



HAL
open science

Are larger labor market more resilient? Evidence of the French army restructuring on exit from unemployment

Mathieu Sanch-Maritan, Lionel Vedrine

► To cite this version:

Mathieu Sanch-Maritan, Lionel Vedrine. Are larger labor market more resilient? Evidence of the French army restructuring on exit from unemployment. 2019. hal-02332809

HAL Id: hal-02332809

<https://hal.science/hal-02332809v1>

Preprint submitted on 25 Oct 2019

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Are larger labor market more resilient? Evidence of the French army restructuring on exit from unemployment

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

¹CESAER, AgroSup, INRA, Université de Bourgogne Franche-Comté

²CREAM, Université de Rouen-Normandie

Abstract

This article explore how the relation between economic shocks and local unemployment can be mitigated by labor market size. 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 an 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.

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 density 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).

This paper contributes to this emerging literature by exploring link between labor market density and local fluctuations in exit from unemployment. More precisely, it contributes to the literature on local labor market resilience 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 défens 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. Military restructuring affect the demand for residential activities (building sectors, tertiary market...) leading to variation in the local demand for work. The observed 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 section 1, we briefly review literature studying agglomeration and local unemployment fluctuations. Section 2 introduces our dataset. In Section 3.1, we describe our quasi-natural experiment and we display the empirical strategy implemented (Section 3). Lastly, our empirical results are presented and discussed in Section 4.

1 Labor market density and resilience

The way that labor market reacts to large exogenous shocks is a long-standing in regional economics literature. We know from urban economics that firms agglomerate to exploit scale economies associated with a large labor pool. Marshall (1927) emphasized that a localized industry gains a great advantage from the fact that it offers a constant market for skill. Marshall's insights have motivated a long line of research on labour market pooling as a microfoundation for agglomeration economies Andini et al. (2013). Krugman (1991) and Duranton and Puga (2004) derive a model where large labor markets induce better risk sharing. The central idea developed by 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. Overman and Puga (2010) extend this approach and predict that sectors whose establishments experience more idiosyncratic volatility will be more spatially concentrated. This study differs from previous work on labor pooling in two important ways. First, 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. Second, this is the first study in this vein to analyze the relationship between agglomeration and unemployment fluctuations. Moreover, this is the first study to assess the

importance of labor pooling in stabilizing unemployment.

Moreover, previous studies analyzing the relationship between local economic pattern and unemployment dynamics focus on industrial diversity. In this paper we disentangle the effect of economic diversification emphasized by previous work from the advantages stemming from pure urban size (Capello et al., 2015). 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. 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, 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 the demand and supply for work 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, 2017). 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 (Haenfler (2002) as instances). But as argued by Combes et al. (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.

2 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.

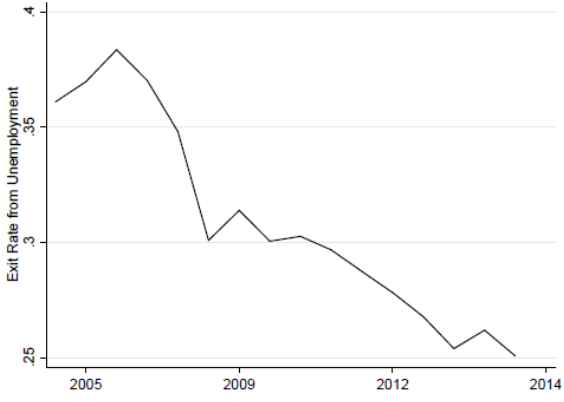


Figure 1. Exit Rate from Unemployment

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:

$$Hhh_{it} = \frac{1}{\sum_{i=1}^S \left(\frac{E_{ist}}{\sum_{i=1}^S E_{ist}} \right)^2}$$

where E_{ist} 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. This information on the local degree of specialisation is central to disentangle the effect of economic diversification emphasized by previous work from the advantages stemming from pure urban size.

3 Empirical Strategy

3.1 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 employee¹ affected by the restructuring by the local workforce. More specifically, our

¹we do not discriminate between military and civilian employees

variable measuring the relative amplitude of the variation of military staff is equal to:

$$Schock_{it} = \frac{(\Delta Military Workforce)}{Local Workforce}$$

Where $\Delta Military Workforce$ 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. In subsection 4.1, we use multiplicative interaction models to test whether the relationship between the local likelihood of finding a job and the amplitude of the army restructuring changes with labor market size. 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 the scatter plot of the amplitude of the shock and 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. Absence of systematic correlation

between shock and density guarantees a sufficient number of observations with distinct density but hit by equal sized shock.

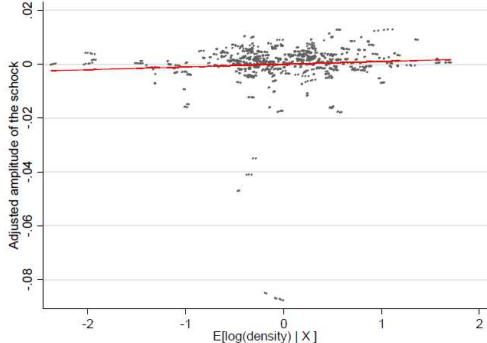


Figure 2. Relation between the amplitude of the shock and the local level of density

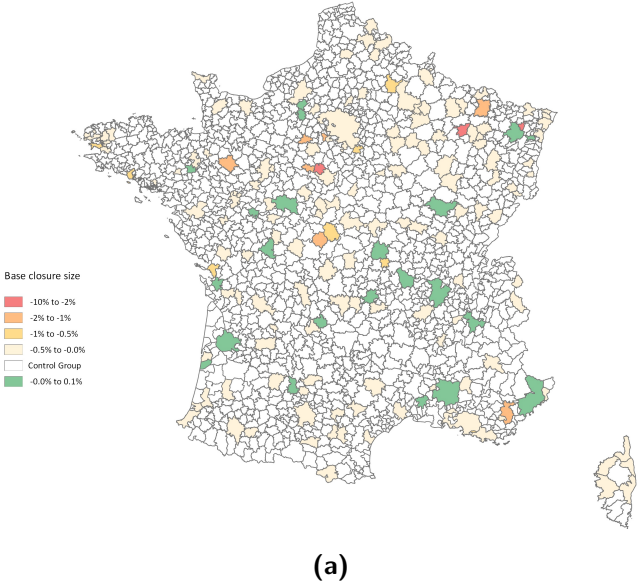


Figure 3. Treated areas between 2003 and 2014

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. In table 1 we regress the ratio between the number of new firms and the

total number of firms on our variable measuring the amplitude of the army restructuring. Coefficients displayed in table 1 reveal that sectors impacted by the restructuring are linked with residential activities (building activities, tertiary markets, financial services...). The army restructuring impacts the local economy via a decline in private consumption of military personnel and their families. Unlike companies in the private sector, military bases interact little with other local economic actors (national procurement procedures). Materials and most services depend on national centralized markets. Therefore the impact of the stimulus on the local economy seems disconnected from local characteristics (industrial specialization in particular). This property is central to our empirical specification because it exempts us from a complex modeling of local output-input linkages.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Industry	Building	Tertiary Market	Communication	Finance	Real Estate	Specialized	Tertiary Non Market
Schock	0.00 (0.067)	0.18*** (0.066)	0.02* (0.012)	0.79* (0.466)	0.15*** (0.048)	-0.10 (0.155)	-0.02 (0.066)	0.04 (0.034)
Observations	32,720	32,720	32,720	32,446	32,720	32,708	32,720	32,720

The table reports the coefficients of the OLS regression. Our variables of interest correspond to the ratio between the number of new firms and the total number of firms by sector. Time trend, and living areas fixed effects are included in all specifications. Standard errors in brackets are clustered at the living areas level; * stands for $p < 0.10$; ** stands for $p < 0.05$; *** stands for $p < 0.001$

Table 1. Impact of Military Restructurations on Enterprise Creation

3.2 Estimating the impact of air base closure on local labor market

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 a 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 unobservable (degree of political connection for instance).

	(1)	(2)	(3)	(4)	p-value		
	All Sample	Control	Negativ Treatment	Positiv Treatment	2=3	2=4	3=4
log(density)	-2.114	-2.216	-1.455	-0.608	0	0	0
Hhi	3.342	3.34	3.347	3.364	0.094	0.01	0.04
Without Any Diploma	48.162	48.662	44.813	41.434	0	0	0.01
High School	12.107	11.962	13.148	13.659	0	0	0.10
University	13.377	13.013	15.636	19.264	0	0	0.01
Industry	31.74	32.229	28.524	24.797	0.01	0.01	0.11
Building Sector	14.253	14.568	11.97	10.976	0	0	0.13
Tertiary Market	33.839	33.56	35.994	35.973	0	0.04	0.99
Communication	0.854	0.709	1.768	3.087	0	0	0.01
Financial Sector	2.533	2.366	3.682	4.632	0	0	0.03
Real Estates	1.496	1.461	1.733	1.998	0.001	0	0.1
Specialized Activities	6.607	6.34	8.211	11.231	0	0	0
Tertiary Non Market	5.984	6.071	5.399	4.867	0.004	0	0.11

(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).

3.2.1 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 effects 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 loadings². This specification may be expressed as:

$$\Lambda_{it}(0) = x_{it}\beta_2 + f_t'\lambda_i + \epsilon_{it} \quad (1)$$

in which x_{it} is a vector of local covariates, and β stands for the effects of covariates on unemployment. λ_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 1, the potential exit rate from unemployment in the presence of a base closure is:

$$\Lambda_{it}(1) = Shock_{it}\beta_1 + x_{it}\beta_2 + f_t'\lambda_i + \epsilon_{it} \quad (2)$$

With $Shock_{it} = \frac{(\Delta Military Workforce)}{Local Workforce}$. $Shock_{it}$ is our variable of interest, it represents the magnitude of the stimuli³. 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.

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). We use the following empirical specification to test this prediction:

²Interactive effect model requires selecting the optimal number of common factors. Results may be dependent on the number of dimensions selected. Indeed, Moon and Weidner (2017) 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, which is similar to a two-way panel model Bada and Liebl (2014).

³In annexe we present alternatives specifications in the way the shock is modeled

$$\lambda_{it}(1) = Shock_i\beta_1 + \ln(density_{it})\beta_2 + Shock_i * \ln(density_{it})\beta_3 + x_{it}\beta_4 + f_t' \lambda_i + \epsilon_{it} \quad (3)$$

4 Results

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 labor pooling models' prediction: unemployment is less affected by a shift in demand for labor in denser area.

4.1 Impact of army restructuring on local labor markets

In this subsection, we display our results from interactive effect models presented in subsection 3.2.1. We regress the likelihood of living unemployment on variables measuring the amplitude of the shocks ⁴.

The results of our regressions are reported in Table 4.1. Column (1) reports our first estimation. Variation in the number of local military workforce is positively associated with the likelihood of leaving unemployment. An influx of soldiers in area increase the likelihood of leaving unemployment. In columns (2) to (4) we assess the robustness of our results to the inclusion of additional fixed effects. In column (2) individual fixed effects are included in addition to interactive fixed effects. In column (3) time fixed effects are added, and in column (4) both time and individual fixed effects are included. Our results are remarkably stable across specification showing that interactive fixed effects capture the majority of unobserved variability.

⁴We have no theoretical guidance for the empirical modeling of the shock. In particular, we have no guidance for the duration of the impact of the restructuring on the labor market. Therefore, in annex we assess the robustness of our finding to the inclusion of past restructuring.

Recall that in our dataset, we observe an overwhelming majority of negative shocks as a results of public spending contraction. In columns (1) to (4) both positive and negative events are included. In columns (5) to (8) we delete from our sample area positively impacted by the reform. Our results are consistent with previous regression, showing that our estimations results are not driven by the presence of a small number of positive events. Then in columns (9) to (12) we restrict our sample to military areas. Those areas are "living areas" in which the Ministry of Defense has at least one military bases. Restricting our sample to "garrison areas" allows us to assess the impact of army restructuring within a homogeneous group of city. Indeed two garrison areas are more likely to be similar in terms of economic structure. Results displayed in columns (9) to (12) are once again very similar to those obtained on the whole sample.

As a robustness check, we report in table 4.1 the treatment effect estimates when additional variables are introduced as controls. 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 economic structure and for local levels of specialization.

-Tableau à Refaire-

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All						Negatively Impacted			Military Areas		
Shock	-1.31** (0.438)	-1.32** (0.438)	-1.28** (0.433)	-1.33** (0.435)	-1.37** (0.445)	-1.38** (0.446)	-1.33** (0.44)	-1.35** (0.442)	-1.1*** (0.322)	-1.07*** (0.324)	-1.17*** (0.322)	-1.14*** (0.323)
Fixed Effects	None	Individual	Time	Twoways	None	Individual	Time	Twoways	None	Individual	Time	Twoways
Observations	1636	1636	1636	1636	1605	1605	1605	1605	135	135	135	135

Table 3. Bases closures and likelihood of leaving unemployment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Exit rate from unemployment							
Shock	1.3** (0.435)	1.3** (0.435)	1.32** (0.438)	1.3** (0.435)	1.35** (0.442)	1.35** (0.442)	1.38** (0.446)	1.37** (0.445)
log(density)	0.0752***	0.0752***	0.0752***	0.0752***	0.0745***	0.0745***	0.0745***	0.0891***
Hhi	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.025)
	0.283**	0.283**	0.283**	0.283**	0.294**	0.294**	0.294**	0.601***
Without Any Diploma	(0.090)	(0.090)	(0.090)	(0.090)	(0.091)	(0.091)	(0.091)	(0.124)
	-0.364**	-0.364**	-0.364**	-0.364**	-0.363**	-0.363**	-0.363**	-1.16***
High School	(0.169)	(0.169)	(0.169)	(0.169)	(0.171)	(0.171)	(0.171)	(0.249)
	-0.73**	-0.73**	-0.73**	-0.73**	-0.72**	-0.72**	-0.72**	-0.447
University	(0.244)	(0.244)	(0.244)	(0.244)	(0.247)	(0.247)	(0.247)	(0.45)
	-0.0188	-0.0188	-0.0188	-0.0188	-0.00494	-0.00494	-0.00494	-0.139
Agriculture	(0.104)	(0.104)	(0.104)	(0.104)	(0.106)	(0.106)	(0.106)	(0.185)
	-0.283*	-0.283*	-0.283*	-0.283*	-0.265*	-0.265*	-0.265*	0.234
Industry	(0.147)	(0.147)	(0.147)	(0.147)	(0.149)	(0.149)	(0.149)	(0.202)
	-0.329**	-0.329**	-0.329**	-0.329**	-0.327**	-0.327**	-0.327**	-0.0181
Building Sector	(0.134)	(0.134)	(0.134)	(0.134)	(0.135)	(0.135)	(0.135)	(0.175)
	-0.337**	-0.337**	-0.337**	-0.337**	-0.333**	-0.333**	-0.333**	0.07
Tertiary Market	(0.148)	(0.148)	(0.148)	(0.148)	(0.149)	(0.149)	(0.149)	(0.201)
	-0.276**	-0.276**	-0.276**	-0.276**	-0.266*	-0.266*	-0.266*	0.0405
Communication	(0.138)	(0.138)	(0.138)	(0.138)	(0.14)	(0.14)	(0.14)	(0.181)
	-0.635**	-0.635**	-0.635**	-0.635**	-0.558*	-0.558*	-0.558*	-0.0448
Financial Sector	(0.296)	(0.296)	(0.296)	(0.296)	(0.302)	(0.302)	(0.302)	(0.397)
	-0.287	-0.287	-0.287	-0.287	-0.249	-0.249	-0.249	-0.0541
Real Estates	(0.192)	(0.192)	(0.192)	(0.192)	(0.196)	(0.196)	(0.196)	(0.238)
	-0.359	-0.359	-0.359	-0.359	-0.339	-0.339	-0.339	-0.675**
Specialized Professional	(0.278)	(0.278)	(0.278)	(0.278)	(0.282)	(0.282)	(0.282)	(0.33)
	-0.27*	-0.27*	-0.27*	-0.27*	-0.261*	-0.261*	-0.261*	0.123
Tertiary non Market	(0.145)	(0.145)	(0.145)	(0.145)	(0.147)	(0.147)	(0.147)	(0.192)
	-0.295**	-0.295**	-0.295**	-0.295**	-0.289**	-0.289**	-0.289**	-0.0553
Observations	32720	32720	32720	32720	32100	32100	32100	32100
Sample	All	All	All	All	Control + Negative	Control + Negative	Control + Negative	Control + Negative
Panel Structure	Twoways	Twoways	Individual	Individual	Twoways	Twoways	Individual	Individual

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

Table 4. Bases closures and likelihood of leaving unemployment: controlling for covariates

In the next subsection, we investigate in more detail the heterogeneous resilience displayed by local labor markets.

4.2 Local characteristics and Resilience

Figure 4 illustrates how the marginal effect of idiosyncratic shocks on unemployment changes with the local employment density. We control for a set of competing explanation, the dampening effect of density remains highly significant when human capital endowment, economic structure or degree of diversification is included. Any particular point on the solid sloping line in figure 4 corresponds to: $\frac{\partial U_{it}}{\partial shock} = \beta_1 + \ln(density_{it})\beta_3$. The gray area depicts the simulated 90 % confidence interval.

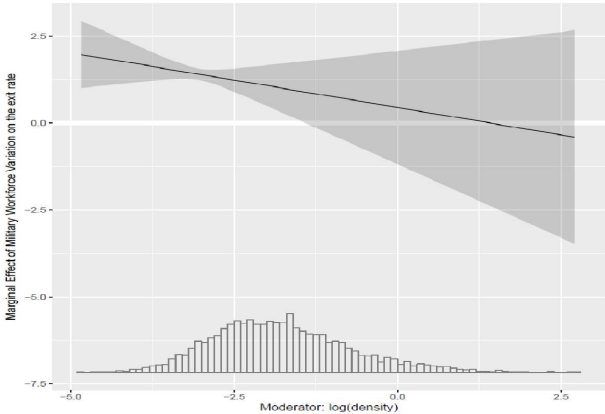


Figure 4. Impact of Employment Density on Unemployment Volatility

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)⁵. 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

⁵Figure 4 correspond to standard linear estimation. In subsection annexe, we relax the hypothesis of linear relationship by allowing for non-linearity between the amplitude of army restructuring and local level of density.

we observe in the histogram displayed in the background of figure 4 ⁶, 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 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). By implementing a interactive effect model we show that this response varies with the size of the affected city. Thick labor market are less affected by equal sized shock than sparsely populated labor market.

⁶city size distribution is displayed along the right y axis

5 Conclusion

This paper 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. The model predicts that a higher city size induces a lower unemployment volatility due to uncertainty in final demand for goods and services. This result confirms the idea of previous papers in economic geography of labor markets (Overman and Puga, 2010), (Andini et al., 2013) : agglomeration reduces uncertainty about future conditions on the labor market.

This paper exploits a shift in the local labor demand to estimate how the impact of a relatively similar shock varies with density of the local labor market. French army restructuring occurring between 2004 and 2014 constitute an exogenous shock. Restructuring provides 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 areas. 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 leads to a reduction in likelihood of leaving unemployment (conversely an increase in military staff increases 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 are less affected in dense areas 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 markets.

References

- Monica Andini, Guido De Blasio, Gilles Duranton, and William C Strange. Marshallian labour market pooling: Evidence from Italy. *Regional Science and Urban Economics*, 43(6):1008–1022, 2013.
- Oualid Bada and Dominik Liebl. The r-package phtt: Panel data analysis with heterogeneous time trends. *arXiv preprint arXiv:1407.6484*, 2014.
- Jushan Bai. Panel data models with interactive fixed effects. *Econometrica*, 77(4):1229–1279, 2009.
- Jushan Bai and Serena Ng. Determining the number of factors in approximate factor models. *Econometrica*, 70(1):191–221, 2002.
- Timothy J Bartik. Boon or boondoggle? the debate over state and local economic development policies. 1991.
- Timothy J Bartik. How effects of local labor demand shocks vary with local labor market conditions. 2014.
- Olivier Jean Blanchard, Lawrence F Katz, Robert E Hall, and Barry Eichengreen. Regional evolutions. *Brookings papers on economic activity*, 1992(1):1–75, 1992.
- Steven Brakman, Harry Garretsen, and Charles van Marrewijk. Regional resilience across Europe: on urbanisation and the initial impact of the great recession. *Cambridge Journal of Regions, Economy and Society*, page rsv005, 2015.
- Roberta Capello, Andrea Caragliu, and Ugo Fratesi. Spatial heterogeneity in the costs of the economic crisis in Europe: are cities sources of regional resilience? *Journal of Economic Geography*, page lbu053, 2015.
- Pierre-Philippe Combes and Laurent Gobillon. The empirics of agglomeration economies. 2014.

- Pierre-Philippe Combes, Thierry Mayer, and Jacques-François Thisse. *Economie géographique: l'intégration des régions et des nations*. Economica, 2006.
- Dario Diodato and Anet BR Weterings. The resilience of regional labour markets to economic shocks: Exploring the role of interactions among firms and workers. *Journal of Economic Geography*, 15(4):723–742, 2015.
- Gilles Duranton and Diego Puga. Micro-foundations of urban agglomeration economies. *Handbook of regional and urban economics*, 4:2063–2117, 2004.
- Martial Foucault. Les budgets de défense en france, entre déni et déclin. *Focus stratégique*, 36, 2012.
- Christina Gathmann, Ines Helm, and Uta Schönberg. Spillover effects in local labor markets: Evidence from mass layoffs. 2014.
- Laurent Gobillon and Thierry Magnac. Regional policy evaluation: Interactive fixed effects and synthetic controls. *Review of Economics and Statistics*, (0), 2015.
- Ross Haenfler. Bones, bombs, and break points: the geography of economic activity. *The American Economic Review*, 92(5):1269–1289, 2002.
- Jens Hainmueller, Jonathan Mummolo, and Yiqing Xu. How much should we trust estimates from multiplicative interaction models? simple tools to improve empirical practice. 2016.
- W Walker Hanlon. Temporary shocks and persistent effects in urban economies: Evidence from british cities after the us civil war. *Review of Economics and Statistics*, 99(1):67–79, 2017.
- Jakob Rubæk Holm, Christian Richter Østergaard, and Thomas Roslyng Olesen. The unleashing of creative potential from exiting firms? not really. In *DRUID Society Conference*, 2012.

- Patrick Kline and Enrico Moretti. Local economic development, agglomeration economies, and the big push: 100 years of evidence from the tennessee valley authority. *The Quarterly Journal of Economics*, 129(1):275–331, 2013.
- Paul R Krugman. *Geography and trade*. MIT press, 1991.
- Livre blanc sur la défens et la sécurité nationale. Livre blanc (le). Technical report, 2008.
- Alfred Marshall. Principles of economics: an introductory volume. 1927.
- Hyungsik Roger Moon and Martin Weidner. Dynamic linear panel regression models with interactive fixed effects. *Econometric Theory*, 33(1):158–195, 2017.
- Henry G Overman and Diego Puga. Labor pooling as a source of agglomeration: An empirical investigation. In *Agglomeration economics*, pages 133–150. University of Chicago Press, 2010.
- Frank Van Oort, Stefan de Geus, and Teodora Dogaru. Related variety and regional economic growth in a cross-section of european urban regions. *European Planning Studies*, 23(6):1110–1127, 2015.
- Simon Wood. *Generalized additive models: an introduction with R*. CRC press, 2006.
- Yu Xiao. Local economic impacts of natural disasters. *Journal of Regional Science*, 51(4):804–820, 2011.
- Ben Zou. The local labor market spillover effects of military personnel contractions. *Job market paper*, 2013.

Annexe

Robustness check: sensitivity to the inclusion of lagged shocks

As shown in the section 4, we have no theoretical guidance for the empirical modeling of the army restructuring. In particular we have no guidance for the duration of the impact of the restructuring on the labor market. In this subsection we assess the robustness of our finding to the inclusion of lagged restructuring. In table 5 our variable measuring the amplitude of the shock corresponds to the sum of the past restructuring occurring between 2004 and 2014. In other words, our variable of interest is equal to:

$$\sum_{i=1}^t Schock_{it} = \sum_{i=1}^t \frac{(\Delta Military Workforce)}{Local Workforce}$$

In table 6 we consider short-lasting effect. Our variable measuring the amplitude of the shock corresponds to the moving sum of past restructuring occurring in the last five quarters. In other words, our variable of interest is equal to:

$$\sum_{i=1}^5 Schock_{it} = \sum_{i=1}^5 \frac{(\Delta Military Workforce)}{Local Workforce}$$

Results displayed in table 5 and 6 confirm the robustness of our finding. Variation in the number of local military workforce is positively associated with the likelihood of leaving unemployment whatever the number of lag included. As expected, coefficients associated with the army restructuring are weaker in table 5 and 6 than thus displayed in 4, showing that areas absorb the shock.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Exit rate from unemployment							
$\sum_{i=1}^t Schock_{it}$	0.643**	0.641**	0.826**	0.641**	0.655**	0.653**	0.825**	0.738**
log(density)	(0.21)	(0.21)	(0.331)	(0.21)	(0.214)	(0.214)	(0.336)	(0.334)
Hhi		0.0749***		0.0749***		0.0742***		0.0888***
		(0.018)		(0.018)		(0.018)		(0.025)
		0.285**		0.285**		0.296**		0.6***
Without Any Diploma		(0.090)		(0.090)		(0.091)		(0.124)
		-0.362**		-0.362**		-0.361**		-1.16***
High School		(0.169)		(0.169)		(0.171)		(0.249)
		-0.733**		-0.733**		-0.723**		-0.451
University		(0.244)		(0.244)		(0.247)		(0.45)
		-0.0206		-0.0206		-0.00718		-0.14
Agriculture		(0.104)		(0.104)		(0.106)		(0.185)
		-0.278*		-0.278*		-0.26*		0.235
Industry		(0.147)		(0.147)		(0.149)		(0.202)
		-0.328**		-0.328**		-0.325**		-0.0143
Building Sector		(0.134)		(0.134)		(0.135)		(0.175)
		-0.335**		-0.335**		-0.331**		0.0703
Tertiary Market		(0.148)		(0.148)		(0.149)		(0.201)
		-0.274**		-0.274**		-0.264*		0.0436
Communication		(0.138)		(0.138)		(0.14)		(0.181)
		-0.631**		-0.631**		-0.554*		-0.0419
Financial Sector		(0.296)		(0.296)		(0.302)		(0.397)
		-0.288		-0.288		-0.25		-0.0517
Real Estates		(0.192)		(0.192)		(0.196)		(0.238)
		-0.354		-0.354		-0.332		-0.673**
Specialized Professional		(0.278)		(0.278)		(0.282)		(0.33)
		-0.263*		-0.263*		-0.255*		0.126
Tertiary non Market		(0.145)		(0.145)		(0.147)		(0.192)
		-0.292**		-0.292**		-0.286**		-0.0529
Observations	32720		32720		32100		32100	
Sample	All	All	All	All	Control + Negative Shock	Control + Negative Shock	Control + Negative Shock	Individual
Panel Structure	Twoways	Twoways	Individual	Individual	Twoways	Twoways	Individual	Individual

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Exit rate from unemployment							
$\sum_{i=1}^5 Shock_{it}$	0.467**	0.46**	0.522*	0.46**	0.47**	0.463**	0.526*	0.49*
log(density)	(0.225)	(0.225)	(0.274)	(0.225)	(0.229)	(0.229)	(0.279)	(0.278)
Hhi	0.075***	(0.018)	0.075***	(0.018)	0.075***	0.0744***	0.0889***	0.0889***
Without Any Diploma	0.283**	0.283**	0.283**	0.283**	0.283**	(0.018)	(0.025)	(0.025)
High School	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)	(0.091)	(0.124)	(0.124)
University	-0.365**	-0.365**	-0.365**	-0.365**	-0.365**	-0.364**	-1.16***	-1.16***
Agriculture	(0.169)	(0.169)	(0.169)	(0.169)	(0.169)	(0.171)	(0.249)	(0.249)
Industry	-0.732**	-0.732**	-0.732**	-0.732**	-0.732**	-0.722**	-0.448	-0.448
Building Sector	(0.244)	(0.244)	(0.244)	(0.244)	(0.244)	(0.247)	(0.45)	(0.45)
Tertiary Market	-0.02	-0.02	-0.02	-0.02	-0.02	-0.0063	-0.14	-0.14
Communication	(0.104)	(0.104)	(0.104)	(0.104)	(0.104)	(0.106)	(0.185)	(0.185)
Financial Sector	-0.28*	-0.28*	-0.28*	-0.28*	-0.28*	-0.263*	0.234	0.234
Real Estates	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)	(0.149)	(0.202)	(0.202)
Specialized Professional	-0.328**	-0.328**	-0.328**	-0.328**	-0.328**	-0.326**	-0.0169	-0.0169
Tertiary non Market	(0.134)	(0.134)	(0.134)	(0.134)	(0.134)	(0.135)	(0.175)	(0.175)
Observations	-0.336**	-0.336**	-0.336**	-0.336**	-0.336**	-0.332**	0.0698	0.0698
Sample	(0.148)	(0.148)	(0.148)	(0.148)	(0.148)	(0.149)	(0.201)	(0.201)
Panel Structure	-0.274**	-0.274**	-0.274**	-0.274**	-0.274**	-0.264*	0.0416	0.0416
Twoways	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)	(0.14)	(0.181)	(0.181)
All	-0.633**	-0.633**	-0.633**	-0.633**	-0.633**	-0.556*	-0.0438	-0.0438
Individual	(0.296)	(0.296)	(0.296)	(0.296)	(0.296)	(0.302)	(0.397)	(0.397)
Twoways	-0.286	-0.286	-0.286	-0.286	-0.286	-0.248	-0.0537	-0.0537
Individual	(0.192)	(0.192)	(0.192)	(0.192)	(0.192)	(0.196)	(0.238)	(0.238)
Twoways	-0.357	-0.357	-0.357	-0.357	-0.357	-0.336	-0.674**	-0.674**
Individual	(0.278)	(0.278)	(0.278)	(0.278)	(0.278)	(0.282)	(0.33)	(0.33)
Twoways	-0.267*	-0.267*	-0.267*	-0.267*	-0.267*	-0.259*	0.124	0.124
Individual	(0.145)	(0.145)	(0.145)	(0.145)	(0.145)	(0.147)	(0.192)	(0.192)
Twoways	-0.293**	-0.293**	-0.293**	-0.293**	-0.293**	-0.287**	-0.0541	-0.0541
Individual	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)	(0.137)	(0.178)	(0.178)
Observations	32720	32720	32720	32720	32720	32100	32100	32100
Sample	All	All	All	All	All	Control + Negative Schock	Control + Negative Schock	Control + Negative Schock
Panel Structure	Twoways	Twoways	Individual	Individual	Twoways	Twoways	Individual	Individual

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

Relaxing the hypothesis of linear relationship

We use Generalized Additive Models (GAM hereafter) (see Wood (2006) for an overview) to estimate non-linear relationship between the amplitude of army restructuring and the local level of density. GAM are very flexible because they do not require any hypotheses about the functional form of the variable of interest. In a linear specification, univariate response is modeled as the sum of a linear predictor and a zero mean random error term. In a linear specification, predictors are constrained to depend linearly on the parameters. Generalized Additive Model (GAM) is a semiparametric model in which part of the linear predictor is specified in terms of a sum of smooth functions of predictor variables. The exact parametric form of these functions is unknown (Wood, 2006). This semiparametric specification is much more flexible than linear specifications and the model is better able to describe the true phenomenon of interest. To assess the conditional impact of the military restructuring on the likelihood of leaving unemployment we estimate:

$$\lambda_{it}(1) = s(\text{Shock}_i)s(\ln(\text{density}_{it})) + s(\text{Shock}_i, \ln(\text{density}_{it})) + x_{it}\beta_4 + u_i + v_t + \epsilon_{it} \quad (4)$$

We allow for an unconstrained non-parametric relationship between the amplitude of the shock, the local level of density and the likelihood of living unemployment. $s(\cdot)$ represents the smooth function. This function is an isotropic smooth (rotation of the covariate co-ordinate system will not change the result of smoothing). This empirical specification prevents any functional form bias. To assess the impact of the restructuring conditional on the local level of density, we add an interaction structure ($s(\text{Shock}_i, \ln(\text{density}_{it}))$) to our specification.

Figure 5 show that for a given level of density, we observe the impact of an increase in local levels of restructuring by shifting along the x axis. At the opposite for ,a given level of restructuring we observe the impact of an increase in the local level of density

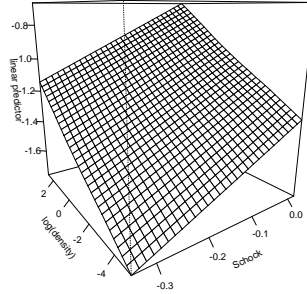


Figure 5. Smooth relation between the amplitude of the shock and the local level of density

by shifting along the y axis. For high levels of density, the impact of an increase the amplitude of the army restructuring is relatively null. At the opposite, for low levels of density, an increase in the number of military job cuts dramatically decreases the likelihood of leaving unemployment.

This finding confirms the stabilizing effect of agglomeration. In addition, we observe that the hypothesis of linear interaction made in subsection 4.2 does not appear to be too strong. Indeed the 3D figure seems rather flat, showing that the interactive term is well approximate with a linear fit.