressions measuring the same employment outcomes in 1990.[19] The results indicate that employment levels in 1990 in treatments and controls were also similar, suggesting common pre-treatment employment trends. The same message is conveyed in Figure 3, which plots the evolution of employment in the industry suffering a plant closure for the treatment and control groups, where both time and employment levels have been normalized for the year of plant closure.

4. Results

Using this matched sample, we use differences-in-differences specifications to estimate the effects of big plant closures on local employment. We focus our attention primarily on the employment changes that occurred between 2000 and 2008.

4.1. Local employment effects in the industry affected by the plant closure

In this section, we seek to estimate the impact of a plant closure on the employment in the industry suffering that closure. We estimate variants of the following equation:

$$\Delta\text{employment}_{ij} = \alpha_c + \beta \text{ job losses}_{ij} + X'_{ij}\delta + u_{ij}, \tag{1}$$

18 A further indication that matching works is given by the fact that the regression estimates of Section 4 are not affected by the inclusion of the variables used in the matching procedure.

19 The 1990 employment outcomes are drawn from *Censo de Locales del INE 1990*.

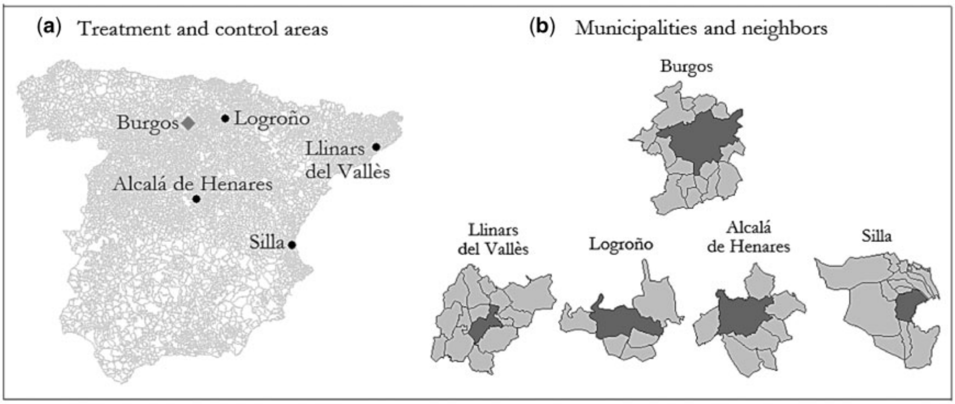

Figure 1. A plant closure example: treatment and control areas.
Notes: The example corresponds to Cellophane Española, a rubber and plastics plant in Burgos closing in 2001. Panel (a) shows the location of treatment and control areas within Spain while Panel (b) shows the selected municipalities (dark gray) and neighbors (light gray).

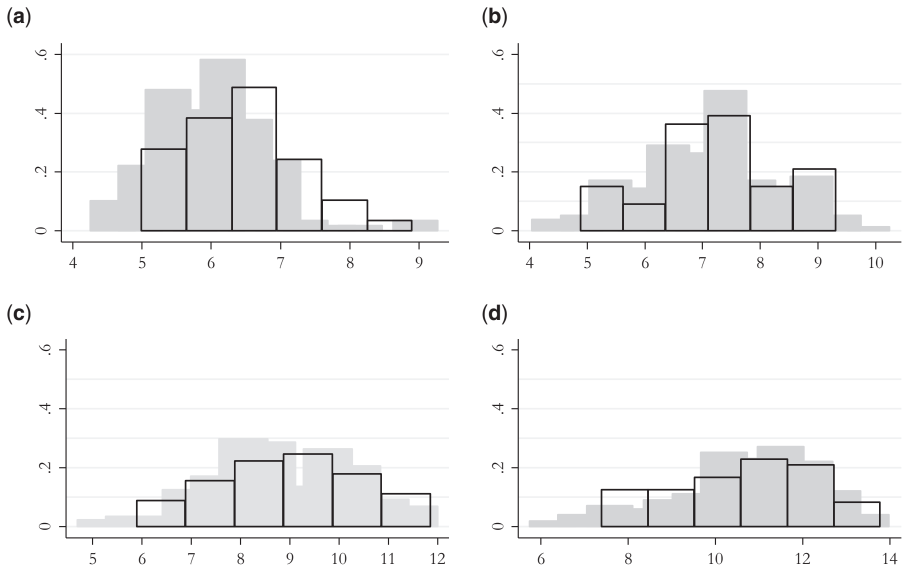

Figure 2. Distribution of matching variables—treatments and controls.
Note: Histograms for treatments (transparent bars) and controls (gray bars). Employment levels in 2000. (a) Employment in the affected industry—municipality, (b) employment in the affected industry—area, (c) overall employment—municipality and (d) overall employment—area.

where $\Delta \text{employment}_{ij}$ is the job change in area i and industry j between 2000 and 2008 and, thus, u_{ij} denotes shocks in employment changes. The key explanatory variable is job losses, which is defined as the layoff count associated with the particular plant closure. If $|\beta|$ equals 1, then each job lost as a result of the closure translates simply as one job lost in the local industry affected by that closure. We label $|\beta|$ equal to unity as 'the mechanical effect', as this is the expected outcome if the closure had zero impact on

Table 1. Differences between treatments and controls

	Employment in the affected industry				Overall employment			
	1990 Municipality	2000	1990 Area (municipality and neighbors)	2000	1990 Municipality	2000	1990 Area (municipality and neighbors)	2000
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatments	198.8	240.2	81.21	39.13	140	955.5	14,704	19,541
	(164.60)	(73.79)	(292.41)	(142.96)	(3112)	(4258)	(20,080)	(28,115)
Case dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.607	0.799	0.882	0.902	0.618	0.635	0.689	0.691
Observations	197	197	197	197	197	197	197	197

Notes: Pre-treatment employment levels in 1990 and 2000. Conley spatial HAC standard errors in parentheses (***$p<0.01$, **$p<0.05$, *$p<0.1$). The dependent variable in Columns 1–4 is the level of employment in the affected industry at the two-digit industry level. The first two columns show the results for the levels of 1990 and 2000 at the municipality level and Columns 3 and 4 show the same at the area level. The dependent variable in Columns 5–8 is the level of overall employment. Columns 5 and 6 present the results at the municipality level for the 1990 and 2000 levels, respectively, whereas the last two columns show the same at the area level. All specifications include case-fixed effects.

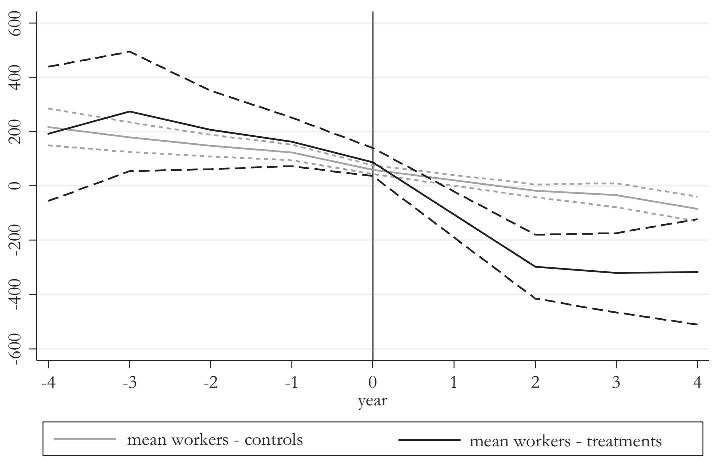

Figure 3. Employment in the plant closing industry.
Note: The year and employment level are normalized at the plant closure year.

the rest of the firms in the affected industry. However, if $|\beta|>1$, then each job lost as a result of the closure generates additional job losses in the affected industry and area. A possible mechanism accounting for such an outcome is that large plants create indirect jobs through the purchase of inputs from local suppliers. The presence of agglomeration economies would also be consistent with $|\beta|>1$ as the productivity of local firms might decrease as the size of the local economy shrinks (Moretti, 2010). Alternatively, if $|\beta|<1$, then each job lost as a result of the closure creates jobs in the local industry affected by the closure. In the presence of workers that are imperfectly mobile across locations and industries, a significant collective dismissal is a negative labor demand shock that would reduce the labor market tightness and wages and, thus, increase employment in other local firms. In terms of control variables, case-fixed effects (α_c) are always included to account for case industry employment trends. In some of the specifications, we also control for the 1990 and 2000 (pre-treatment) employment outcomes used in the matching procedure. Finally, in the more complete specifications, we further include the share of employment in manufacturing, services and construction sectors, the average firm size in the affected industry and in the manufacturing sector as a whole, the unemployment rate and, finally, the proportion of inhabitants with no completed studies, compulsory, upper-secondary and tertiary levels of education. To control for trends in these variables, we include these variables measured both in 2000 and in 1990 (2001 and 1991 for the educational levels). The baseline results are reported in the first three columns of Table 2. The standard errors have been obtained with the estimator proposed by Conley (1999) which is robust to heteroscedasticity and spatial correlation in the error term.[20]

The first column shows the estimates of a specification that only includes case-fixed effects. The results imply that a job lost as a result of a large plant closure reduces employment in the affected industry and area by −0.567, implying that the closure spurs employment growth in local firms operating in the same industry and area as the closing plant. In the second column, we add the 2000 and 1990 industry and overall employment levels. As expected, the main estimate of interest, β, is not greatly affected by the inclusion of these pre-treatment outcomes (the point estimate is −0.626) as these controls are orthogonal to treatment status as shown in Table 1. In the third column of Table 2, we report the results of our preferred specification which also includes the 2000 and 1990 levels of the control variables that are not used in the matching procedure. The coefficient remains largely unaltered, being the point estimate of −0.658. In the fourth column, we estimate a slightly different model by pooling all manufacturing industries so as to account for (possible) area-specific trends in employment. Here, the specifications include case industry-fixed effects and area-fixed effects, as well as all the other variables' pre-treatment levels. The results yield a point estimate of −0.639, confirming that when a large plant closes, employment in the rest of the firms within the local area and sector increases rather than decreases. As noted in Section 2.1, the plant closures that we analyze are relatively large (the median layoff is 264 workers) but, on average, the employment of the closing plant represents around 30% of the total local industry employment. Hence, the results that we find here might not carry over to closures of the 'million dollar plant' type examined by Greenstone et al. (2010) or to instances where the closing plant represents a very large share of the local industry.

We check the robustness of our results to the specific matching procedure adopted in two ways. First, we re-run the baseline specification selecting only the two closest controls (as opposed to four). The results, reported in Columns 1–4 in Table A2 (deferred to the Appendix), are largely unchanged, suggesting that our findings do not hinge on the exact number of controls selected. Second, we run a placebo exercise in which we drop the actual treatment and randomly assign it to any of the four controls.

20 We use the term Conley spatial HAC standard errors to refer to these standard errors. We use the code developed and described in Hsiang (2010).

Table 2. Impact of a plant closure on the affected industry

	A: 2000–2008 long differences				B: 2000–2008 yearly differences			
	Industry affected by plant closure			Pooled industries	Industry affected by plant closure			Pooled industries
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Job losses	−0.567**	−0.626***	−0.658*	−0.639*				
	(0.216)	(0.211)	(0.313)	(0.372)				
Job losses (−3)					−0.039	−0.008	−0.015	−0.035
					(0.027)	(0.069)	(0.062)	(0.046)
Job losses (−2)					−0.030	−0.0045	0.007	−0.026
					(0.103)	(0.074)	(0.063)	(0.087)
Job losses (−1)					0.001	0.029	0.059	0.059
					(0.097)	(0.100)	(0.072)	(0.071)
Job losses (0)					−0.702***	−0.682***	−0.682***	−0.707***
					(0.122)	(0.138)	(0.139)	(0.118)
Job losses (+1)					−0.049	−0.043	−0.051	0.055
					(0.064)	(0.063)	(0.058)	(0.054)
Job losses (+2)					−0.095	−0.088	−0.063	−0.081
					(0.130)	(0.117)	(0.078)	(0.111)
Job losses (+3)					−0.065	−0.055	−0.013	−0.019
					(0.057)	(0.046)	(0.060)	(0.056)
Case-fixed effects	Yes	Yes	Yes	No	No	No	No	No
Matching variables' controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Other controls	No	No	Yes	Yes	No	No	Yes	Yes
Case year-fixed effects	No	No	No	No	Yes	Yes	Yes	No
Case industry-fixed effects	No	No	No	Yes	No	No	No	No
Case industry year-fixed effects	No	No	No	No	No	No	No	Yes
Area-fixed effects	No	No	No	Yes	No	No	No	Yes
R^2	0.640	0.762	0.772	0.804	0.287	0.301	0.332	0.209
Observations	197	197	197	4531	1460	1460	1460	30,475

Notes: Conley spatial HAC standard errors in parentheses (***$p<0.01$, **$p<0.05$, *$p<0.1$). The dependent variable in Columns 1–4 is the change in employment between 2000 and 2008 at the two-digit industry level. The dependent variable in Columns 5–8 are 2000–2008 yearly changes. Columns 1, 2, 3, 5, 6 and 7 include only the treated industry for each case while Columns 4 and 8 include all manufacturing industries. Matching variables' controls are the 2000 and 1990 industry and total employment levels. Other controls are the share of employment in manufacturing, services and construction sectors, the average firm size in the affected industry and in the manufacturing sector as a whole, the unemployment rate and the proportion of inhabitants with no completed studies, compulsory, upper-secondary and tertiary levels of education. These are measured both in 2000 and in 1990 (2001 and 1991 for the educational levels). There are 23 (two-digit) industries in Columns 4 and 8.

The results, presented in Columns 5–8, are reassuring as none of the coefficients of interest are statistically significant.

In the baseline regressions (panel A in Table 2), we focus on changes in employment in an 8-year time window. We do this as opposed to examining yearly changes for two reasons. First, (potential) anticipation effects might mean that employment falls in the year(s) prior to a plant closure. Second, the local response to a plant closure might take more than 1 year to take effect. To determine whether these possibilities are relevant in our application, in panel B of Table 2 we examine yearly employment changes between 2000 and 2008. In these regressions, we include the main explanatory variable (job losses) in the year the closure occurs as well as three lags and leads of this variable. In terms of control variables, Panels A and B adhere to the same logic, although the addition of the time dimension changes the nature of the fixed effects that can be accounted for. Specifically, Column 5 only includes case year-fixed effects, Column 6 further includes the 2000 and 1990 employment levels, while Column 7 also adds the variables not included in the matching procedure. Finally, in Column 8, we report the results of the specification that pools all manufacturing industries where case industry year-fixed effects and area-fixed effects are introduced. We find no statistically significant results for any of the lag and lead variables. This finding suggests that anticipation effects are not especially relevant in our application and that the bulk of the adjustment takes place within a year of plant closure. These results are largely consistent with Figure 3 which shows the evolution in the level of employment in the treated and control groups. However, the contemporaneous closure point estimates are slightly higher (in absolute value) than those found using 2000–2008 differences. Specifically, the point estimates using yearly variation range between −0.682 and −0.707. This is consistent with a slight recovery in employment levels in the treated areas in the years after the plant closure.

In Section 3, when describing the matching procedure used, it was acknowledged that the effects of a plant closure might extend beyond the borders of a municipality. In Table 3, we explore in depth the geographical scope of the effects under study. To this end, we estimate variants of the following specification:

$$\text{employment}_{mj} = \alpha_c + \beta_0 \text{ job losses}_{mj}\, I_0 + \beta_{10} \text{ job losses}_{ij}\, I_{10} + \gamma I_0 + X'_{mj}\delta + u_{mj}, \tag{2}$$

where $\Delta\text{employment}_{mj}$ is the 2000–2008 change in the number of jobs in municipality m and industry j. Note that there are four types of municipality. Returning to the example illustrated in Figure 1, there is one treated area (*Burgos*) and four control areas (*Llinars del Vallès*, *Logroño*, *Alcalá de Henares* and *Silla*). In turn, each area comprises the municipality itself (dark gray) and the municipalities within a 10-km radius of it (light gray). Hence, we have treated municipalities, treated neighbors, untreated municipalities and untreated neighbors. I_0 indicates if the municipality itself is a treatment or a control (dark gray municipality) while I_{10} takes the value of 1 for the remaining municipalities within the treated and control areas (light gray municipalities). In the regressions we interact these indicators with our main explanatory variable and, thus, we estimate the employment effect in the municipality directly affected by the closure (β_0) and in the municipalities within a 10-km radius of the plant that has been closed down (β_{10}). Since the number of jobs in the plant being closed down does not form part of the neighbors' employment figures, no effects being recorded in neighboring municipalities implies $\beta_{10} = 0$. The results are presented in Table 3.

Here again Column 1 only includes case-fixed effects and the indicator variable I_0. Column 2 additionally includes, as controls, 1990 and 2000 (pre-treatment) employment levels measured here at the municipality level. Column 3 includes the latter controls and all control variables not directly employed at the matching stage. Finally, Column 4 pools the data from all manufacturing industries. We find no evidence that the effects of a big plant closure extend beyond the municipality in which the closure has occurred as soon as we control for employment pre-treatment levels. Hence, our finding that plant

Table 3. The geographical scope of the employment effects of a big plant closure; 2000–2008 long differences

	Industry affected by plant closure			Pooled industries
	(1)	(2)	(3)	(4)
Job losses in own municipality (β_0)	−1.137***	−0.777***	−0.642***	−0.688***
	(0.219)	(0.161)	(0.172)	(0.179)
Job losses in neighboring municipality (β_{10})	0.066***	0.002	0.014	−0.007
	(0.015)	(0.008)	(0.054)	(0.031)
Case-fixed effects	Yes	Yes	Yes	No
I_0 indicator	Yes	Yes	Yes	Yes
Matching variables' controls	No	Yes	Yes	Yes
Other controls	No	No	Yes	Yes
Case industry-fixed effects	No	No	No	Yes
Area-fixed effects	No	No	No	Yes
R^2	0.108	0.349	0.364	0.510
Observations	2348	2348	2348	54,004

Notes: Conley spatial HAC standard errors in parentheses (***$p<0.01$, **$p<0.05$, *$p<0.1$). The dependent variable is the change in employment between 2000 and 2008 at the industry and municipality level. I_0 as defined in the text. Columns 1, 2 and 3 include only the treated industry for each case, while Column 4 includes all manufacturing industries in each municipality. Matching variables' controls are the 2000 and 1990 industry and total employment levels at the municipality level. Other controls are the share of employment in manufacturing, services and construction sectors, the average firm size in the affected industry and in the manufacturing sector as a whole, the unemployment rate and the proportion of inhabitants with no completed studies, compulsory, upper-secondary and tertiary levels of education. These are measured both in 2000 and in 1990 (2001 and 1991 for the educational levels). There are 23 (two-digit) industries in Column 4.

closures spur employment growth in local firms operating in the same industry and area is driven solely by the behavior of firms located in the same municipality as that which has suffered the plant closure.[21]

4.2. The employment effects of plant closures on incumbents and new entrants

The results reported in Section 4.1 indicate that for each job lost due to a plant closure only around 0.6–0.7 jobs are lost in the affected industry. This suggests that jobs are created in the industry and area directly affected by the closure. In this regard, it is interesting to determine whether these jobs are created by new or incumbent firms. To answer this question we draw on data from the SABI (firm-level) database. Although SABI does not cover the universe of Spanish firms, its coverage is extensive (around 80% of the firms on the Social Security register).[22] We identify in the SABI database all

21 Additional evidence that interactions between firms are highly localized has been provided by Rosenthal and Strange (2003) and Arzaghi and Henderson (2008) for the USA and by Viladecans-Marsal (2004) and Jofre-Monseny (2009) for the Spanish case.

22 SABI is a firm and not a plant database. Nevertheless, the Spanish economy is dominated by small and medium sized firms. In fact, only 1.1% of the firms in Spain in 2006 were multi-plant firms (Encuesta sobre Estrategias Empresariales, 2008).

firms reported as being active in the industry affected by the plant closure. This means the industry definition applied here is somewhat wider than that used above as a firm might be active in more than one industry. Columns 1–4 in Table 4 re-estimate the baseline analysis using local employment levels built with the SABI database. We exclude the jobs in the plant being closed and, thus, the 'mechanical effect' now becomes zero.

The results in Table 4 indicate that local employment in same-industry firms increases due to a plant closure. Focusing on our preferred specification, Column 3, the estimates imply that 0.3 jobs are created for each job lost in a plant closure. These estimates constitute an important robustness check as the multipliers obtained in Tables 2 and 4 are remarkably close to each other despite the fact that they have been obtained using two entirely different datasets. Moreover, these results also suggest that measurement error in the plant layoffs is not seriously biasing our estimates. Measurement error should bias the estimates toward zero in both specifications, over-estimating the employment increase in other firms in Table 2 and under-estimating it in Table 4. Fortunately, the implied effects are remarkably similar.[23]

In Table 5, we exploit the firm-level nature of the data and estimate whether the increase in employment in other firms takes place in new or in incumbent firms. Columns 1–4 report the results for new firms while Columns 5–8 show the corresponding employment effects for incumbent firms. According to the results, most of the job increase takes place in incumbent firms, that is, in firms that existed before the plant was closed down. According to our preferred specification, Columns 3 and 7, for each job lost, 0.08 and 0.22 jobs are created in new and incumbent firms, respectively. The relatively larger effect found for incumbent firms can be rationalized by the fact described above, namely, that our closing plants are not isolated but are co-located with same-industry firms.

4.3. Effects on closely linked industries

If some of the input suppliers are local firms, the plant closure might reduce the local employment in these industries. At the same time, the negative local labor demand shock might reduce local wages, increasing the incentives to hire more workers. Hence, the employment effect on closely linked industries is theoretically ambiguous (Moretti, 2010). To carry out the empirical analysis, we will use the SABI database as it contains the industry of firms at the three-digit level, which allows us to build more accurate input–output linkages between industries. More precisely, using the 2001 Catalan Input–Output Table built by Statistics Catalonia, we compute, for each treated industry, the input–output linkages with all the other industries.[24] Then, we estimate the effects of closures on changes in local employment between 2000 and 2008 in the industries which are the main input suppliers of the closing plant. We adopt two alternative definitions of input supplier industries. In panel A, we consider the three main industries measured at the three-digit level while in panel B we specify a less

23 Additionally, for the plant closures in the region of Catalonia, we gained access to administrative data regarding the employment affected by the closures. These employment figures are remarkably close to the records contained in the closures database that we examine.

24 We use the Catalan Input–Output Table instead of the Spanish one because it is more disaggregated and allow us to measure links between industries beyond the three-digit level.

Table 4. Impact of a plant closure on the affected industry; SABI database; 2000–2008 changes; overall effects

	Industry affected by plant closure			Pooled industries
	(1)	(2)	(3)	(4)
Job losses	0.440***	0.303**	0.297**	0.227*
	(0.139)	(0.144)	(0.132)	(0.124)
Case-fixed effects	Yes	Yes	Yes	No
Matching variables' controls	No	Yes	Yes	Yes
Other pre-treatment controls	No	No	Yes	Yes
Case industry-fixed effects	No	No	No	Yes
Area-fixed effects	No	No	No	Yes
R^2	0.240	0.191	0.185	0.410
Observations	197	197	197	4531

Notes: Conley spatial HAC standard errors in parentheses (***$p<0.01$, **$p<0.05$, *$p<0.1$). The dependent variable is the change in employment between 2000 and 2008 at the two-digit industry level computed using the SABI database and excluding the plant forced to close. Columns 1, 2 and 3 include only the treated industry for each case while Column 4 includes all manufacturing industries. Matching variables' controls are the 2000 and 1990 industry and total employment levels. Other pre-treatment controls are the share of employment in manufacturing, services and construction sectors, the average firm size in the affected industry and in the manufacturing sector as a whole, the unemployment rate and the proportion of inhabitants with no completed studies, compulsory, upper-secondary and tertiary levels of education. These are measured both in 2000 and in 1990 (2001 and 1991 for the educational levels). There are 23 (two-digit) industries in Column 4.

Table 5. Impact of a plant closure on the affected industry; SABI database; 2000–2008 changes; new and incumbent firms

	New firms				Incumbent firms			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Job losses	0.102**	0.089*	0.075*	0.089*	0.338***	0.214*	0.221*	0.138*
	(0.051)	(0.047)	(0.046)	(0.045)	(0.126)	(0.106)	(0.130)	(0.071)
Case-fixed effects	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Matching variables' controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Other controls	No	No	Yes	Yes	No	No	Yes	Yes
Case industry-fixed effects	No	No	No	Yes	No	No	No	Yes
Area-fixed effects	No	No	No	Yes	No	No	No	Yes
R^2	0.082	0.121	0.155	0.255	0.150	0.171	0.179	0.292
Observations	197	197	197	4531	197	197	197	4531

Notes: Conley spatial HAC standard errors in parentheses (***$p<0.01$, **$p<0.05$, *$p<0.1$). The dependent variable is the change in employment between 2000 and 2008 at the two-digit industry level computed using the SABI database and excluding the plant forced to close. Columns 1, 2, 3, 5, 6 and 7 include only the treated industry for each case while Columns 3 and 8 include all manufacturing industries. Matching variables' controls are the 2000 and 1990 industry and total employment levels. Other controls are the share of employment in manufacturing, services and construction sectors, the average firm size in the affected industry and in the manufacturing sector as a whole, the unemployment rate and the proportion of inhabitants with no completed studies, compulsory, upper-secondary and tertiary levels of education. These are measured both in 2000 and in 1990 (2001 and 1991 for the educational levels). There are 23 (two-digit) industries in Columns 4 and 8.

restrictive definition and consider the 25% most related industries. Each regression pools observations from different industries and, thus, sample sizes in panels A and B differ and are larger than those corresponding to Tables 2–5. The results are reported in Columns 1–4, which follow the structure of the previous tables in terms of specification and control variables.

The results indicate that there is a significant positive effect for the two definitions. The estimates reported in Column 3 of Table 6 imply that, for each job directly lost in a plant closure, 0.091 jobs are created in each of the three industries which are the main input providers. For the less restrictive definition (25% of closest industries), the effect goes down to 0.034, but it still is statistically significant. One fact to keep in mind is that many providers at the three-digit level tend to be within the same two-digit industry.[25] In Columns 4–8 in Table 6 we replicate the same analysis excluding the input providers found within the same two-digit industry. That is, we estimate the employment effects for input providers found in two-digit industries that are distinct from the closing plant. The results indicate that the positive employment effect found in Columns 1–4 completely disappears. This pattern suggests that besides the positive employment effect at two-digit industry level documented above (Tables 2–4), no employment effects are detected in closely linked industries.

4.4. Effects on other manufacturing industries and services

After having analyzed the effect of plant closures on closely linked industries, for completeness, we also report estimates of the employment effects in other manufacturing firms. The analysis is conducted here at the two-digit level with Social Security employment data. We pool all manufacturing sectors except that of the plant closure. The results are reported in Columns 1–3 in Table 7. The results are obtained from a specification that only includes case industry-fixed effects. In Column 2, we further include the industry and overall employment levels in 1990 and 2000. Finally, in Column 3 we further include the additional control variables contained in the baseline specification reported in the third column in Tables 2–4. The results indicate no significant employment effects of plant closures other than manufacturing industries.

Many services are non-tradable implying that, in reducing local income, plant closures might negatively impact the employment in local services (Moretti, 2010). Hence, in Columns 4–6 we replicate the analysis for the services sector. All coefficients are statistically insignificant and close to zero, indicating that plant closures have no effect on the services' sector, either.

4.5. Effects on population growth, labor force participation and unemployment

A plant closure constitutes a negative labor demand shock which might affect migration (by increasing out-migration and reducing in-migration). Since mobility is costly and workers might have idiosyncratic preferences for locations, less jobs can also increase unemployment and decrease labor force participation (Blanchard and Katz, 1992). To test if the plant closures had an impact on these margins, we use data on total and working-age (16–64) population from the Municipal Population Registry (*Padrón*

25 In our sample of closures, almost half of the intermediate inputs are actually purchased from firms within the two-digit industry.

Table 6. Impact of a plant closure on the most related industries; SABI database; input–output linkages; 2000–2008 changes; three-digit industries

	Including industries within two-digit classification				Excluding industries within two-digit classification			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Three most related industries								
Job losses	0.130**	0.123**	0.091*	0.118**	−0.064	−0.070	−0.255	−0.226
	(0.057)	(0.052)	(0.050)	(0.050)	(0.500)	(0.489)	(0.714)	(0.777)
Case-fixed effects	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Pre-treatment employment controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Other controls	No	No	Yes	Yes	No	No	Yes	Yes
Case industry-fixed effects	No	No	No	Yes	No	No	No	Yes
Area-fixed effects	No	No	No	Yes	No	No	No	Yes
R^2	0.673	0.905	0.939	0.905	0.555	0.752	0.771	0.821
Observations	676	676	676	12,148	756	756	756	12,148
B: 25% most related industries								
Job losses	0.069**	0.084**	0.034*	0.068**	−0.024	0.021	−0.111	−0.090
	(0.031)	(0.036)	(0.018)	(0.030)	(0.040)	(0.021)	(0.117)	(0.108)
Case-fixed effects	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Pre-treatment employment controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Other controls	No	No	Yes	Yes	No	No	Yes	Yes
Case industry-fixed effects	No	No	No	Yes	No	No	No	Yes
Area-fixed effects	No	No	No	Yes	No	No	No	Yes
R^2	0.221	0.367	0.369	0.334	0.184	0.302	0.510	0.565
Observations	3056	3056	3056	12,148	3202	3202	3202	12,148

Notes: Conley spatial HAC standard errors in parentheses (***$p<0.01$, **$p<0.05$, *$p<0.1$). The dependent variable is the change in employment of the most related industries between 2000 and 2008 at the three-digit industry level computed using the SABI database. Panel A shows the three main related industries while panel B considers the 25% most related industries. Columns 1–4 can include three-digit industries within the affected two-digit industries while Columns 4–8 exclude all three-digit industries within the two-digit industry affected by the closure. There is not always a one-to-one correspondence between two-digit industries and the sectors considered in the input–output table that we use. Specifically, in some cases, the input–output sector comprises several three-digit industries. This is why the numbers of industries in Columns 1–4 and 5–8 do not coincide. Pre-treatment employment controls are the 2000 and 1990 industry and total employment levels. Other controls are the share of employment in manufacturing, services and construction sectors, the average firm size in the affected industry and in the manufacturing sector as a whole, the unemployment rate and the proportion of inhabitants with no completed studies, compulsory, upper-secondary and tertiary levels of education. These are measured both in 2000 and in 1990 (2001 and 1991 for the educational levels). There are 102 (three-digit) industries in Columns 4 and 8.

Table 7. Impact of a plant closure on other industries

	Other manufacturing industries			Services		
	(1)	(2)	(3)	(4)	(5)	(6)
Job losses	0.022	0.035	0.027	0.053	0.104	0.057
	(0.127)	(0.051)	(0.035)	(0.311)	(0.085)	(0.095)
Case industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Pre-treatment employment controls	No	Yes	Yes	No	Yes	Yes
Other controls	No	No	Yes	No	No	Yes
R^2	0.195	0.297	0.319	0.262	0.656	0.657
Observations	4334	4334	4334	2955	2955	2955

Notes: Conley spatial HAC standard errors in parentheses (***$p<0.01$,**$p<0.05$, *$p<0.1$). The dependent variable is the change in employment between 2000 and 2008 at the industry and area level. Pre-treatment employment controls are the 2000 and 1990 industry and total employment levels. Other controls are the share of employment in manufacturing, services and construction sectors, the average firm size in the affected industry and in the manufacturing sector as a whole, the unemployment rate and, finally, the proportion of inhabitants with no completed studies, compulsory, upper-secondary and tertiary levels of education. These are measured both in 2000 and in 1990 (2001 and 1991 for the educational levels). There are 23 (two-digit) industries in Columns 1, 2 and 3 and 15 industries in Columns 4, 5 and 6

Municipal) between 2000 and 2008, and data on registered unemployment from the Spanish Employment Office (*Servicio Público de Empleo Estatal*) for the same years. In order to control for possible pre-trends in these outcomes, we will include as controls lagged outcomes drawn from the 1991 Population and Housing Census. To estimate the effect of plant closures on mobility, labor force participation and unemployment rates we estimate variants of the following specification:

$$\Delta y_i \;=\; \alpha_c + \rho \text{ closure}_i + X_i'\delta \;+\; u_i, \tag{3}$$

where y_i is, alternatively, the population growth rate over the 2000–2008 period, or the change in the labor force participation or unemployment rate over the same period of time. The main explanatory variable, closure$_i$, is here a treatment indicator, X_i is a set of control variables, while u_i is an error term. Table 8 shows the results, with the estimates for each of the outcomes analyzed being reported in a different row. Column 1 reports the results when only case-fixed effects are included. Column 2 adds in the 1990 and 2000 values of the variables directly used in the matching procedure, while Column 3 also includes the (1990 and 2000) values of the variables not included in the matching procedure. In all cases, the coefficients are statistically insignificant and close to zero, showing no impact of the plant closures on the population growth rate, the labor force participation rate and the unemployment rate. Note that the fact that closures do not impact mobility implies that our control units are unlikely to be affected by migration triggered by the plant closures.[26]

26 Note that the employment affected by the 45 closures is small relative to national employment. This further reduces the concerns related to the violation of the Stable Unit Treatment Value Assumption (SUTVA).

Table 8. Impact of a plant closure on population growth rate, labor force participation rate and unemployment rate; 2000–2008 changes

	(1)	(2)	(3)
Population growth rate			
Closure	−0.021	−0.021	−0.001
	(0.024)	(0.025)	(0.022)
R^2	0.524	0.524	0.665
Labor force participation rate			
Closure	−0.0004	0.0003	0.0014
	(0.0021)	(0.002)	(0.0018)
R^2	0.326	0.432	0.547
Unemployment rate			
Closure	−0.003	−0.005	−0.002
	(0.006)	(0.004)	(0.004)
R^2	0.552	0.734	0.773
Observations	197	197	197
Case-fixed effects	Yes	Yes	Yes
Matching variables' controls	No	Yes	Yes
Other pre-treatment controls	No	No	Yes

Notes: Conley spatial HAC standard errors in parentheses (***$p<0.01$, **$p<0.05$, *$p<0.1$). The dependent variable is the change in the outcome between 2000 and 2008 at the area level. Each row shows the estimate of a different regression. Matching variables' controls are the 2000 and 1990 industry and total employment levels. Other controls include the share of employment in manufacturing, services and construction sectors, the average firm size in the affected industry and in the manufacturing sector as a whole, the unemployment rate and the proportion of inhabitants with no completed studies, compulsory, upper-secondary and tertiary levels of education. These are measured both in 2000 and in 1990 (2001 and 1991 for the educational levels).

5. Conclusions

Local and regional governments around the world use subsidies to attract large plants. Similarly, large incumbent plants will often try to hold regional governments to 'ransom' under the threat of relocating production. The argument frequently made to justify such subsidies is that large plant closures have marked effects on employment that can extend beyond those of the collective dismissal itself. In this paper, we have empirically estimated the net local employment responses to large manufacturing plant closures.

Specifically, we have estimated the employment effects of the closure of 45 large manufacturing plants in Spain, which relocated to low-wage countries between 2001 and 2006. We match each municipality experiencing a closure to a small set of comparable municipalities in terms of employment level and mix in the year 2000. We find that treatments and controls do not differ in their 1990–2000 (pre-treatment) employment trends, thereby lending credence to the identification assumption underpinning our differences-in-differences estimates. Our results show that when a plant closes, for each job directly lost in the plant closure, between 0.3 and 0.4 jobs are actually created by other firms in the same local area and industry. Hence, the indirect effects of plant closures offset rather than magnify the employment consequences of the collective dismissal. We find no effects of the closure on the employment of other industries. We do not find effects along the migration, participation and unemployment margins, either.

A few considerations are worth making regarding the external validity of our findings. First, among the countries of the OECD, Spain's employment protection regulations are among the strictest. At the same time, following a big plant closure, Spain's regional governments often intervene to facilitate the re-employment of some of the dismissed workers in local firms. Hence, employment responses may differ in contexts with less government intervention. Second, the closures we analyze occurred in a period (2001–2006) in which the Spanish economy was growing. It could well be that the consequences of massive layoffs are far more negative in stagnant economies. Finally, while the closures that we examine constitute a significant shock for the affected local industry (representing around 30% of its employment), the shock on the local economy as a whole is moderate (about 3% of total employment). Hence, our results might not carry over to instances in which a closure represents a large share of the local economy or in cases in which the closing plant is not surrounded by other same-industry firms. This said, our findings indicate that the net employment responses to plant closures do not always justify large subsidies to avoid the relocation of large manufacturing plants.

Acknowledgments

We gratefully acknowledge helpful comments from the Editor, two anonymous referees, Henry Overman, Olmo Silva, Giulia Faggio, Rosa Sanchís-Guarner, and participants at the SERC work in progress seminar, IEB PhD seminar, 2014 SERC Annual Conference, INFER Workshop (Reus), UEA Meeting (Washington, DC), and the 2015 SAE Meeting (Girona). We acknowledge the financial support from Ministerio de Economía y Competitividad [ECO2013-41310 and ECO2016-75941-R] and Generalitat de Catalunya [2014SGR420].

References

Abadie, A., Gardeazabal, J. (2003) The economic costs of conflict: a case study of the Basque Country. *The American Economic Review*, 93: 113–132.

Arzaghi, M., Henderson, J. V. (2008) Networking off Madison Avenue. *Review of Economic Studies*, 75: 1011–1038.

Blanchard, O., Katz, L. (1992) Regional evolutions. *Brookings Papers on Economic Activity*, 23: 1–75.

Conley, T. G. (1999) GMM estimation with cross sectional dependence. *Journal of Econometrics*, 92: 1–45.

Couch, K., Placzek, D. (2010) Earnings losses of displaced workers revisited. *American Economic Review*, 100: 572–589.

Crozet, M., Mayer, T., Mucchielli, J. L. (2004) How do firms agglomerate? A study of FDI in France. *Regional Science and Urban Economics*, 34: 27–54.

Diamond, R. (2016) The determinants and welfare implications of US workers' diverging location choices by skill: 1980–2000. *American Economic Review*, 106: 479–524.

Edmiston, K. D. (2004) The net effects of large plant locations and expansions on county employment. *Journal of Regional Science*, 44: 289–320.

Encuesta sobre Estrategias Empresariales. (2008) Las empresas industriales en 2006. Madrid. Fundación SEPI.

Faggio, G., Overman, H. (2014) The effect of public sector employment on local labour markets. *Journal of Urban Economics*, 79: 91–107.

Fox, W. F., Murray M. N. (2004) Do economic effects justify the use of fiscal incentives? *Southern Economic Journal*, 71: 78–92.

Garda, P. (2013) Essays on the Macroeconomics of Labor Markets. Doctoral dissertation, Universitat Pompeu Fabra.
Glaeser, E. L (2001) *The Economics of Location-Based Tax Incentives*. Discussion Paper No. 1932. Cambridge, MA: Harvard Institute of Economic Research.
Greenstone, M., Moretti, E. (2004) Bidding for industrial plants: does winning a 'million dollar plant' increase welfare? Mimeo.
Greenstone, M., Hornbeck, R., Moretti, E. (2010) Identifying agglomeration spillovers: evidence from winners and losers of large plant openings. *Journal of Political Economy*, 118: 536–598.
Hooker, M. A., Knetter, M. M. (2001) Measuring the economic effects of military base closures. *Economic Inquiry*, 39: 583–598.
Hsiang S. M. (2010) Temperatures ad cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of Science of the United States of America*, 107: 15367–15372.
Imbens, G., Wooldridge, J. (2009) Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, 47: 5–86.
Jacobson, L., LaLonde, R., Sullivan, D. (1993) Earnings losses of displaced workers. *American Economic Review*, 83: 685–709.
Jofre-Monseny, J. (2009) The scope of agglomeration economies: evidence from Catalonia. *Papers in Regional Science*, 88: 575–590.
Moretti, E. (2010) Local multipliers. *The American Economic Review*, 100: 373–377.
Moretti, E. (2011) Local labor markets. In D. Card and O. Ashenfelter (eds) *Handbook of Labor Economics*, vol. 4, part B, pp. 1237–1313. Amsterdam: Elsevier.
Myro, R., Fernández-Otheo, C. M. (2008) Profitability of Spanish foreign direct investment. *Journal GCG Georgetown University-Universia*, 2: 76–99.
Neal, D. (1995) Industry-specific human capital: evidence from displaced workers. *Journal of Labor Economics*, 13: 653–677.
Notowidigdo, M. (2013) The incidence of labor demand shocks. University of Chicago, Mimeo.
Poppert, P. E., Herzog, H. W., Jr. (2003) Force reduction, base closure, and the indirect effects of military installations on local employment growth. *Journal of Regional Science*, 43: 459–482.
Rosenthal, S. S., Strange, W. C. (2003) Geography, industrial organization, and agglomeration. *Review of Economics and Statistics*, 85: 377–393.
Rosenthal, S., Strange, W. (2004) Evidence on the nature and sources of agglomeration economics. In J. V. Henderson and J. F. Thisse (eds), *Handbook of Urban and Regional Economics*, vol. 4, pp. 2119–2172. Amsterdam: North-Holland.
Viladecans-Marsal, E. (2004) Agglomeration economies and industrial location: city-level evidence. *Journal of Economic Geography*, 4: 565–582.
von Wachter, T., Song, J., Manchester, J. (2011) Long-term earnings losses due to mass-layoffs during the 1982 recession: an analysis using longitudinal administrative data from 1974 to 2008. University of California at Los Angeles, Mimeo.
Wilson, J. D. (1999) Theories of tax competition. *National Tax Journal*, 52: 269–304.

Appendix

Table A1. Big plant closures sample

Case	Firm	Municipality	Two-digit industry classification	Year	Number of job losses	Destination
1	Jumberca S.A.	Badalona	29—Machinery and equipment	2002	201	China
2	Proflex S.A.	Calaf	24—Chemicals and chemical products	2004	105	Czech Republic
3	Torcidos Ibéricos S.A.	Castellbell i el Vilar	17—Textiles	2005	116	India
4	Braun Española S.L.	Esplugues de Llobregat	29—Machinery and equipment	2006	684	China
5	DB Apparel Spain S.A.	Igualada	17—Textiles	2003	255	Morocco
6	Tenería Moderna S.A.L.	Mollet del Vallès	19—Leather and leather Products	2003	131	–
7	Hilados y Tejidos Puigneró S.A.	Sant Bartomeu del Grau	17—Textiles	2002	502	–
8	Galler Textiles S.A.	Sant Boi de Llobregat	17—Textiles	2003	313	Thailand
9	ZF Sistemas de dirección Nacam S.L.	Sant Boi de Llobregat	34—Motor vehicles, trailers and semi-trailers	2006	185	Germany/France
10	José Ribatallada S.L.	Cerdanyola del Vallès	15—Food products and beverages	2005	117	–
11	Celestica S.L.	Cerdanyola del Vallès	30—Office machinery and computers	2004	320	Czech Republic
12	Selecciones Americanas S.A.	Sitges	18—Wearing apparel, dressing and dyeing of fur	2005	124	China
13	IMC Toys S.A.	Terrassa	36—Furniture and other manufacturing	2003	139	China
14	Autotex S.A.	Viladecavalls	17—Textiles	2004	189	Czech Republic
15	TRW Automotive España S.L.	Burgos	34—Motor vehicles, trailers and semi-trailers	2005	318	Poland/Czech Republic
16	La Cellophane Española S.A.	Burgos	25—Rubber and plastics products	2001	310	–
17	Delphi Automotive Systems España S.L.	Puerto Real	34–Motor vehicles, trailers and semi-trailers	2006	1600	Morocco
18	Panasonic Iberia S.A.	Celrà	29—Machinery and equipment	2004	214	China
19	Tybor S.A.	Massanes	17—Textiles	2003	149	China
20	La Preparación Textil S.A.	Ripoll	17—Textiles	2004	145	China
21	Promek S.L.	Azuqueca de Henares	34—Motor vehicles, trailers and semi-trailers	2004	350	Poland/Czech Republic
22	Moulinex España, S.A.	Barbastro	29—Machinery and equipment	2003	270	China
23	JoyCo España S.A.	Alcarràs	15—Food products and beverages	2004	213	China
24	Lear Corporation Spain S.L.	Cervera	31—Electrical machinery and apparatus	2001	1280	Poland
25	Delphi Componentes S.A.	Agoncillo	34—Motor vehicles, trailers and semi-trailers	2001	578	Poland

(continued)

Table A1. Continued

Case	Firm	Municipality	Two-digit industry classification	Year	Number of job losses	Destination
26	Electrolux España S.A.	Fuenmayor	29—Machinery and equipment	2005	454	Hungary
27	Yoplait España S.L.	Alcobendas	15—Food products and beverages	2001	185	France
28	Sanmina-SCI España S.L.	Leganés	32—Radio, television and communication equipment	2001	250	Hungary
29	Vitelcom Mobile Technology S.A.	Málaga	32—Radio, television and communication equipment	2004	433	Korea
30	Calseg S.A.	Artajona	19—Leather and leather Products	2001	150	Tunisia
31	Findus España S.L.	Marcilla	15—Food products and beverages	2001	471	Italy/UK
32	Viscofan S.A.	Pamplona	25—Rubber and plastics products	2006	742	Brazil/Czech Republic
33	TRW Automotive España S.A.	Orkoien	34—Motor vehicles, trailers and semi-trailers	2002	382	Poland
34	Valeo Sistemas de Conexión Eléctrica S.L.	San Cibrao das Viñas	31—Electrical machinery and apparatus	2004	264	Poland
35	MMN&P Acconta S.A.	Segovia	34—Motor vehicles, trailers and semi-trailers	2001	190	Morocco
36	Levi Strauss de España S.A.	Ólvega	17—Textiles	2003	561	Poland/Hungary
37	Delphi Packard España S.L.	Ólvega	34—Motor vehicles, trailers and semi-trailers	2001	560	Morocco/Romania
38	GDX Automotive Ibérica S.L.	Valls	25—Rubber and plastics products	2005	153	Germany/Czech Republic
39	Sanmina-SCI España S.L.	Toledo	32—Radio, television and communication equipment	2005	430	Thailand/China
40	Alcatel Lucent España S.A.	Toledo	32—Radio, television and communication equipment	2002	150	Hungary
41	Grupo Tavex S.A.	Alginet	17—Textiles	2006	300	Brazil/Mexico
42	Bayer Cropscience S.A.	Quart de Poblet	24—Chemicals and chemical products	2006	300	Portugal
43	Valeo España S.A.	Abrera	31—Electrical machinery and apparatus	2001	406	Morocco/Tunisia
44	IAR Ibérica S.A.	Montcada i Reixac	29—Machinery and equipment	2004	423	Hungary
45	Fisipe Barcelona S.A.	El Prat de Llobregat	17—Textiles	2006	270	China

Note: In cases 6, 7, 10 and 16, we have been unable to identify the country to which the firm relocated.
Source: Derived from data in Myro and Fernández-Otheo (2008) with additional information collected from news sources by the authors.

Table A2. Impact of a plant closure in the affected industry; 2000–2008 employment changes; Robustness checks

	Industry affected by plant closure			Pooled industries	Industry affected by plant closure			Pooled industries
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Job losses	−0.550**	−0.673***	−0.760***	−0.553**	−0.007	0.077	0.171	0.061
	(0.238)	(0.228)	(0.262)	(0.234)	(0.255)	(0.201)	(0.211)	(0.181)
Case-fixed effects	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Matching variables' controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Other controls	No	No	Yes	Yes	No	No	Yes	Yes
Case industry-fixed effects	No	No	No	Yes	No	No	No	Yes
Area-fixed effects	No	No	No	Yes	No	No	No	Yes
R^2	0.603	0.789	0.800	0.823	0.611	0.816	0.829	0.845
Observations	135	135	135	3105	152	152	152	3496

Notes: Conley spatial HAC standard errors in parentheses (***$p<0.01$, **$p<0.05$, *$p<0.1$). The dependent variable is the change in employment between 2000 and 2008 at the two-digit industry level. The first four columns show the results of running the baseline specification selecting only the two closest controls while the last four columns present the results for a placebo exercise in which we drop the actual treatment and randomly assign it to any of the four controls. Columns 1, 2, 3, 5, 6 and 7 include only the treated industry for each case while Columns 4 and 8 include all manufacturing industries. Matching variables' controls are the 2000 and 1990 industry and total employment levels. Other controls are the share of employment in manufacturing, services and construction sectors, the average firm size in the affected industry and in the manufacturing sector as a whole, the unemployment rate and the proportion of inhabitants with no completed studies, compulsory, upper-secondary and tertiary levels of education. These are measured both in 2000 and in 1990 (2001 and 1991 for the educational levels). There are 23 (two-digit) industries in Columns 4 and 8.