City size and exit from unemployment in bad times:
evidences from the French army restructuring

Mathieu Sanch-Maritan $^{1,2}$ and Lionel Védrine $^{1}$

$^1$CESAER, AgroSup, INRA, Université de Bourgogne Franche-Comté
$^2$Economix, CNRS, Université Paris-Nanterre

Abstract

This article explores the role of city size on unemployment volatility. We present a simple new economic geography model of labor pooling to illustrate how the relation between economic shocks and local unemployment can be mitigated by city size. Then we exploit a quasi-natural experiment by studying the economic impact of 357 local shocks both negative and positive generated by the reform and the restructuring of the French army. Exploiting a geo-referenced dataset of unemployment spell over an extensive period of time (2005-2014), we are able to measure the impact of these local shock on the rate at which unemployed workers find a job. To construct a credible counterfactual for each zone which experienced a closure, we use and interactive fixed effects model. We show that contractions in military personnel reduce the local likelihood of finding a job. Moreover, our results reveal some heterogeneity in the local economy’s resilience. In line with our theoretical model, we show that city size is a relevant explanation for the observed heterogeneity in resilience: the likelihood of finding a job is less affected in denser area by a relative equal-sized shift in labor demand.

Keywords: Labor market shocks; Resilience; Common factor panel; Heterogeneous effects; Urban-Rural gradient.
Introduction

Despite its political relevance, the role of local economic conditions to mitigate the effects of economic shocks remains understudied (Bartik, 2014). As emphasized by Brakman et al. (2015), it has been well established that regions differ in their resilience to shocks, but theoretical and empirical insights in the determinants of regional resilience are still limited (Diodato and Weterings, 2015). When a negative local shock occurs, the characteristics of the local market are detrimental on individual’s trajectory. For instance, Holm et al. (2012) show that after the closure of the shipyards in Denmark, individuals are faced with different possibilities for finding new jobs depending on where they are located. This issue is of central importance, because in absence of perfect insurance to cover such cost, fluctuations in the labor market are a major source of uncertainty for households.

This paper contributes to this emerging literature by exploring the role of agglomeration economies on local unemployment fluctuations. We study the impact of cities size on unemployment volatility and on the absorption of the flow of unemployed people. As emphasized by Combes and Gobillon (2014), the impact of agglomeration economies on regional unemployment has received little attention from the theoretical and applied literature on economic geography. Due to friction on the labor market, we suppose that large labor markets might be better able to absorb the flow of unemployed people. As previous studies on New Economic Geography literature, we consider labor markets size as a source of agglomeration: large labor markets may provide insurance against idiosyncratic shocks by reducing the likelihood that a worker remains unemployed for a long period when firms are hit by negative idiosyncratic shocks (Krugman, 1991).

First, we develop a model where city size strengthen local capabilities to adjust to economic volatility. This spatial heterogeneity is produced by risk-sharing mechanisms. Risk-sharing mechanisms between firms and workers may drive people into more agglomerated places. In turbulent market conditions, the likelihood to be unemployed
is decreasing with respect to labor market size: finding a new-job for laid-off workers is easier in thick labor markets (Combes et al., 2008). Pooling creates an advantage for both workers and firms as it improves adjustment to shocks. In line with previous work on labor pooling, we develop a model with an imperfect labor market and idiosyncratic shocks. In the first stage, individual firms and individual unions bargain over wages in a Nash game. In a second step, firms unilaterally choose the employment level. Each firm is specialized in the production of a single output. Output price is hit by exogenous idiosyncratic shocks. Establishment responds to the shock by adjusting its levels of production and employment. Idiosyncratic shocks occurring in the market for goods and services, leads to volatility in the labor market. Our model shows that local unemployment fluctuations due to idiosyncratic shocks are higher in thin markets than in thick ones. This stabilizing effect of thick labor market is an expression of risk-sharing mechanisms identified as a source of agglomeration economies (Duranton and Puga, 2004).

In the second part of the paper, we assess the link between city size and local unemployment fluctuations, by exploiting an exogenous shift in the local demand for goods and services induced by the restructuring of the French army. The end of the cold war in the 1990s completely redesigned the French Defense Policy, and lead to a mass reduction in defense’s budget. For instance, between 2008 and 2015, the government schedules the cuts of 54,000 employment in the French army (Livre blanc sur la défense et la sécurité nationale, 2008). Papers studying the impact of military activity on local labor market are very scarce. Zou (2013) estimates that cutting military expenditure in United-Sates by one, reduces about 0.4 jobs in the private sector in the same county in the contemporaneous year, and 1.2 jobs cumulatively. The trend in military staff contraction offers a good empirical design to respond our problematic. First, due to the spatial concentration of military staff, spillovers between local markets must be reduced. Second, due to national public procurement rules, the recessionary impact on the local economy is only mediated by a reduction of private consumption of military
personnel and their families. Heterogeneity in restructuring’s size and accurate data on the personnel impacted by the restructuring are detrimental to the design of our study. We exploit this information by dividing the number of job cuts by the local workforce. This ratio enables us to observe relative equal sized idiosyncratic shocks across markets. This analysis raises crucial questions regarding the endogeneity of central government decisions. We use an interactive panel structure (Bai, 2009) to control endogeneity accurately due to unobserved confounders and spatial correlation.

By exploiting a geo-referenced dataset of unemployment spells over an extensive period of time (2005-2014), we are able to measure the impact of military staff’s variation. We show that the restructuring of the French army reduces the likelihood of finding a job for unemployed workers. Common factor panel regressions show that the likelihood of finding a job is reduced after job cuts (conversely increase when military staff increase). Then, we explore the link between city size and fluctuation in the likelihood of finding a job. Our empirical analysis is in line with our theoretical prediction. Indeed, local job markets are less affected after idiosyncratic shocks in thick labor market irrespective of the economic structure or the degree of economic diversification. This finding has important political implications because it shows that contra-cyclical interventions should be differentiated between areas.

In the next section, we briefly review literature studying agglomeration and local unemployment fluctuations. In Section 2, we develop our theoretical model of labor pooling with unemployment. In Section 4.1, we describe the quasi-natural experiment we exploit. In Section 4, we display the empirical strategy implemented. Section 3 introduces our dataset. Lastly, our empirical results are presented and discussed in Section 5.
1 City size and local labor market fluctuations

The way that labor market reacts to large exogenous shocks is a long-standing question both in labor economics and in regional economics literature. Our study differs from previous literature studying demand shocks and economy dynamics. To the best of our knowledge, this paper is the first to consider unemployment in a model of agglomeration and risk sharing. Instead of the competitive wage setting assumption usually made in labor pooling models, we allow for a non-competitive labor market, thus implying unemployment at the equilibrium. Secondly, previous studies analyzing the relationship between local economic pattern and economy dynamics focus on industrial diversity. In this paper we disentangle the effect of economic diversification emphasized by previous work from the effect of city size. Bartik (2014) shows that the reduction of unemployment is more pronounced after positive shocks in a distress area than in a prosperous local economy. Xiao (2011) exploits downturns caused by the 1993 US Midwest flood, and shows that more diverse economies bounce back more quickly after a disaster. Van Oort et al. (2015) suggest that unrelated variety can be a key factor in making a local economy more resilient against negative shocks. Our paper substantially differs from these works, because we rather focus on city size than on economic diversification.

Our model developed in section 2, shows that dense areas are less affected by exogenous variations irrespective of their economic structure, or their degree of diversification \( i.e \) or portfolio effect as named by Van Oort et al. (2015)). Labor market size provides ”insurance” against idiosyncratic shocks through labor pooling mechanism. Our empirical analyses confirm this prediction, because we show that densely populated areas are less affected by an exogenous shock. This finding is robust to the inclusion of competing explanation, because, the dampening effect of density remains highly significant when human capital endowment, economic structure or degree of diversification is included in our specification.

Isolating exogenous variation in demand and supply has a strong tradition in labor
economics. Literature on labor shocks has reached varied finding on whether the effects of shocks are persistent or transitory. Bartik (1991) instruments local labor demand shocks by interacting cross-sectional differences in industrial composition with national changes in industry employment. Bartik (1991) finds significant effects of a shift in demand for labor. Long-run effects are similar to short-run effects regarding labor force participation and wages. Long-run effects are also found on unemployment, but lower than short-run effects. Blanchard et al. (1992) using a different specification than Bartik (1991), find dissimilar results. Blanchard et al. (1992) argue that locations affected by negative shocks experience permanent losses in employment, temporary increases in unemployment rates and temporary decreases in local wages. Geographic relocation help to mitigate negative local shock, because workers leave affected states. Gathmann et al. (2014), studying mass lay off in Germany, argue that only a small share of the adjustment is reflected in higher unemployment rates. In contrast, return to equilibrium comes from reduced inflows into regions hit by a negative shock.

A large strand of applied literature on economic geography focus on the reaction of cities to large temporary shocks. This focus is related to predictions arising from theoretical model of economic geography. If increasing returns to scale is the key determinant of agglomeration, then sufficiently large temporary shocks should generate long-lasting effects (Hanlon, 2014). Empirical finding arising from these studies are not very conclusive, this literature has delivered mixed results, with some studies finding evidence of permanent effect of shocks (as Kline and Moretti (2013)), while others show recovery even from very large shocks (Davis and Weinstein (2001) as instances). But as argued by Combes (2006), the theoretical prediction that even small shocks may give rise to large and irreversible structural changes in relative city sizes should be considered with caution.

Beyond the consideration of structural changes, a strand of literature in economic geography study the way that economic uncertainty shapes agglomerations. The central idea developed in labor pooling models is that firms tend to be located in agglomerated
areas because labor supply in cities is inelastic with respect to their own productivity variation. In other words, the covariance between wages and firms productivity shocks is decreasing with respect to labor market size. In the next section, we set up a model of labor pooling in which firms experience exogenous output price shocks, and where wages are negotiated at the firms level between firms and individual unions.

2 Labor pooling, shock in the final demand for goods and services, and unemployment fluctuation

A larger pool of workers in a region increases the likelihood that a firm finds workers with the characteristics they need. Workers are also more likely to find a job suited to their skills in large labor markets. Moreover, at the local labor market scale, prosperous industries absorb the unemployment of those experiencing bad situation. Canonical model of labor pooling build by Krugman (1991) considers $n$ firms producing a homogeneous good under decreasing returns to scale, and hiring workers on a local labor market. In this setting, an idiosyncratic firm-specific shock hit firm $i$. Firms decide how many workers to hire after experiencing their firm-specific shock. The benefit of labor pooling increases with the number of firms and with the variance of idiosyncratic shocks. In this canonical setting, wage adjustments are perfect and instantaneous. There is therefore no unemployment in equilibrium, and workers adjust their choices according to wages.

In our setting, firms produce a standardized product, and sell their outputs in a local market. As in previous models of labor pooling, workers are risk-neutral. Due to exogenous demand volatility (for instance a shift in the local population), local markets for good and services are hit by specific price shock denoted $\epsilon_i$. Price shocks are identical and independently distributed over $[-\epsilon; \epsilon]$ with mean 0 and variance $\sigma_2$. Firms hire workers on a local labor market, and labor is the only factor of production. Local labor markets are completely segmented with workers being immobile between
them. In each labor market, there is an exogenous finite supply of homogeneous labor denoted $L$. Wage adjustment is not perfect. Each local labor market is unionized implying some rigidity in the wage setting. Bargaining takes place between individual firms and individual unions (decentralized bargaining regime). Unions and firms bargain over wages, denoted $\omega$, and firms unilaterally choose employment levels denoted $\ell$ so as to maximize profits (i.e. Right to Manage Models).

The profit of each the firm $i$ is given by $\pi_i(\ell) = p_i q(\ell) - \omega \ell$. Price of the commodity produced by the firm $i$ is denoted $p_i$ and is fluctuating around 1: $p_i(\epsilon_i) = 1 + \epsilon_i$. This price fluctuates exogeneously regarding local conditions. Each firm’s technology is described by the production function $q(\ell) = \alpha \ell - \ell^2 / 2$. Each firm chooses how many workers to hire taking wages as given. From the first-order conditions we obtain labor demand for each firm:

$$\ell_i = \alpha - \frac{\omega}{1 + \epsilon_i} \tag{1}$$

By introducing equation (1) in the profit expression we obtain:

$$\pi_i(\ell) = \frac{(\alpha(1 + \epsilon) - \omega)^2}{2(1 + \epsilon)} \tag{2}$$

Firm picks the employment level but there is bargaining between the firm and the union over wages. We assume a decentralized and uncoordinated wage-setting structure, in which firms and firm-specific unions bargain bilaterally over the match-specific wage rate. We consider firm-specific collective agreements, where wages are determined non-cooperatively at the firm level. Since workers are identical, we assume that available jobs are allocated randomly among them.

Let $\gamma \in [0; 1]$ denotes the firm’s bargaining power where $\gamma$ is common to all matches. We consider that there is no search costs for finding better matches. We also assume that the reservation wage is given by $\bar{\omega}$. Firms workforce is assumed to be represented by a union which negotiates a uniform wage rate at the firm’s level. The union is
engaged in a Nash bargain with the firms over the wage-rate only, and then maximizes
the Nash product \( N = \pi^\gamma (\omega - \bar{\omega})^{(1-\gamma)} \). The bargaining procedure is a two-stage game.
In the first stage, unions and firms agree on a wage rate. In the second stage, each
firm chooses a profit-maximizing level of employment. Maximizing the Nash product
\( N \) with respect to the wage rate gives the equilibrium wage denoted \( \omega^* \):

\[
\omega^* = \frac{2\gamma\bar{\omega} + \alpha(1-\gamma) + \alpha\epsilon(1-\gamma)}{1+\gamma}
\]  

(3)

Firms observe the wage ensuing from negotiations and decide how much labor to hire
from the local labor pool. Each establishment hires workers until marginal productivity
of labor equal wages. From (1) and (3) we obtain \( \ell_i \), the labor demand arising from
firm \( i \):

\[
\ell_i = \frac{2\gamma(\alpha\epsilon_i + \alpha - \bar{\omega})}{(1+\gamma)(1+\epsilon)}
\]  

(4)

Let \( n \) denotes the number of firms, so \( J \), the overall demand for work is equal to:

\[
J = \sum_{i=1}^{n} \ell_i = n \frac{2\gamma(\alpha - \bar{\omega})}{(1+\gamma)(1 + \sum_{i=1}^{n} \epsilon_i)} + \frac{2n\alpha\gamma}{(1+\gamma)(1 + \sum_{i=1}^{n} \epsilon_i)} \sum_{i=1}^{n} \epsilon_i
\]  

(5)

By the law of large numbers, the probability of being unemployed is equal to \( u = 1 - \frac{\sum_{i=1}^{n} \ell_i}{L} \), where \( L \) is the overall local labor force:

\[
u = 1 - \frac{\sum_{i=1}^{n} \ell_i}{L} = 1 - n \frac{2\gamma(\alpha - \bar{\omega})}{L(1+\gamma)(1 + \sum_{i=1}^{n} \epsilon_i)} - \frac{2n\alpha\gamma}{L(1+\gamma)(1 + \sum_{i=1}^{n} \epsilon_i)} \sum_{i=1}^{n} \epsilon_i
\]  

(6)

Expected unemployment rate \( E(u) \) is given by:

\[
E(u) = 1 - n \frac{2\gamma(\alpha - \bar{\omega})}{L(1+\gamma)}
\]  

(7)
Unemployment is on average unaffected by idiosyncratic shocks arising in the output market. This result is expected because price shocks are independent and identically distributed over \([-\epsilon; \epsilon]\) with mean 0 and variances denoted \(\sigma^2\). More interestingly, unemployment volatility is equal to:

\[
V(u) = \frac{\hat{\omega}^2}{L^2(1 + \gamma)^2} \frac{\sigma^2}{1 + \sigma^2^2} \tag{8}
\]

Output price fluctuations trigger an increase in unemployment volatility:

\[
\frac{\partial V(u)}{\partial \sigma^2} = \frac{2\omega^2 \sigma^2}{L^2(1 + \gamma)^2(\sigma^2 + 1)^2} > 0 \tag{9}
\]

In this article, we are interested in the way that unemployment volatility is affected by a marginal increase in local labor forces.

\[
\frac{\partial V(u)}{\partial \sigma^2 \partial L} = -\frac{4\hat{\omega} \sigma^2}{L^3(1 + \alpha)^4(\sigma^2 + 1)^2} < 0 \tag{10}
\]

Equation 10 is the central result of our model. Unemployment in agglomerated places is less affected by output price fluctuations. Industries hit by positive shocks absorb the unemployed of those experiencing bad situation. This result is in line with previous work: Gan and Zhang (2006) show that large cities have shorter unemployment cycles, and lower peaks of unemployment; Neumann and Topel (1991) argue that cities with a more diversified industry structure have a lower variance in labor demand. Agglomeration arises because of efficiency gains from sharing resources among firms that do not know ex-ante how much of these resources they will need (Duranton and Puga, 2004)

3 Data

We use the historical file of job applicants to the National Agency for Employment (“Pôle Emploi”) for 1636 French living areas (we exclude from our sample the French
overseas departments) for the period 2005–2014. This dataset covers the large majority of unemployment spells in the country given that registration with the national employment agency is a prerequisite for unemployed workers to claim unemployment benefits. This dataset is of crucial importance because it contains individual information on: the registration date, the unemployment duration in days, and the municipality where the individual resides. We observe 6,271,600 unemployment spells ending in the period of interest running from January 2005 to December 2014. We aggregate unemployment spell at the level of the "living areas”. “Living areas” (bassins de vie) are functional units defined by the French Institute of Statistics (INSEE) as the smallest territorial units in which residents have access to basic infrastructure and services. The division into living areas provides the most relevant breakdown of the territory to study the impact of local shock hitting the demand for final good and services. It is within their boundaries that residents have access to most of their consumption premises.

For each "living area”, and for each semester, we compute an exit rate from unemployment defined as the logarithm of the ratio between the number of unemployed workers leaving unemployment throughout the period and the number of unemployed. Figure 1 reports the evolution of the exit rates in the sample of treated municipalities and in three control groups. We can easily observe the breakup of the crisis in 2007, which leads to a dramatic decline in the exit rate from unemployment until the end of our period of interest.

To assess the robustness of our finding to competing explanation, we control for a rich set of variables. First, we control for human capital endowments, by computing for each area the share of the total population without any diploma, graduated from high school and graduate from university. We also control for local economic pattern by including local sectoral composition. These informations are extracted from the French business register (Répertoire des entreprises et des établissements) collected by the INSEE. This register records the civil status of all enterprises and their establishments regardless of their legal status and business sector. We also exploit this register by
computing for each area the inverse of an Herfindahl index to measure the level of local specialization. To compute the inverse of an Herfindahl index, a sectoral disaggregation in ten activities is used. For each area and each year we compute an index such as:

\[
H_{hh_{ist}} = \frac{1}{\sum_{s} \left( \frac{E_{i_{lst}}}{\sum_{i=1}^{S} E_{i_{lst}}} \right)^2}
\]

where \( E_{i_{lst}} \) is the number of establishment of area \( i \) in sector \( s \) at time \( t \). Therefore, the higher is the value of the index, the more diverse would a given area be.

4 Empirical Strategy

4.1 Exploiting a shift in local demand for work: the restructuring of the French army

French Army has experienced many changes since the end of the cold war. French borders are not directly threatened since the breakup of the Warsaw Pact. This unprecedented situation leads to a decrease in national budget devoted to Army (to 3% of GDP in 1982 to 1.7% in 2011 (Foucault, 2012)). For instance, between 2008 and
2015, the government scheduled the cuts of 54,000 posts (Livre blanc sur la défens et la sécurité nationale, 2008). These significant structural changes lead to the closure or the restructuring of military facilities. At the living area level, we collect all restructuring occurring in the French army between 2004 and 2014. We then divide the number of employee\(^1\) affected by the restructuring by the local workforce. More specifically, our variable measuring the relative amplitude of the variation of military staff is equal to:

\[
S_{\text{chock}}_{it} = \frac{\Delta \text{Military Workforce}}{\text{Local Workforce}}
\]

Where \(\Delta \text{Military Workforce}\) stands for the local variation of military staff in area \(i\) at time \(t\). This information is of crucial importance, because it enables us to observe equal sized idiosyncratic shocks across heterogeneous markets. In addition to this quantitative decrease, we observe a reallocation of defense spending within national borders, because areas of potential conflict shift from the north-east part of the country to the south (closer to overseas operations). Figure 4a shows the location of the affected areas.

This map reveals that base closure (red areas in figure 4a) are concentrated in the North-East part of the country. Closures hit heterogeneous territories; some are part of Paris’s suburb (Taverny, Compiègne), other are regional metropolis (Toulouse), and some are located in rural areas (Dieuze in region Grand-Est). This variation in military facilities’ size lead to a decorrelation between the amplitude of the shock and the size of the local economy. This feature is of crucial importance for estimating heterogeneous effects. As argued by Hainmueller et al. (2016), using the interactive term for estimating heterogeneous effect is based on the assumptions of sufficient common support. For the interactive model to work, one needs a bunch of units with similar magnitudes of shocks, but with varying degrees of density. To assess the reliability of this assumption we run a falsification test. We regress the amplitude of the shock on the local level of density and on a set of covariates. Figure 2 shows scatter plot of the amplitude of the shock and

\(^1\)We do not discriminate between military and civilian employees
the level of density. The red line corresponds to a linear regression of the local level of density on the amplitude of the shock, controlling for a set of covariates. The estimated regression coefficient is 0.001 and is not significant at conventional levels. Coefficients displayed in Table 1, show that local density is not a good predictor for the amplitude of the shock. The effect of the local level of density is largely insignificant. The coefficient is only significant in specification (3), but it goes to zero with the inclusion of control variables (specification (4)), suggesting a disconnection between the amplitude of the shock and the local density.

![Relation between the amplitude of the shock and the local level of density](image)

**Figure 2.** Relation between the amplitude of the shock and the local level of density

The design of our study avoids some confounding effects. First, due to the spatial concentration of military staff spillovers between local markets must be reduced. Second, due to national public procurement rules, the impact on the local economy is only mediated by a variation of private consumption of military personnel and their families. Unlike companies in the private sector, military bases interact little with other local economic actors. Materials and most services depend on national centralized markets. The impact of army restructurating must have a recessionary impact on the local economy only through a decline in private consumption of military personnel and their families. Therefore the stimulus on the local economy seems disconnected from local characteristics (industrial specialization in particular).
4.2 Estimating the impact of air base closure on local unemployment

A key issue in our analysis is that even if army restructurings are shaped by the international security context, they may be influenced by local characteristics. Statistics displayed in table 2 confirm this threat. The first four columns of table 2 present summary statistics across treatment status, and the last three columns present balancing tests. In the analysis below, we compare areas which have not experienced army restructuring (i.e. control), areas which have seen a contraction in the military personnel (i.e. negative treatment), areas which have seen an expansion in the military personnel (i.e. positive treatment). We thus present the p-values for three types of tests: control versus negative treatment, control versus positive treatment, and negative versus positive treatment. The vast majority of our control variable are not randomly distributed across treatment status, therefore we cannot simply compare outcomes between treated and control areas to assess the impact of the restructuring. Moreover, restructurings are made by political leaders. This political dimension may result in a correlation between military workforce variations and potential outcomes because of the presence of...
<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Negative Treatment</th>
<th>Positive Treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>$S_{it}$</td>
<td>$S_{it}$</td>
<td>$S_{it}$</td>
<td>$S_{it}$</td>
</tr>
<tr>
<td>log(density)</td>
<td>0.00</td>
<td>0.00**</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Controls</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Observations</td>
<td>32,720</td>
<td>32,720</td>
<td>317</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.000</td>
<td>0.008</td>
<td>0.031</td>
</tr>
</tbody>
</table>

The table reports the coefficients of the OLS, where our variable of interest measuring the amplitude of the shock is regressed on control variables. Reported coefficients are the local level of density in a number of specifications. In regressions (1) and (2) report the result for the entire sample, regressions (3) and (4) report the result for area impacted by job cuts, regressions (5) and (6) report the result for areas positively impacted by an increase of the number of military personnel.

Controls are the local proportion of individuals without Any Diploma, with High School degree, with university degree. We also control for the local proportion of individual working in agriculture, in industry, in building Sector, in tertiary markets and in tertiary non-market.

Time trend and a constant are included in all specifications, Standard errors are in brackets; and * stands for $p < 0.10$; ** stands for $p < 0.05$; *** stands for $p < 0.001$.

**Table 1.** The effect of the level of density on the amplitude of the local shock unobservable (degree of political connection for instance).
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>2=3</th>
<th>2=4</th>
<th>3=4</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(density)</td>
<td>-2.114</td>
<td>-2.216</td>
<td>-1.455</td>
<td>-0.608</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Hhi</td>
<td>3.342</td>
<td>3.34</td>
<td>3.347</td>
<td>3.364</td>
<td>0.094</td>
<td>0.01</td>
<td>0.04</td>
</tr>
<tr>
<td>Without Any Diploma</td>
<td>48.162</td>
<td>48.662</td>
<td>44.813</td>
<td>41.434</td>
<td>0</td>
<td>0</td>
<td>0.01</td>
</tr>
<tr>
<td>High School</td>
<td>12.107</td>
<td>11.962</td>
<td>13.148</td>
<td>13.659</td>
<td>0</td>
<td>0</td>
<td>0.10</td>
</tr>
<tr>
<td>University</td>
<td>13.377</td>
<td>13.013</td>
<td>15.636</td>
<td>19.264</td>
<td>0</td>
<td>0</td>
<td>0.01</td>
</tr>
<tr>
<td>Industry</td>
<td>31.74</td>
<td>32.229</td>
<td>28.524</td>
<td>24.797</td>
<td>0.01</td>
<td>0.01</td>
<td>0.11</td>
</tr>
<tr>
<td>Building Sector</td>
<td>14.253</td>
<td>14.568</td>
<td>11.97</td>
<td>10.976</td>
<td>0</td>
<td>0</td>
<td>0.13</td>
</tr>
<tr>
<td>Tertiary Market</td>
<td>33.839</td>
<td>33.56</td>
<td>35.994</td>
<td>35.973</td>
<td>0</td>
<td>0.04</td>
<td>0.99</td>
</tr>
<tr>
<td>Communication</td>
<td>0.854</td>
<td>0.709</td>
<td>1.768</td>
<td>3.087</td>
<td>0</td>
<td>0</td>
<td>0.01</td>
</tr>
<tr>
<td>Financial Sector</td>
<td>2.533</td>
<td>2.366</td>
<td>3.682</td>
<td>4.632</td>
<td>0</td>
<td>0</td>
<td>0.03</td>
</tr>
<tr>
<td>Real Estates</td>
<td>1.496</td>
<td>1.461</td>
<td>1.733</td>
<td>1.998</td>
<td>0.001</td>
<td>0</td>
<td>0.1</td>
</tr>
<tr>
<td>Specialized Activities</td>
<td>6.607</td>
<td>6.34</td>
<td>8.211</td>
<td>11.231</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Tertiary Non Market</td>
<td>5.984</td>
<td>6.071</td>
<td>5.399</td>
<td>4.867</td>
<td>0.004</td>
<td>0</td>
<td>0.11</td>
</tr>
</tbody>
</table>

(1), (2), (3), (4) and report the mean value of variables at the beginning of the period respectively for the entire sample, for area not impacted by army restructuring, for area impacted by job cuts, and for area positively impacted by an increase of the number of military personnel. P-values correspond to t-tests of equality of means.

Table 2. Local characteristics across Treatment Status
Second, the issue of spatial dependence between local units is crucial in the evaluation of regional intervention. Outcomes are likely to be spatially correlated in addition to the more usual issue of serial correlation in panel data. There is thus a need for a better control of spatial dependence and more generally of cross-section dependence when evaluating regional policies. Interactive effect models facilitate the control of cross-section dependence not only because of spatial correlations but also because areas can be closed in economic dimensions which depart from purely geographic characteristics (Gobillon and Magnac, 2015).

4.2.1 Interactive fixed effects Models

As discussed earlier, our econometric specification needs to control for local unobserved characteristics that can be correlated with the treatment indicator. As argued by Gobillon and Magnac (2015), traditional methods such as panel data, difference in differences are not well tailored to study regional economy because specific issues such as spatial dependence, or correlation between treatment and outcomes are very likely to arise. Despite their relevance interactive fixed effect models are still barely used in regional economic (Gobillon and Magnac (2015) as the exception). Interactive fixed are very appealing in our setting for three main reasons. First, unobservable individual effects are allowed to have heterogeneous individual time trends in interactive effect models. This property is very attractive because it allows dissimilar reaction after a shock. Secondly, this model allows unobservable characteristics to be multidimensional. The unobservable local characteristics must be multidimensional, because local economies are affected by multiple economic cycles. As emphasized by Gobillon and Magnac (2015), treated regions may be affected by shock hitting different economic sectors. Factor loadings depict the heterogeneity in the sensitivity to these sectoral shocks. Thirdly, interactive fixed effects models are a good way to control for interference between units. As demonstrated by Gobillon and Magnac (2015), interactive fixed effects facilitate the control of cross section dependence.
Similar to Bai (2009), we specify the exit rate from unemployment in the absence of base closure as a function of the interaction between factors varying over time and heterogeneous individual terms called factor loadings. This specification may be expressed as:

$$\lambda_{it}(0) = x_{it}\beta_2 + f_t/\lambda_i + \epsilon_{it}$$

(11)

in which $x_{it}$ is a vector of local covariates, and $\beta$ stands for the effects of covariates on unemployment. $\lambda_i$ is a $L \times 1$ vector of individual effects or factor loadings, and $f_t$ is a $L \times 1$ vector of time effects or factors. One of the major issues in implementing factors models is the determination of the number of factors. We use the dimension criterion sets by Bai and Ng (2002). This test seems to perform very well, especially when the idiosyncratic errors are cross-correlated (Bada and Liebl, 2014).

From equation 11, the potential exit rate from unemployment in the presence of a base closure is:

$$\lambda_{it}(1) = \text{Shock}_{it}\beta_1 + x_{it}\beta_2 + f_t/\lambda_i + \epsilon_{it}$$

(12)

With $\text{Shock}_{it} = (\Delta \text{Military Workforce}) / \text{Local Workforce}$. $\text{Shock}_{it}$ is our variable of interest, it represents the magnitude of the stimuli. It is equal to zero for areas not affected by army restructuring. This variable is of crucial importance, because it enables us to observe comparable idiosyncratic shocks occurring in market of heterogeneous size.

Lastly, our model displayed in section 2 argue that denser area may be better dotted to react after a downward shift. Large labor markets may provide insurance against idiosyncratic shocks, by reducing the likelihood that a worker remains unemployed for a long period when firms are hit by negative idiosyncratic shocks (Krugman, 1991). In subsection 2, we set up a theoretical model in which firms are hit by idiosyncratic shocks. We show that unemployment in denser area is less affected by economic volatility. We use the following empirical specification to test this prediction:

---

2In annexe we present alternatives specifications in the way the shock is modeled
\[
\lambda_{it}(1) = \text{Shock}_i\beta_1 + \ln(\text{density}_{it})\beta_2 + \text{Shock}_i \times \ln(\text{density}_{it})\beta_3 + x_{it}\beta_4 + f(t)\lambda_i + \epsilon_{it} \quad (13)
\]

Multiplicative interaction models are a good way to assess if the relationship between idiosyncratic shock and unemployment depends on the local density (Brambor et al., 2006).

5 Results

In section 2, we see that unemployment in denser area is less affected by an exogenous shift in the demand for work. To assess empirically this finding, we estimate the impact of the army restructuring by implementing interactive effect model (in subsection 5.1). Lastly, by using interactive effect model we assess to what extent density shape unemployment fluctuation, and how density mitigates the effect of economic volatility. The findings of our quantitative analysis are two folds. First, our regressions show that people living in areas impacted by the closure of military facilities are less likely to leave unemployment. Conversely, an increase in the number of local military workforce raises the likelihood of leaving unemployment. Secondly, our empirical analysis confirms our theoretical finding: unemployment is less affected by a shift in demand for labor in denser area.

5.1 Interactive fixed Effect Model

In this subsection, we present results from interactive effect models presented in subsection 4.2.1. We regress the likelihood of living unemployment on variables measuring the amplitude of the shocks and on a set of covariates as displayed in equation 12.

Interactive effect model requires selecting the optimal number of common factors. Results may be dependent on the number of dimensions selected. Indeed, Moon and
Weidner (2014) show that under-specification may cause inconsistency, and Bada and Liebl (2014) argue that introducing an oversized number of dimensions can lead to inefficient estimation and spurious interpretation due to over-parameterization. To avoid misspecification, we rely on the information criteria of Bai and Ng (2002) to determine the optimal factor dimension. In this application we set the number of factors to two.

Variation in the number of local military workforce is positively associated with the likelihood of leaving unemployment (1). As emphasized by the literature, human capital is not evenly distributed throughout space. We control for human capital endowments by including the distribution of the population by levels of qualification. We also control for the local specialization. Results displayed in table 4 are in line with regressions carried out on annual data (not shown in this document). This positive impact seems robust across specification (cf. equations 1 to 4).
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Shock</strong></td>
<td>1.3**</td>
<td>1.3**</td>
<td>1.32**</td>
<td>1.3**</td>
<td>1.35**</td>
<td>1.35**</td>
<td>1.38**</td>
<td>1.37**</td>
</tr>
<tr>
<td>(0.435)</td>
<td>(0.435)</td>
<td>(0.435)</td>
<td>(0.435)</td>
<td>(0.442)</td>
<td>(0.442)</td>
<td>(0.446)</td>
<td>(0.445)</td>
<td></td>
</tr>
<tr>
<td><strong>log(density)</strong></td>
<td>0.0773***</td>
<td>0.0773***</td>
<td>0.0772***</td>
<td>0.0888**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.019)</td>
<td>(0.019)</td>
<td>(0.019)</td>
<td>(0.029)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Hhi</strong></td>
<td>0.276**</td>
<td>0.276**</td>
<td>0.286**</td>
<td>0.567***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.090)</td>
<td>(0.092)</td>
<td>(0.127)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Without Any Diploma</td>
<td>-0.378**</td>
<td>-0.378**</td>
<td>-0.376**</td>
<td>-1.19***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.169)</td>
<td>(0.171)</td>
<td>(0.247)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High School</td>
<td>-0.701**</td>
<td>-0.701**</td>
<td>-0.69**</td>
<td>-0.426</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.244)</td>
<td>(0.247)</td>
<td>(0.45)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>University</td>
<td>-0.0141</td>
<td>-0.0141</td>
<td>-0.00153</td>
<td>-0.143</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.104)</td>
<td>(0.106)</td>
<td>(0.184)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture</td>
<td>-0.37**</td>
<td>-0.37**</td>
<td>-0.353**</td>
<td>0.171</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.153)</td>
<td>(0.155)</td>
<td>(0.215)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry</td>
<td>-0.389**</td>
<td>-0.389**</td>
<td>-0.388**</td>
<td>-0.0306</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.141)</td>
<td>(0.142)</td>
<td>(0.191)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Building Sector</td>
<td>-0.416**</td>
<td>-0.416**</td>
<td>-0.412**</td>
<td>0.00597</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.152)</td>
<td>(0.154)</td>
<td>(0.216)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tertiary Market</td>
<td>-0.401**</td>
<td>-0.401**</td>
<td>-0.392**</td>
<td>-0.0247</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.145)</td>
<td>(0.147)</td>
<td>(0.198)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Communication</td>
<td>-1.05***</td>
<td>-1.05***</td>
<td>-0.975**</td>
<td>-0.545</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.307)</td>
<td>(0.315)</td>
<td>(0.437)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Financial Sector</td>
<td>-0.0842</td>
<td>-0.0842</td>
<td>-0.0371</td>
<td>0.343</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.235)</td>
<td>(0.239)</td>
<td>(0.312)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Real Estates</td>
<td>0.0507</td>
<td>0.0507</td>
<td>0.08</td>
<td>-1.03*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.393)</td>
<td>(0.399)</td>
<td>(0.56)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Specialized Activities</td>
<td>-0.333**</td>
<td>-0.333**</td>
<td>-0.324**</td>
<td>0.136</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.152)</td>
<td>(0.154)</td>
<td>(0.21)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tertiary non Market</td>
<td>-0.37**</td>
<td>-0.37**</td>
<td>-0.364**</td>
<td>-0.0962</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.142)</td>
<td>(0.143)</td>
<td>(0.193)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Observations   | 32720     | 32720     | 32100     | 32100     |
| Sample         | All       | All       | Control + Negative | Control + Negative |
| Panel Structure| Twoaways  | Individual | Twoaways   | Individual |

Standard errors are in brackets; and * stands for \( p < 0.10 \); ** stands for \( p < 0.05 \); *** stands for \( p < 0.001 \); Table 3. Restructuring and exit rate from unemployment
In the next subsection, we investigate in more detail the heterogeneous resilience displayed by local labor markets.

### 5.2 Local characteristics and Resilience

Figure 4 illustrates how the marginal effect of idiosyncratic shocks on unemployment changes with the local employment density. Any particular point on the solid sloping line in figure 4 corresponds to: \( \frac{\partial U_{it}}{\partial \text{shock}} = \beta_1 + \ln(density_{it}) \beta_3 \). The gray area depicts the simulated 90% confidence interval.

![Figure 4. Impact of Employment Density on Unemployment Volatility](image)

Figure 4 clearly shows that the impact of the idiosyncratic shocks on exit rate from unemployment decreases (along the left y axis) with an increase in employment density (along the x axis). This figure shows that the impact of proportional idiosyncratic shocks on unemployment decreases with density. From a logarithm density higher than -1 employment by square meter, the impact of the restructuring may be insignificant. A logarithm density of -1 employee by square kilometers is relative high in France, and we observe in the histogram displayed in the background of figure 4 \(^3\), that the majority of french areas have a logarithm density lower than -1.

In a nutshell, the central conclusion of our empirical investigation is that for the vast

---

\(^3\)city size distribution is displayed along the right y axis
majority of local labor market, army restructuring lead to an increase in the likelihood of
leaving unemployment (conversely a decrease in the likelihood of leaving unemployment
if the variation in military employment is negative).
6 Conclusion

This article explores the link between city size and unemployment volatility. We develop a labor pooling model with an imperfect labor market in which risk-neutral agents made decisions under uncertainty. The market for goods and services is hit by idiosyncratic shocks. From this model, we show that a higher city size induces a lower unemployment volatility due to uncertainty in final demand for good and services. This idea is in line with previous paper on regional science: agglomeration reduces uncertainty about future conditions on the labor market.

This paper exploits a shift in the local demand for works to estimates how the impact of a relatively similar shock varies with local labor market. French army restructurings occurring between 2004 and 2014 constitute an exogenous schock. Restrurings provide a good empirical design because military facilities are spatially concentrated. In addition, reduced link between military infrastructure and local productive sphere allow the identification of symmetric shock between area. We use common factor panel (Bai, 2009) to control endogeneity accurately due to unobserved confounders and spatial correlation.

Common factor panel shows that a negative variation in the military staff lead to a reduction in likelihood of living unemployment (conversely an increase in military staff increase exit from unemployment). In line with our theoretical model, our analysis shows that city size disparity is the most relevant explanation for the observed heterogeneity in resilience. We observe that the negative impact of the restructuring on unemployment is decreasing with city size. Exit rates from unemployment is less affected in dense area by a relative equal-sized shift in demand for work. This finding has important political implications because it shows that place-based policy implemented after negative downturn should be differentiated between areas, especially between thick and small labor market.
References


Timothy J Bartik. How effects of local labor demand shocks vary with local labor market conditions. 2014.


Pierre-Philippe Combes and Laurent Gobillon. The empirics of agglomeration economies. 2014.


Annexe
### Table 4. Sum of past shock and exit rate from unemployment

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sum_{i=1}^{t} \text{Shock}_{it}$</td>
<td>0.643**</td>
<td>0.651**</td>
<td>0.826**</td>
<td>0.651**</td>
<td>0.655**</td>
<td>0.662**</td>
<td>0.825**</td>
<td>0.747**</td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
<td>(0.21)</td>
<td>(0.331)</td>
<td>(0.21)</td>
<td>(0.214)</td>
<td>(0.214)</td>
<td>(0.336)</td>
<td>(0.334)</td>
</tr>
<tr>
<td>log(density)</td>
<td>0.0773***</td>
<td>0.0773***</td>
<td>0.0771***</td>
<td>0.0884**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.019)</td>
<td>(0.019)</td>
<td>(0.029)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hhi</td>
<td>0.278**</td>
<td>0.278**</td>
<td>0.289**</td>
<td>0.565***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.090)</td>
<td>(0.090)</td>
<td>(0.092)</td>
<td>(0.127)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Without Any Diploma</td>
<td>-0.376**</td>
<td>-0.376**</td>
<td>-0.374**</td>
<td>-1.19***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.169)</td>
<td>(0.169)</td>
<td>(0.171)</td>
<td>(0.247)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High School</td>
<td>-0.703**</td>
<td>-0.703**</td>
<td>-0.694**</td>
<td>-0.43</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.244)</td>
<td>(0.244)</td>
<td>(0.247)</td>
<td>(0.45)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>University</td>
<td>-0.0156</td>
<td>-0.0156</td>
<td>-0.00354</td>
<td>-0.144</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.104)</td>
<td>(0.106)</td>
<td>(0.183)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture</td>
<td>-0.365**</td>
<td>-0.365**</td>
<td>-0.348**</td>
<td>0.173</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.153)</td>
<td>(0.153)</td>
<td>(0.155)</td>
<td>(0.215)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry</td>
<td>-0.387**</td>
<td>-0.387**</td>
<td>-0.386**</td>
<td>-0.026</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.141)</td>
<td>(0.141)</td>
<td>(0.142)</td>
<td>(0.191)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Building Sector</td>
<td>-0.413**</td>
<td>-0.413**</td>
<td>-0.409**</td>
<td>0.00671</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.152)</td>
<td>(0.152)</td>
<td>(0.154)</td>
<td>(0.216)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tertiary Market</td>
<td>-0.4**</td>
<td>-0.4**</td>
<td>-0.39**</td>
<td>-0.0206</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.145)</td>
<td>(0.145)</td>
<td>(0.147)</td>
<td>(0.198)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Communication</td>
<td>-1.04***</td>
<td>-1.04***</td>
<td>-0.972**</td>
<td>-0.541</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.307)</td>
<td>(0.307)</td>
<td>(0.315)</td>
<td>(0.437)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Financial Sector</td>
<td>-0.0804</td>
<td>-0.0804</td>
<td>-0.0358</td>
<td>0.344</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.235)</td>
<td>(0.235)</td>
<td>(0.239)</td>
<td>(0.312)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Real Estates</td>
<td>0.0631</td>
<td>0.0631</td>
<td>0.0945</td>
<td>-1.03*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.393)</td>
<td>(0.393)</td>
<td>(0.399)</td>
<td>(0.56)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Specialized Activities</td>
<td>-0.327**</td>
<td>-0.327**</td>
<td>-0.317**</td>
<td>0.14</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.152)</td>
<td>(0.152)</td>
<td>(0.154)</td>
<td>(0.21)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tertiary non Market</td>
<td>-0.367**</td>
<td>-0.367**</td>
<td>-0.361**</td>
<td>-0.0931</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.142)</td>
<td>(0.142)</td>
<td>(0.143)</td>
<td>(0.193)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Observations: 32720 32720 32100 32100
Sample: All All Control + Negative Schock Control + Negative Schock
Panel Structure: Twoways Individual Twoways Individual

Standard errors are in brackets; and * stands for $p < 0.10$; ** stands for $p < 0.05$; *** stands for $p < 0.001$. 

Table 4. Sum of past shock and exit rate from unemployment.
\[
\sum_{i=1}^{5} \text{Shock}_{it} = 0.467^{**} \quad 0.467^{**} \quad 0.522^{*} \quad 0.467^{**} \quad 0.47^{**} \quad 0.469^{**} \quad 0.526^{*} \quad 0.496^{*} \\
(0.225) \quad (0.225) \quad (0.274) \quad (0.225) \quad (0.229) \quad (0.229) \quad (0.279) \quad (0.278) \\
\log(\text{density}) = 0.0772^{***} \quad 0.0772^{***} \quad 0.0771^{***} \quad 0.0885^{**} \\
(0.019) \quad (0.019) \quad (0.019) \quad (0.029) \\
\text{Hhi} = 0.276^{**} \quad 0.276^{**} \quad 0.287^{**} \quad 0.566^{***} \\
(0.090) \quad (0.090) \quad (0.092) \quad (0.127) \\
\text{Without Any Diploma} = -0.379^{**} \quad -0.379^{**} \quad -0.377^{**} \quad -1.19^{***} \\
(0.169) \quad (0.169) \quad (0.171) \quad (0.247) \\
\text{High School} = -0.702^{**} \quad -0.702^{**} \quad -0.692^{**} \quad -0.427 \\
(0.244) \quad (0.244) \quad (0.247) \quad (0.45) \\
\text{University} = -0.0152 \quad -0.0152 \quad -0.00284 \quad -0.144 \\
(0.104) \quad (0.104) \quad (0.106) \quad (0.184) \\
\text{Agriculture} = -0.367^{**} \quad -0.367^{**} \quad -0.351^{**} \quad 0.172 \\
(0.153) \quad (0.153) \quad (0.155) \quad (0.215) \\
\text{Industry} = -0.388^{**} \quad -0.388^{**} \quad -0.386^{**} \quad -0.0291 \\
(0.141) \quad (0.141) \quad (0.142) \quad (0.191) \\
\text{Building Sector} = -0.414^{**} \quad -0.414^{**} \quad -0.411^{**} \quad 0.00588 \\
(0.152) \quad (0.152) \quad (0.154) \quad (0.216) \\
\text{Tertiary Market} = -0.4^{**} \quad -0.4^{**} \quad -0.39^{**} \quad -0.0232 \\
(0.145) \quad (0.145) \quad (0.147) \quad (0.198) \\
\text{Communication} = -1.05^{***} \quad -1.05^{***} \quad -0.974^{**} \quad -0.543 \\
(0.307) \quad (0.307) \quad (0.315) \quad (0.437) \\
\text{Financial Sector} = -0.0827 \quad -0.0827 \quad -0.0361 \quad 0.342 \\
(0.235) \quad (0.235) \quad (0.239) \quad (0.312) \\
\text{Real Estates} = 0.0547 \quad 0.0547 \quad 0.0846 \quad -1.03^{*} \\
(0.393) \quad (0.393) \quad (0.399) \quad (0.56) \\
\text{Specialized Professional} = -0.331^{**} \quad -0.331^{**} \quad -0.321^{**} \quad 0.138 \\
(0.152) \quad (0.152) \quad (0.154) \quad (0.21) \\
\text{Tertiary non Market} = -0.368^{**} \quad -0.368^{**} \quad -0.362^{**} \quad -0.0947 \\
(0.142) \quad (0.142) \quad (0.143) \quad (0.193) \\
\]

Table 5. Rolling sum of five past semestrer and unemployment rate.