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ABSTRACT

Local Agglomeration, Entrepreneurship and the Great Recession: Evidence from Italian Industrial Districts*

We ask whether local agglomeration affects how recessions impact on entrepreneurship by comparing the probability of being an entrepreneur before and after the Great 2008 Recession in local labour markets where industrial districts are present and in comparable areas. Using Italian Labour Force quarterly data from 2006 to 2011 and a "difference-in-differences" approach, we find that for males aged 40 to 55, who are more likely to be entrepreneurs, the negative effect of the recession on entrepreneurship has been sharper in areas with industrial districts. After examining alternative explanations – ranging from specialization to access to credit, from propensity to export to the industrial sector – we conclude that our findings are consistent with the view that intense social interaction in industrial districts acts as a multiplier that amplifies the response to shocks.

JEL Classification: J21, J24

Keywords: entrepreneurship, recession, Italy, industrial districts

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Introduction

Economic recessions have ambiguous effects on entrepreneurship. On the one hand, they decrease potential business income and wealth, thereby reducing the incentive to start or stay in business. On the other hand, they restrict employment opportunities, and consequently increase inflows into self-employment as alternatives to inactivity and unemployment. Do these effects vary with local economic conditions? There is ample evidence that agglomeration economies affect economic activity and entrepreneurship, because of the presence of consumer/supplier linkages, entrepreneurial and knowledge spillovers and labour market pooling (see for instance Rosenthal and Strange, 2010, Glaeser and Kerr, 2009, and Delgado et al, 2010). Less is known on whether these economies influence how entrepreneurship reacts to recessions.

In this paper, we address this question by focusing on the 2008 recession and on industrial districts (in short ID), an important variety of local agglomeration. Districts specialize in manufacturing and are characterized by the prevalence of small and medium firms, production similarity, proximity and substantial social interactions. Glaeser et al, 1992, distinguish between two types of local spillovers: a) Marshall-Arrow-Romer (MAR) externalities from specialization, or knowledge spillovers within the industry; b) Jacobs externalities, or spillovers from industrial variety and diversification. Industrial districts clearly belong to the first type.

Several factors may explain why the effects of a recession can differ across comparable areas that vary in their degree of agglomeration, some insulating local entrepreneurs, and some others favouring the propagation of the crisis. On the one hand, as remarked by Guiso and Schivardi, 2007, intense social interactions within networks of entrepreneurs might amplify the effects of aggregate negative shocks, because of the *social multiplier* and of information spillovers (see also Glaeser et al, 2000). Higher local agglomeration may also favour the entry of entrepreneurs by developing a culture of risk taking and by reinforcing social models that individuals imitate. When the tide raises all boats, increasingly less talented individuals may be attracted into entrepreneurship. When a recession hits, these individuals are more likely to be swept away.

On the other hand, positive agglomeration effects may reduce the costs of being an entrepreneur, and build a safety net of reciprocal support, thereby sustaining the ability to survive during a global recession. The literature on social capital suggests that industrial clusters are areas where the level of trust among people is higher. This may not only facilitate the access to credit, but also improve the economic performance of local banks, with positive effects on entrepreneurship when the local economy is in dire

straits.

Our empirical analysis focuses on Northern and Central Italy, the part of the country where industrial districts are more widespread (see for instance Porter, 1998). Placing the start of the 2008 recession in the third quarter of 2008, we divide our sample into a pre-treatment period (2006.1-2008.2) and a treatment period (2008.3-2011.4). Using quarterly data from the Italian Labour Force Survey,[1] we aggregate Italian municipalities into travel to work areas - or local labour markets (LLM) - following the classification provided by the 2001 Census.[2] Industrial districts are travel to work areas that satisfy additional conditions in term of production specialization and presence of medium and small firms.[3] We assign LLMs with industrial districts to the treatment group and comparable LLMs without districts to the control group.

Adopting a "difference-in-differences" (DiD) approach and controlling for individual observables, a quadratic common trend and LLM fixed effects, we find that – for men aged 40 to 55, who are more likely to be entrepreneurs - the 2008 recession has had a larger (statistically significant) negative effect on entrepreneurship in areas with industrial districts than in comparable areas. Measured in terms of the pre-treatment average share of entrepreneurs, the estimated differential effect of the treatment is around 8 percent, a sizeable effect.

We examine alternative explanations of this differential effect, including industrial specialization, the sector of production, the propensity to export, access to credit and population density. We conclude that none can credibly account for our findings. Our evidence is consistent instead with the presence of a social multiplier effect, as described by Guiso and Schivardi, 2007: the intense social interaction typical of industrial districts can amplify the effects of a shock in closely connected economies, mainly by accelerating information flows.[4] It is also consistent with the view that industrial districts, with their higher density of entrepreneurship and their stronger entrepreneurial culture, may attract into entrepreneurship relatively less talented individuals, who in comparable areas without districts would work as employees. When a recession hits, these entrepreneurs tend to lose or leave their business, affecting the share of entrepreneurship to a larger extent in district than in other areas.

Although our evidence is limited to the period immediately before and after the 2008 recession, both

[1] These data are repeated cross sections of representative samples of the Italian population.

[2] A travel to work area is a local labour market where at least 75% of the resident economically active population works in the area.

[3] According to the 2001 Census, Italy has 686 LLM, 156 of them classified as industrial districts.

[4] In models with social multiplier effects, agents face a common problem in an uncertain environment and each agent has a piece of private information, which can be inferred from the actions of other agents. The possibility of observing the behaviour of others induces an incentive to delay adjustments in order to gather more information. Once someone does act, however, the information revealed could trigger further actions, and start a self-reinforcing process that prompts many agents to undertake the adjustment within a short time span.

explanations suggest that entrepreneurship may be more responsive to business cycle conditions in industrial districts than in comparable areas. If this is the case, we expect that in the event of an economic expansion the share of entrepreneurs will increase faster in district areas.

The paper is organized as follows. In Section 1 we briefly review the literature on agglomeration effects and entrepreneurship; Section 2 introduces the model, which illustrates the main relations at stake; in Sections 3 and 4 we define industrial clusters and present the data. The empirical strategy is described in Section 5 and results are presented and discussed in Section 6. Conclusions follow.

1. Literature review

Our empirical investigation brings together two important strands of economic literature, the effect of unemployment on entrepreneurship and the impact of local agglomeration on economic activity and performance. To our knowledge, no attempt has been done so far to investigate the interaction between recessions, local agglomeration and entrepreneurship. In this section, we offer a very quick tour of the relevant literature.

Several studies have investigated the relationship between entrepreneurship and the unemployment rate. Yet there is still disagreement on whether higher unemployment acts to increase or decrease entrepreneurship. Blanchflower, 2000, reviews the early literature and concludes that for most OECD countries there is evidence of a negative relationship between unemployment and self-employment. In a more recent investigation, Fairlie, 2013 examines the effects of the 2008 recession in the US and finds evidence of a positive relationship.

The idea that the geographical concentration of firms and individuals can have beneficial effects on local economic performance dates back to the early 20^{th} century. Marshall, 1920, for instance, argued that a higher geographic concentration of specialized inputs increases productivity by improving the match between input factors and firms. Substantial theoretical and empirical research has followed, with special focus on the determinants of the local concentration of firms and of individuals (see for instance Ciccone and Hall, 1996; Glaeser, Rosenthal and Strange, 2010; Glaeser, 2010 and Rosenthal and Strange, 2010). According to this literature, differences in entry costs and the presence of knowledge spillovers are the key factors affecting the formation of cities and industrial clusters.

Research has also been devoted to understanding why agglomeration effects concentrate in some areas. One source of local variation is social capital. Tabellini, 2010, and Guiso et al, 2004a; Guiso et al, 2004b, and Guiso et al, 2008, among others, use the exogenous differences in political history across European

regions to develop an instrumental variables strategy and assess the causal effect of local social capital accumulation on regional economic growth and financial development. Guiso et al, 2004b, document that local financial development affects positively the probability of becoming an entrepreneur.

Some contributions have emphasized that local agglomeration effects are important in explaining spatial differences in entrepreneurship. Glaeser and Kerr, 2009, for instance, identify as drivers of the geographical concentration of entrepreneurs: (i) demographic differences such as education and age; (ii) differences in natural resources; (iii) agglomeration economies. The presence of a cluster of related industries in a location can foster entrepreneurship by lowering the cost of starting a business, enhancing opportunities for innovation and enabling better access to a more diverse range of inputs and complementary products (Delgado, Porter and Stern, 2010). The colocation of companies, customers and suppliers also increases the perception of business opportunities (see Porter, 1998).

As argued by Minniti, 2005, everything else being the same, the larger the number of entrepreneurs that the candidate entrepreneur observes in the local area, the lower the ambiguity she experiences. By observing others, the potential entrepreneur acquires information and skills. She meets other individuals who have similar or complementary expertise. She learns the ropes of how to find competent employees, inputs at affordable prices, financial support and, most important, potential buyers. Throughout this process her social environment becomes important, and her participation in a broadly defined network helps her to define the contour of the set of her entrepreneurial tasks. The existence of a significant number of entrepreneurs also legitimizes her activity and enables her to exploit a number of established routines. Areas with a higher density of entrepreneurs have a stronger entrepreneurial culture, which encourages entry.

2. Agglomeration Effects in the Presence of Negative Shocks: an Illustrative Model.

We illustrate the economic interactions between local agglomeration effects, entrepreneurship and recessions with a simple economic model, which draws from Lucas' model of entrepreneurial ability (see Lucas,1978, and Guiso and Schivardi, 2011 for a recent application). We show that, even in a simple model, these interactions are complex. Since their sign cannot be determined a priori, an empirical investigation is required.

Consider an economy composed of several local labour markets. In each market, individuals reside and work. We ignore labour mobility between markets[5] and focus instead on the individual choice between

[5]This simplifying assumption is supported by two pieces of evidence. First, according to the Italian Labour Force Survey, the

private sector employment and entrepreneurship within each locality. We assume that individuals residing in a local labour market are endowed with entrepreneurial ability x, which we posit for tractability to be uniformly distributed in the support $[0, 2\rho]$, with $\rho \geq 0$. Therefore, average ability in the area is ρ. Individuals choose to become entrepreneurs if expected profits from business activity - net of the setup costs c - are at least as high as expected income from either employment or unemployment, otherwise they choose to become employees. Local labour markets differ in the setup cost *c,* average ability ρ and in the size of the land area, θ. Define population density in a local labour market σ as the ratio of the population residing in that market to the land area. In line with the existing literature, we treat density as a source of agglomeration effects (see for instance Ciccone and Hall, 1996).

Consider a local labour market with average ability $\rho = \frac{1}{2}$. Let output prices be normalized to 1 and define revenue in firm *f* as $\lambda x_f [A + \ln(1 + k_f)]$, where λ is an agglomeration effect that improves productivity, k_f is employment, $g(k_f) = [A + \ln(1 + k_f)]$ the production function, and x_f the entrepreneurial ability of the individual running firm *f*. With A>0, production is positive even in the absence of employees and is concave in employment. To focus on aggregate negative shocks - or recessions - we characterize the environment faced by each firm with the random variable ζ, which takes the value $-\varepsilon$ with probability p and the value 0 with probability $1-p$. Recessions affect expected profits

$$E\pi_f = p\left[\lambda g(k_f) x_f - k_f w - \varepsilon\right] + (1-p)\left[\lambda g(k_f) x_f - k_f w\right] = \lambda g(k_f) x_f - k_f w - p\varepsilon \qquad (1)$$

where *w* is for wages. In line with the institutional features of the Italian labour market, we assume that wages are set at the national rather than at the local level,[6] and that they vary with the negative shock ε. Therefore, we assume that local employers take the common wage $w = w(\varepsilon)$ as given.

Maximization of expected profits with respect to k_f yields

$$k_f = \frac{\lambda x_f}{w} - 1 \qquad (2)$$

Conditional on the national wage, more talented entrepreneurs run larger firms. Let Ω be the threshold

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percentage of individuals changing province or region because of work reasons was relatively low during the sample period (less than 3 percent), and went up only marginally between 2006 and 2011, from 0.0263 in 2006 to 0.0268 in 2011. Second, recent research by Michelacci and Silva (2007) has shown that the vast majority of Italian entrepreneurs start a business in their place of birth.

[6] Wage bargaining in Italy occurs mainly at the national and sectorial level (Du Caju et al, 2008). Ammermuller et al, 2010, find that wages in Italy do not respond to local unemployment.

level of ability such that the individual with that ability is indifferent between being an entrepreneur and an employee. Then individuals with higher ability become entrepreneurs and hire employees if $x_f > \frac{w}{\lambda}$, do not hire employees if $\Omega \le x_f \le \frac{w}{\lambda}$ and become employees or unemployed if $x_f < \Omega$. In this section, we shall assume that $\Omega > \frac{w}{\lambda}$, so that entrepreneurs always have a positive number of employees. The case $\Omega \le \frac{w}{\lambda}$ is briefly sketched in the Appendix.

When entrepreneurs hire employees, their expected profits are $E\pi_f = \lambda A x_f - p\varepsilon$ and total employment demand *D* is given by

$$D = \int_{\Omega}^{1} (\frac{\lambda}{w} x_f - 1) dx_f = \frac{\lambda}{2w}(1-\Omega^2) - (1-\Omega) \tag{3}$$

Since supply to the employment sector is *Ω*, unemployment *u* is the difference between supply and demand: $u = 1 - \frac{\lambda}{2w}(1-\Omega^2)$. As expected, unemployment increases with the wage *w* and with the threshold *Ω,* and declines with the agglomeration effect λ. Assuming that income from unemployment is zero, expected income from employment is $Ew = w(1-u) = \frac{\lambda}{2}(1-\Omega^2)$, increasing in the agglomeration effect and decreasing in threshold ability *Ω*.

In each local labour market, the allocation of individuals between entrepreneurship and employment (or unemployment) is regulated by the arbitrage condition that expected profits net of the setup costs must be equal to expected income, or $E\pi = Ey + c$, which can be written as

$$\lambda\Omega(A-2) + \lambda\Omega^2(\frac{\lambda}{w(\varepsilon)} + \frac{1}{2}) + w(\varepsilon) = \frac{\lambda}{2} + c + p\varepsilon \tag{4}$$

We notice that the negative shock ε affects the arbitrage condition both directly and indirectly, by altering the wage rate. Condition (4) yields the threshold value of ability $\Omega = \Omega(\lambda, c, p, \varepsilon, A)$, such that individuals with ability at or above the threshold become entrepreneurs and individuals with less than threshold ability

are either employees or unemployed.

We characterize the local agglomeration effect λ as

$$\lambda = \lambda_0 + \lambda_1 \sigma + \lambda_2 ID \tag{5}$$

where ID is a dummy equal to 1 if the local labour market is an industrial district, and σ is local population density, defined above. The empirical evidence suggests that $\lambda_1 > 0$ (see for instance Ciccone and Hall, 1996). If industries grow faster in places where they are over-represented, so that MAR externalities prevail, λ_2 is also positive. If instead specialization generates excessive competition and congestion costs, and industrial diversification prevails (Jacobs externalities), λ_2 can be either negative or zero.[7]

The equilibrium share on entrepreneurs in the local labour market is 1- Ω . We can study the effects of the negative shock ε and of the presence of industrial districts *ID* on entrepreneurship by differentiating the arbitrage condition (4) to obtain

$$\frac{\partial \Omega}{\partial \varepsilon} = \frac{p - \frac{\partial w}{\partial \varepsilon}(1 - \frac{\lambda^2 \Omega^2}{w^2})}{\lambda(A-2) + 2\lambda\Omega(\frac{\lambda}{w} + \frac{1}{2})} = \frac{p - \frac{\partial w}{\partial \varepsilon}(1 - \frac{\lambda^2 \Omega^2}{w^2})}{\Delta} \tag{6}$$

$$\frac{\partial \Omega}{\partial ID} = \frac{\partial \Omega}{\partial \lambda}\frac{\partial \lambda}{\partial ID} = \lambda_2 \frac{\frac{1}{2} - \Omega(A-2) - \frac{2\lambda\Omega^2}{w}}{\Delta} \tag{7}$$

Both marginal effects cannot be signed without specifying the values of key parameters. For instance, a sufficient condition for a positive denominator Δ is $A \geq 2$. The numerator of (6) is positive if the direct effect of the shock, captured by *p,* is not offset by the indirect effect operating through wages. The two effects go in opposite directions because $\frac{\partial w}{\partial \varepsilon}$ is negative and $1 - \frac{\lambda^2 \Omega^2}{w^2}$ is negative under our assumptions. Therefore, a negative shock can increase entrepreneurship is wages fall enough.

Next, consider the effect of the presence of industrial districts ID on the threshold value Ω – equation (7) - and assume that $\Omega > \frac{1}{2}$, a plausible assumption given that the share of entrepreneurs is typically

[7]Glaeser et al, 1992, find that (employment) growth is faster in areas where Jacobs externalities prevail, and slower in areas with important MAR externalities.

below 50 percent of the population. Under this assumption, the numerator of (7) is negative if λ_2 is positive and $A \geq 2$, because $\lambda > w$ for the condition $\Omega > \frac{w}{\lambda}$ to hold. If this is the case, areas with industrial districts have a higher share of entrepreneurs in the population.

We are particularly interested on how the presence of industrial districts *ID* in a local labour market impacts on the marginal effect of a negative shock on entrepreneurship. By differentiating (6) with respect to ID we obtain

$$\frac{\partial^2 \Omega}{\partial ID \partial \varepsilon} = \frac{\partial^2 \Omega}{\partial \lambda \partial \varepsilon}\frac{\partial \lambda}{\partial ID} = \frac{\lambda_2}{\Delta}\left\{\frac{\partial w}{\partial \varepsilon}\left(1+\frac{\lambda}{\Omega}\frac{\partial \Omega}{\partial \lambda}\right)\frac{2\lambda\Omega}{w^2}\right\}$$
$$-\frac{\lambda_2}{\Delta^2}\frac{\partial \Omega}{\partial \varepsilon}\left[(A-2)+(2\Omega+2\lambda\frac{\partial \Omega}{\partial \lambda})\left(\frac{\lambda}{w}+\frac{1}{2}\right)+2\lambda\frac{\Omega}{w}\right] \qquad (8)$$

The sign of this derivative depends on the values of the underlying parameters and cannot be determined a priori. Therefore, to establish whether the effects of a negative shock on entrepreneurship is attenuated or amplified by the presence of industrial districts, we need to turn to the empirical analysis.

3. The Definition of Industrial Districts

Local labour markets - defined as travel to work areas where most residing people live and commute to work - and industrial districts are defined by the National Statistical Institute (ISTAT) in the occasion of the national population census, which takes place every ten years. For the purposes of this paper, we use the definitions provided by the 14^{th} *Census of Population and Services,* held in 2001, which identifies 686 LLM and 156 industrial districts.

Industrial districts are LLM that satisfy the following additional criteria:

a) specialization in the manufacturing sector, i.e. $l_a = \frac{x_{am}/x_a}{x_{.m}/x_{..}} > 1$, where x_{am} and x_a denote the number of manufacturing employees and total employment in area *a*, and $x_{.m}$ and $x_{..}$ are the corresponding figures at the national level;

b) relative high share of small and medium firms, or $s_a = \frac{x_{am}^{small}/x_{am}}{x_{.m}^{small}/x_{.m}} > 1$, where the superscript "small" indicates the number of employees in small and medium-sized enterprises;

c) presence of a dominant manufacturing industry. Letting $l_{as} = \frac{x_{as} / x_{am}}{x_{.s} / x_{.m}}$ denote the location quotient for each specific manufacturing industry *s*, the dominant manufacturing industry d is such that $l_{ad} > 1$ and the level of employment is maximum among the local specialized industries. For *d*, the following condition must hold: $s_{ad} = \frac{x_{ad}^{small}}{x_{ad}} > 0.5$;

d) where there is only one medium-sized enterprise, the share of employment in small enterprises must exceed half that of the medium-sized firm.

Figure 1 is a map of industrial districts in Italy. These industrial agglomerations are virtually absent in the South and tend to concentrate in Lombardy and Veneto in the North, and in Tuscany and Marche in the Center. Notice that condition a) nearly automatically rules out the possibility that urban areas can be defined as industrial districts, since the former are usually characterized by an extensive presence of services.

4. The Data

Our data are drawn from the Italian *Labour Force Survey*, a quarterly survey on labour market conditions covering a representative sample of almost 77,000 households and 175,000 individuals per quarter. We have access to the micro data from the first quarter of 2006 to the last quarter of 2011. Using the available information on the place of residence, we assign individuals to LLMs.[8]

In line with the existing literature, we define *entrepreneurs* as individuals who work in their own business or professional practice for the purpose of earning a profit, with or without employees. As discussed by Faggio and Silva, 2012,[9] the empirical literature tends to identify entrepreneurship with self-employment. Yet the two measures are hardly equivalent, for instance because some self-employment spells are due to the lack of alternative employment opportunities, especially during recessions.

In this paper, we treat as entrepreneurs the individuals who meet all the following criteria: (i) self-employment status; (ii) decide their working time; (iii) work more than 480 hours per year; (iv) neither work exclusively on the customer's premises nor employed by a temporary agency; (v) operate as managers, professionals, or in other skilled jobs. Criteria (ii) to (iv) exclude those who report self-employment status but are working as employees. Criterion (v) is used also by Faggio and Silva, 2012, and allows us to exclude the bulk of self-employed who have selected this status because alternative employment opportunities are

[8] By definition of travel to work area, place of residence and place of work coincide for the large majority of individuals.
[9] See also Glaeser and Kerr, 2009.

not available.

We further classify entrepreneurs in two groups, depending on whether they have employees or not. In the empirical analysis, we will focus on the former group. We retain only males aged 25 to 55 who are employed, self-employed, unemployed or inactive at the time of the interview, and exclude those working in the public sector. We exclude females because of their low labour force participation, and workers older than 55 because of their attrition into retirement. Finally, we exclude Southern Italy because of its structural difference with the rest of the country and its lower degree of economic development.

We compare how entrepreneurship responds to a negative shock in areas with industrial districts and in comparable areas without districts. The difficulty of this exercise is that areas differ in several dimensions other than the presence of ID. To enhance comparability, we use propensity score matching and exclude from the estimation sample the areas lying outside the common support. The matching procedure is discussed in detail in the next Section. Since the Labour Force Survey randomly selects a sample of municipalities, we can only identify 540 LLMs in the data - out of a total of 686. The elimination of Southern Italy and of the areas outside the common support leaves us with a sample of 240 local labour markets and 94 industrial districts.

Table 1 shows the share of male entrepreneurs with employees before and after the Great Recession in the treated and control areas both for the full sample and for the two sub-samples of young (25-39) and senior individuals (40-55). Before the recession, this share was almost twice as high in the latter sub-sample (12 versus 6.8 percent). During the three years after the recession, it declined from 9.73 to 8.50 percent in the areas with industrial districts and from 9.42 to 8.38 in comparable areas. The decline has been more pronounced in the treated areas for senior entrepreneurs (from 12.14 to 10.36 percent) and in control areas for the younger age group (from 6.96 to 5.62). Figure 2 for the full sample and Figure 3 for the two sub-samples of younger and older individuals illustrate the variation over time in the share of entrepreneurs with employees. Inspection of these figures suggests that the difference in pre-treatment trends is relatively small. Formal tests of this difference are discussed below.

Table 2 presents the summary statistics of the relevant variables, separately for treated and control areas. Since we have eliminated the areas outside the common support using the estimated propensity score, sample averages are remarkably similar. The local unemployment rate is 3 percent in both areas;[10] the regional (log) real GDP as well as regional real exports[11] are slightly higher on average in the areas with industrial districts; the percentage of individuals with a college degree is 9 and 11 percent in the treated and

[10]The low rate might seem surprising. Notice however that unemployment in Italy is highest among those living in the South, who are excluded from our sample.

[11] Regional values are from the regional accounts.

control areas respectively; population density (inhabitants per 100 km^2) is slightly lower in treated areas (236 inhabitants per squared kilometer versus 262 in control areas). We also report an index of economic specialization, computed as $SP_{cs} = \frac{L_{cs}}{L_c}$, where L_{cs} is the sum of employees and self-employed workers in local area c and sector s, and L_c is the total number of workers in the area (Cingano and Schivardi, 2004). The index is only marginally higher in treated areas, namely 0.15 versus 0.14.

5. The Empirical Setup

We investigate how entrepreneurship in areas with and without industrial districts has reacted to the 2008 recession using a difference-in-differences approach. The treatment group is composed of local areas with industrial districts – where local agglomeration with important within-industry spillovers is important - and the control group consists of comparable areas without districts. Our empirical model is

$$SH_{it} = \beta_0 + \beta_1 Post2008.3_{it} + \beta_2 ID_i + \beta_3 Post2008.3_{it} * ID_i + \beta_4 X_{it} + u \qquad (9)$$

where i is for the individual, t for the quarter, SH is a dummy equal to one if the person is an entrepreneur and to zero otherwise, ID is a dummy that identifies the presence of industrial clusters, $Post2008.3$ is a dummy taking value one after the beginning of the Great Recession, which we set in the third quarter of 2008, and zero otherwise, and X is a vector of controls, which includes individual variables (age, education, marital status, the presence of children in the household and nationality), a quadratic trend and local labour market dummies.[12]

We estimate (9) using a linear probability model. The key parameter in this regression is β_3, which measures the differential effect of the recession in areas with industrial districts relative to other comparable areas. This coefficient corresponds to marginal effect (8) in Section 2 of the paper. As mentioned in the previous section, a potential risk in this analysis is that geographical areas may not be completely comparable, due to intrinsic differences that are not fully captured by the degree of agglomeration measured by the dummy *ID*.

To increase the comparability between treatment and control areas, we estimate a probit model on the sample of LLMs over the pre-treatment period 2006.1 to 2008.2, using as dependent variable the dummy

[12] We have also experimented with richer specifications that include the log of regional real GDP in manufacturing and services, the log of regional exports, and the local unemployment rate, with no qualitative change of results.

ID and as control variables log regional real exports and GDP, the local unemployment rate, the index SP of industrial specialization, the prevailing industrial sector, population density, dummies for the macro area (North-West or North-East) and a quadratic trend. We use these estimates to compute the propensity score,[13] the distribution of which is shown in Figure 4, and eliminate from our sample the local labour markets with a propensity score falling outside the intersection of the support for the treated and the control group (Sianesi, 2005). Clearly, these areas are not comparable to the rest in term of the selected vector of observables. We find that the reduction in the average difference in the observables between treated and control areas after restricting the sample to the common support is significant.

We estimate (9) on the selected sample. Our identification assumption is

$$E[u_{i1} - u_{i0} \mid ID = 1, X] = E[u_{i1} - u_{i0} \mid ID = 0, X] \tag{10}$$

where the index "1" is for the post-treatment and "0" is for the pre-treatment period, implying that selection on untreated outcomes is ruled out in first differences and after conditioning on the vector X (Blundell and Costa Dias, 2009). In our setup, we do not expect to observe an immediate jump in the share of entrepreneurs just after the start of the recession. Rather, we expect to observe a change in the entrepreneurship trend after the shock, and that this change in trend differs between the two groups of areas because of the presence of industrial districts.

6. Results

"Difference–in–differences" estimates identify the effect of the treatment if pre-treatment trends in the treated and control group are parallel. To test whether this is the case, we consider the pre-treatment period, regress entrepreneurship on the vector of controls *X*, a quadratic trend and the interactions of the trend with the treatment dummy, and test whether these interactions are jointly equal to zero. In support of our empirical strategy, we cannot reject the null both in the full sample and in the sub-samples of older and younger workers.[14]

Table 3 presents our baseline results, both for the full sample and for the two sub-samples of young and senior individuals. For the full sample, column (1) in the table shows that the differential effect of the

[13] The propensity score is defined as $e(x) = \Pr ob(ID = 1 \mid X = x)$, the probability of belonging to the treatment conditional on observables X. See Sianesi, 2005.

[14] The p-values of the tests are equal to 0.61, 0.82 and 0.55 respectively.

recession on entrepreneurship in treated and control areas - β_3 in Eq. (9) - is negative, small and not statistically significant. We also find that entrepreneurship increases with age and education, is higher for married natives and decreases with the presence of children in the household.

When we run the same regressions separately for the group of men aged 25 to 39 and the group aged 40 to 55 – columns (2) and (3) in the table – we find that estimated β_3 is positive, small and imprecisely estimated for the former group, and negative, sizeable and statistically different from zero for the latter group. In particular, we estimate that for senior men the probability of being an entrepreneur after the recession is 7.72 (-0.0094/0.117) percent lower in the areas with industrial districts than in comparable areas.[15] We test whether the differential effect of the treatment does not vary significantly between older and younger men and reject the hypothesis (p-value of the test: 0.012). We also run separate regressions by industry, by distinguishing between manufacturing and business services on the one hand and other private sector services on the other hand, but find no statistically significant differences in the relevant effects.[16]

Our qualitative results remain virtually unaffected when we use a broader definition of entrepreneurship, which includes also entrepreneurs without employees (see Table 4). In the full sample and in the subsample of younger men, we find no statistically significant differential effect of the crisis on the treated and the control group. However, for the sample of senior men we find that the recession has had a sizeable negative effect (-7.26 percent) on those operating in areas with industrial districts.

The percentage of entrepreneurs is higher among senior individuals than in the younger group. On the one hand, senior males are more likely to have accumulated the relevant human capital and the experience required to start a business. In the parlance of our model, they have higher entrepreneurial ability. On the other hand, they may have higher access to financial resources. Our estimates suggest that the negative impact of the recent recession has been larger on the entrepreneurship of this group in areas with industrial districts than in comparable areas.

How do we explain this result? The literature suggests as a candidate the higher level of production specialization typical of industrial clusters. On the one hand, Glaeser et al, 1992, find that industries grow slower in places where they are over-represented. There is also some evidence that specialization accelerates firm exit.[17] On the other hand, Delgado et al., 2010, find that, after netting out the convergence dynamics across areas, the presence of industrial clusters accelerates the growth of newly established firms and their performances.

[15] In all estimates we cluster standard errors at the local labour market level.

[16] These results are available from the authors upon request.

[17] Staber, 2001, for instance, finds that belonging to a specialized industrial district in Germany reduces firm survival. See also the discussion in Antonietti et al, 2013.

We believe that there are two reasons to exclude specialization as the explanation of our findings: first, since the index of specialization has been used to define the common support from which the sample of LLMs has been selected, the differences in the level of specialization between treatment and control are small (see Table 2). Second, we have redefined treatment and control groups by assigning to treatment the LLMs with higher than median value of the index of specialization before the treatment period, and to the control group the remaining LLMs. By so doing, each redefined group contains both industrial districts and areas without districts. We have re-estimated (9) on the sub-sample of senior men using these new definitions of treatment and control and found - see Table 5, column (1) - that the effects of the Great Recession on self-employment are not significantly different.[18]

Alternatively, our findings could be driven by the fact that industrial districts concentrate in specific production sectors, which may have been hit especially hard by the recession. These sectors are: textiles and apparel, furniture, house goods and mechanical engineering. To verify this hypothesis, we redefine once again our treatment and control groups in equation (9) in such a way that the former consists of areas where the sectors above have an important share of total employment and the latter includes the remaining areas. Again, this re-assignment implies that industrial districts are present in both groups. We re-estimate equation (9) on the sub-sample of senior men using this new definition of treatment and control and find no statistically significant differential effect of the recession (Table 5, column (2)).

The differential effect of the recession for senior men in areas with industrial districts could be driven by the fact that firms in these areas have a higher propensity to export than firms in other areas, and therefore have been more exposed to the contraction of international demand. To illustrate, consider the four regions where industrial districts are more widespread (Lombardy, Veneto, Tuscany and Marche) and the four regions where they are less present (Liguria, Trentino, Umbria and Lazio). If we compare real GDP growth between 2007 (before the recession) and 2009 (after the recession) in the two groups of regions, we find that real GDP in manufacturing declined by 17.8% in the former group and by 19.1% in the latter group. Services were less affected, with a decline equal to 5.0% and 6.1% respectively. These differences are small when compared with the performance of real exports, which plummeted during the same period by 20.1% in the regions where industrial districts prevail and by 9.0% in the other regions.

We check whether our findings are driven by different propensities to export by adding to Eq. (9) the interaction between the recession dummy *Post2008.3* and a dummy equal to one if the local labour market is located in a region where the level of real exports before the recession was above the median, and to

[18] Prior to estimating equation (9) using the new definition of treatment, we have re-estimated the probit model after excluding the index of specialization and re-selected the sample of LLMs within the common support. This explains why the number of observations in Table 5, column (1), is different from that in Table 3, column (3).

zero otherwise. If our results were driven by exports, this inclusion should affect in a significant way the estimate of β_3. Yet Table 6 shows that this is not the case.[19]

Our results could also be driven by differences in the access to credit across local labour markets rather than to the presence of industrial districts. To address this possibility, we collect three measures of credit accessibility for the pre-treatment period: a) the number of bank branches per thousand inhabitants; b) the loan – deposit ratio;[20] c) the percentage of firms in the province that claim to have been credit rationed in 2003.[21] As for exports, for each of these three variables we construct a dummy variable taking the value one for values above the median, and zero otherwise, and interact each dummy in Eq. (9) with the dummy *Post2008.3*. If access to credit was the reason of the uncovered differences, we should find that adding these interactions significantly reduces or even eliminates the differential effect associated to the presence of industrial districts. As shown in Table 7, the addition of these interactions leave our estimates broadly unaffected. We therefore rule out this explanation.

As discussed in the model of Section 2, local agglomeration effects could depend also on population density. We investigate whether our estimated effects are driven by differences in population density by proceeding as in the case of exports. First, we re-do our sample selection by excluding density from the probit equation. Second, we add to Eq. (9) the interaction between the dummy variable *Post2008.3* and a dummy equal to one for the local labour markets where population density before the treatment was above the median, and to zero otherwise. As shown in Table 8, adding this interaction has virtually no effect on our estimates of coefficient β_3. Thus, differences in population density do not explain our results.

A key difference between population density and industrial clusters as measures of local agglomeration is that the second emphasizes production similarity as well as proximity. As remarked by Guiso and Schivardi, 2007, industrial districts are characterized by a high concentration of similar, supposedly connected firms, where social interaction is particularly intense. Production similarity facilitates information flows between network members and accelerates learning. Intense interaction gives rise to amplified responses to shocks, because "..the initial impulse is magnified by the response of the other members of the reference group". (p.70). In their own study of Italian industrial districts, these authors find that firms in these areas "..should display a lower sensitivity to aggregate shocks in non-adjustment years and a higher sensitivity in adjustment years, because those should be the years in which the response to shocks is

[19] Prior to the estimates in Table 6, we re-define the common support by excluding exports from the vector of covariates in the probit analysis.
[20] Measures (a) and (b) are calculated for the time interval 2004-2005 on the basis of municipal data (source: Banca d'Italia) which we aggregate at the LLM level.
[21] Source: Capitalia, (2005) *Indagine sulle imprese italiane.*

amplified by information flows.." (p.88). Our results are consistent with Guiso and Schivardi, 2007, inasmuch as we interpret the years after the Great Recession as adjustment years.

Do these amplifying effects extend from entrepreneurship to private employment and inactivity (inclusive of unemployment)? As shown in Tables 9 and 10, where we present the estimates of equation (9) when the dependent variable is either private employment or unemployment / inactivity, the answer is generally no: employment falls and inactivity increases after the recession in all LLMs, independently of whether they are industrial clusters or not. A notable exception, however, is the private employment rate of senior individuals aged 40 or older, which increased marginally after the recession in the areas where industrial districts are located. We speculate that in these areas entrepreneurs leaving or losing their business because of the recession may have turned into employees of surviving businesses. In support of this, we find that average firm size has slightly increased - from 8.27 employees in 2008 to 8.38 employees in 2011 - in the four regions where industrial districts are more present, and declined - from 7.74 to 7.17 employees – in the four regions where they are less widespread.

Another candidate explanation of our results is that in areas with industrial districts the higher density of entrepreneurs[22] and the stronger entrepreneurial culture may attract into entrepreneurship relatively less talented individuals. In other areas, these individuals typically work as employees. When a recession hits, less talented entrepreneurs in industrial districts lose or leave their business (turning perhaps into employees), with larger negative effects on the overall share of entrepreneurs.

We test the robustness of our results by conducting four exercises on the subsample of senior males. First, we interact the LLM dummies with quadratic trends. As shown in the first column of Table 11, our estimates lose precision due to the large number of additional regressors, but remain qualitatively unchanged. Second, we exclude from the sample the small percentage (less than 3 percent) of individuals who have changed region of residence for work - related reasons, in order to verify whether the differential effects estimated in Table 3 are driven by endogenous mobility patterns. As shown in the second column of the table, our qualitative results are again unchanged. Third, we run placebo regressions by randomly assigning areas to the treatment (industrial districts) and control groups (other LLM). With random assignment, we should not find any significant difference between the two groups in the effects of the recession on self-employment. The last column in Table 11 confirms that this is the case. Last but not least, we replicate our estimates in Table 3 and 4 using a probit specification, again without significant differences in our main results.[23]

[22] In 2006 the number of entrepreneurs (with and without employees) per squared kilometre was 22.54 in district areas and 17.29 in other areas.

[23] These estimates are available from the authors upon request.

Conclusions

In this paper, we have investigated whether local agglomeration affects the impact of recessions on entrepreneurship. We have started with a theoretical model in the spirit of Lucas, 1978, which determines the equilibrium share of entrepreneurship in a local labour market as the solution to an arbitrage condition involving expected profits, wages and income from unemployment. Since the effect of local agglomeration on the marginal effect of a negative shock on entrepreneurship cannot be signed a priori, we have turned to an empirical investigation

Using a "difference-in-differences" approach that compares the probability of being an entrepreneur before and after the Great 2008 Recession in areas where industrial districts are present and in comparable areas, we have found that the Great Recession has had a larger, and statistically significant, negative effect on the probability that senior men aged 40 to 55 are entrepreneurs in areas with industrial districts than in comparable areas. We have explored alternative explanations of this differential effect, including industrial specialization, the sector of production, differences in the level of exports and credit accessibility. Our results suggest that none of these possible channels can credibly account for our findings.

We have argued that both *entrepreneurial culture* and the *social multiplier* are candidate mechanisms that could explain, at least in part, our results. On the one hand, in areas with industrial districts the stronger entrepreneurial culture may attract relatively less talented individuals into entrepreneurship. When a recession hits, these entrepreneurs typically lose their business and exit. On the other hand, the social multiplier effect suggests that the intense social interaction typical of industrial districts can amplify the effects of a shock in closely connected economies, mainly by accelerating information flows. Since these mechanisms operate also in the presence of positive aggregate shocks, this mechanism leads us to speculate that the positive response of entrepreneurs to an economic expansion might be stronger in areas where industrial districts prevail.

Our empirical investigation has focused on labour market stocks. Further insight on how industrial districts respond to a recession most likely requires that we complement this investigation with one that explores the demography of firms and illustrates how firm revenues and costs vary over the business cycle. We plan to pursue this in our future research.

Appendix

In this Appendix we sketch the local labour market equilibrium when $\Omega \leq \frac{w}{\lambda}$. In this event, there are two groups of entrepreneurs: those without employees, who make profits $E\pi_f = \lambda A x_f - p\varepsilon$, and those with employees, who have expected profits equal to $E\pi_f = \lambda(A-2)x_f + w + \frac{\lambda^2 x_f{}^2}{w} - p\varepsilon$. The size of the two groups is $\frac{\frac{w}{\lambda} - \Omega}{1-\Omega}$ and $\frac{1-\frac{w}{\lambda}}{1-\Omega}$ respectively.

Differences in ability identify three groups: those with lowest ability are either employed or unemployed, those with intermediate ability are entrepreneurs without employees and those with highest ability are entrepreneurs with employees.

Total employment is

$$D = \int_{\frac{w}{\lambda}}^{1} (\frac{\lambda}{w} x_f - 1) dx_f = \frac{\lambda}{2w}[1 - (\frac{w}{\lambda})^2] - (1 - \frac{w}{\lambda}) \qquad \text{(A.1)}$$

and unemployment is $u = 1 + \Omega - \frac{\lambda}{2w} - \frac{w}{2\lambda}$. Therefore, the arbitrage condition can be written as

$$\lambda\Omega A + \frac{1-\frac{w}{\lambda}}{1-\Omega}[w(\varepsilon) - 2\lambda\Omega + \frac{\lambda^2\Omega^2}{w}] = w[\frac{\lambda}{2w} + \frac{w}{2\lambda} - \Omega] + c + p\varepsilon \qquad \text{(A.2)}$$

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A Graphs and Tables

Figure 1: Map of Italian industrial districts (grey areas). Source: Istat, 8th Census of Industries and Services.

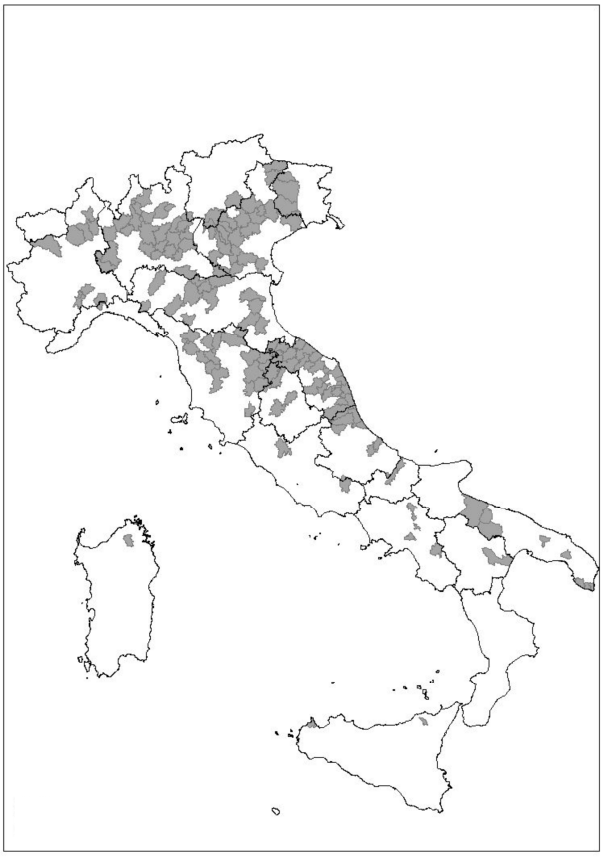

Figure 2: The share of male entrepreneurs with employees over time. By type of area.

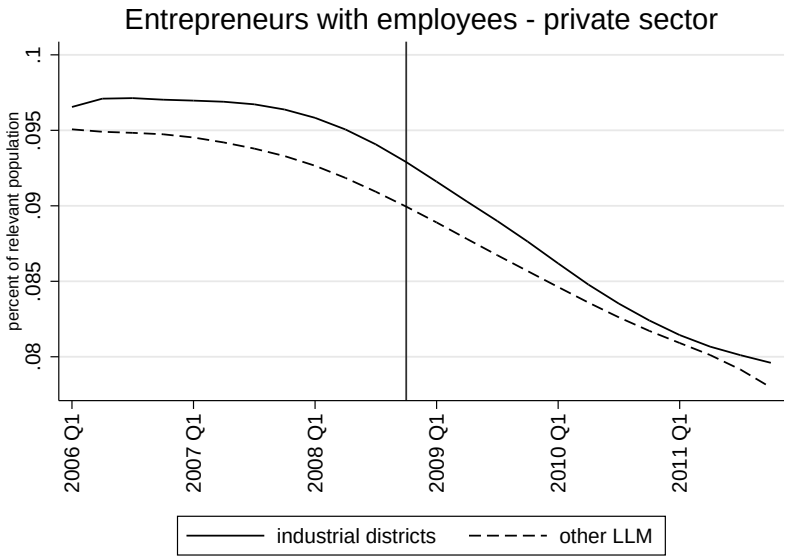

Figure 3: The share of male entrepreneurs with employees over time. By type of area and age group.

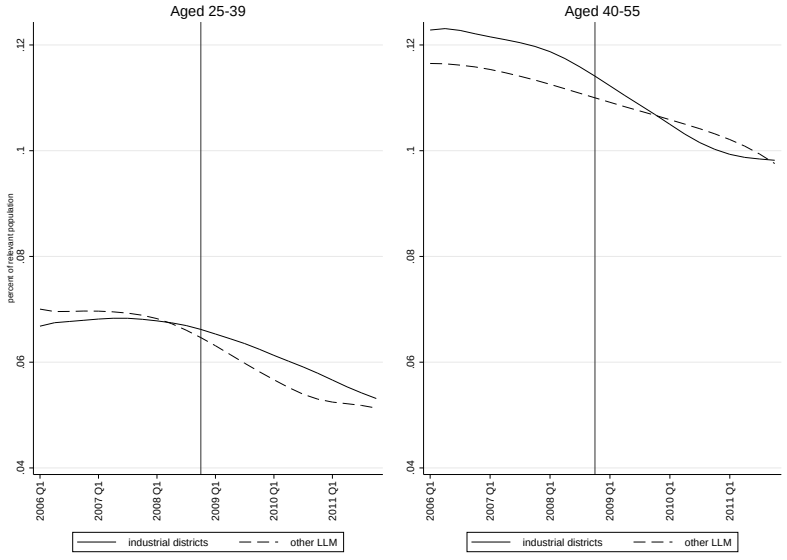

Figure 4: The distribution of the propensity score.

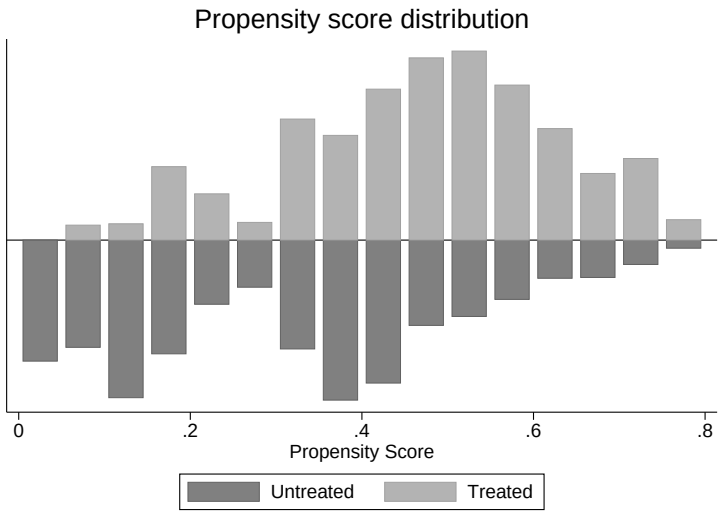

Table 1: Share of entrepreneurs with employees before and after the crisis. All ages and by age. Treated sample: industrial districts. Control sample: other local labour markets.

Age group		Before the crisis	After the crisis
25-55	Treated group	9.73	8.50
	Control group	9.42	8.38
25-39	Treated group	6.86	6.01
	Control group	6.96	5.62
40-55	Treated group	12.14	10.36
	Control group	11.47	10.48

Table 2: Summary statistics.

	Industrial Districts	Other LLM
Native	0.89	0.90
	(0.31)	(0.30)
Has children	0.62	0.60
	(0.48)	(0.49)
Married	0.59	0.56
	(0.49)	(0.50)
Education: ISCED 2	0.41	0.39
	(0.49)	(0.49)
Education: ISCED 3	0.44	0.45
	(0.50)	(0.50)
Education: ISCED 5 or higher	0.09	0.11
	(0.28)	(0.31)
log GDP	10.8	10.53
	(1.01)	(1.16)
log real exports	2.2	2.15
	(0.11)	(0.15)
Specialisation index	0.15	0.14
	(0.07)	(0.03)
Population density	235.91	261.76
	(222.05)	(349.12)
Local unemployment rate	0.03	0.03
	(0.02)	(0.02)

Table 3: 'Difference - in differences' estimates. Dependent variable: dummy equal to 1 if the individual is self employed with employees, to 0 otherwise. Full sample and sub-samples of men aged 25 to 39 and 40 to 55.

	(1)	(2)	(3)
	Full sample	Sub-sample of men aged 25-39	Sub-sample of men aged 40-55
Post 2008.3	-0.0018	-0.0050	0.0010
	(0.002)	(0.003)	(0.004)
(Post 2008.3)*Treated	-0.0035	0.0043	-0.0094**
	(0.003)	(0.004)	(0.005)
Native	0.0595***	0.0482***	0.0808***
	(0.003)	(0.003)	(0.004)
Has children	-0.0003	-0.0036*	0.0114***
	(0.002)	(0.002)	(0.003)
Age	0.0021***	0.0044***	-0.0002
	(0.000)	(0.000)	(0.000)
Married	0.0411***	0.0330***	0.0299***
	(0.002)	(0.003)	(0.003)
Lower secondary education	0.0356***	0.0090*	0.0351***
	(0.003)	(0.005)	(0.004)
Upper secondary education	0.0493***	0.0175***	0.0542***
	(0.003)	(0.006)	(0.004)
College	0.0549***	-0.0042	0.0974***
	(0.004)	(0.006)	(0.006)
Constant	-0.0306***	-0.1761***	0.1232***
	(0.011)	(0.015)	(0.018)
Mean dependent variable	0.089	0.063	0.11
Marginal effect evaluated at the mean of dependent variable (percent)	-2.360	6.825	-7.727
Observations	368,604	162,948	205,656

Note: Each regression includes a quadratic trend and LLM dummy variables. Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by LLM.

Table 4: 'Difference - in differences' estimates. Dependent variable: dummy equal to 1 if the individual is self employed with or without employees, to 0 otherwise. Full sample and sub-samples of men aged 25 to 39 and 40 to 55.

	(1)	(2)	(3)
	Full sample	Sub-sample of men aged 25-39	Sub-sample of men aged 40-55
Post 2008.3	0.0251***	0.0189***	0.0299***
	(0.002)	(0.003)	(0.004)
(Post 2008.3)*Treated	-0.0064	0.0060	-0.0154***
	(0.005)	(0.006)	(0.006)
Native	0.1179***	0.1027***	0.1495***
	(0.005)	(0.005)	(0.005)
Has children	-0.0045*	-0.0039	0.0104***
	(0.002)	(0.003)	(0.004)
Age	0.0034***	0.0082***	-0.0004
	(0.000)	(0.000)	(0.000)
Married	0.0458***	0.0326***	0.0272***
	(0.003)	(0.004)	(0.004)
Lower secondary education	0.0633***	0.0211***	0.0606***
	(0.004)	(0.006)	(0.005)
Upper secondary education	0.0986***	0.0448***	0.1069***
	(0.005)	(0.007)	(0.005)
College	0.1693***	0.0651***	0.2466***
	(0.007)	(0.008)	(0.010)
Constant	0.1452***	-0.0421**	0.3483***
	(0.013)	(0.019)	(0.021)
Mean dependent variable	0.185	0.151	0.212
Marginal effect evaluated at the mean of dependent variable (percent)	-3.460	3.974	-7.264
Observations	368,604	162,948	205,656

Note: Each regression includes a quadratic trend and LLM dummy variables. Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by LLM.

Table 5: 'Difference - in differences' estimates when treatment and controls are re-defined. Dependent variable: dummy equal to 1 if the individual is self employed with employees, to 0 otherwise. Senior males only.

	(1)	(2)
	Treatment and control defined by the index of specialization. Senior males.	Treatment and control defined by sector of production. Senior males.
Post 2008.3	-0.002	-0.002
	(0.005)	(0.004)
(Post 2008.3)*Treated	0.005	-0.002
	(0.007)	(0.006)
Native	0.087***	0.080***
	(0.004)	(0.004)
Has children	0.013***	0.011***
	(0.003)	(0.003)
Age	-0.000	-0.000
	(0.000)	(0.000)
Married	0.028***	0.031***
	(0.004)	(0.003)
Lower secondary education	0.041***	0.035***
	(0.005)	(0.004)
Upper secondary education	0.063***	0.053***
	(0.005)	(0.004)
College	0.112***	0.092***
	(0.009)	(0.006)
Constant	0.109***	0.130***
	(0.009)	(0.006)
Observations	129,888	177,499

Note: Each regression includes a quadratic trend and LLM dummy variables. Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by LLM.

Table 6: 'Difference - in differences' estimates. Dependent variable: dummy equal to 1 if the individual is self employed with employees, to 0 otherwise. With the interaction of Post2008.3 with pre-treatment exports.

	(1)	(2)	(3)
	Full sample	Sub-sample of men aged 25-39	Sub-sample of men aged 40-55
Post 2008.3	0.0032	-0.0015	0.0069
	(0.003)	(0.005)	(0.005)
(Post 2008.3)*Treated	-0.0032	0.0038	-0.0086**
	(0.003)	(0.004)	(0.004)
(Post 2008.3)*High Export	-0.0058*	-0.0031	-0.0078*
	(0.003)	(0.004)	(0.005)
Native	0.0578***	0.0467***	0.0782***
	(0.003)	(0.003)	(0.004)
Has children	-0.0007	-0.0038**	0.0107***
	(0.002)	(0.002)	(0.003)
Age	0.0020***	0.0042***	-0.0003
	(0.000)	(0.000)	(0.000)
Married	0.0405***	0.0321***	0.0296***
	(0.002)	(0.002)	(0.003)
Lower secondary education	0.0342***	0.0090*	0.0332***
	(0.003)	(0.005)	(0.003)
Upper secondary education	0.0476***	0.0169***	0.0526***
	(0.003)	(0.005)	(0.004)
College	0.0521***	-0.0034	0.0903***
	(0.004)	(0.006)	(0.006)
Constant	-0.0172*	-0.1675***	0.1424***
	(0.010)	(0.014)	(0.017)
Observations	391,544	173,262	218,282

Note: Each regression includes a quadratic trend and LLM dummy variables. Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by LLM.

Table 7: 'Difference - in differences' estimates. Dependent variable: dummy equal to 1 if the individual is self employed with employees, to 0 otherwise. With the interaction of Post2008.3 with pre-treatment indicators of access to credit.

	(1)	(2)	(3)
	Full sample	Sub-sample of men aged 25-39	Sub-sample of men aged 40-55
Post 2008.3	-0.002	-0.005	0.001
	(0.003)	(0.004)	(0.005)
(Post 2008.3)*Treated	-0.004	0.004	-0.010**
	(0.003)	(0.004)	(0.005)
(Post 2008.3)*High Branches	0.002	0.001	0.002
	(0.003)	(0.003)	(0.004)
(Post 2008.3)*High Loan/Deposit	0.002	0.001	0.002
	(0.002)	(0.003)	(0.003)
(Post 2008.3)*High Rationed	-0.002	-0.000	-0.003
	(0.003)	(0.004)	(0.004)
Native	0.061***	0.050***	0.081***
	(0.003)	(0.003)	(0.004)
Has children	-0.000	-0.004*	0.012***
	(0.002)	(0.002)	(0.003)
Age	0.002***	0.004***	-0.000
	(0.000)	(0.000)	(0.000)
Married	0.041***	0.033***	0.030***
	(0.002)	(0.003)	(0.003)
Lower secondary education	0.036***	0.008	0.035***
	(0.003)	(0.005)	(0.003)
Upper secondary education	0.049***	0.017***	0.055***
	(0.003)	(0.005)	(0.004)
College	0.055***	-0.005	0.099***
	(0.004)	(0.006)	(0.006)
Constant	-0.034***	-0.176***	0.122***
	(0.011)	(0.014)	(0.018)
Observations	356,165	157,369	198,796

Note: Each regression includes a quadratic trend and LLM dummy variables. Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by LLM.

Table 8: 'Difference - in differences' estimates. Dependent variable: dummy equal to 1 if the individual is self employed with employees, to 0 otherwise. With the interaction of Post2008.3 with pre-treatment indicators of population density.

	(1)	(2)	(3)
	Full sample	Sub-sample of men aged 25-39	Sub-sample of men aged 40-55
Post 2008.3	-0.001	0.002	-0.002
	(0.003)	(0.004)	(0.005)
(Post 2008.3)*Treated	-0.003	0.004	-0.009**
	(0.003)	(0.004)	(0.004)
(Post 2008.3)*High density	-0.001	-0.008**	0.005
	(0.003)	(0.004)	(0.005)
Native	0.058***	0.047***	0.078***
	(0.003)	(0.003)	(0.004)
Has children	-0.001	-0.004**	0.011***
	(0.002)	(0.002)	(0.003)
Age	0.002***	0.004***	-0.000
	(0.000)	(0.000)	(0.000)
Married	0.040***	0.032***	0.029***
	(0.002)	(0.002)	(0.003)
Lower secondary education	0.034***	0.009*	0.033***
	(0.003)	(0.005)	(0.003)
Upper secondary education	0.048***	0.017***	0.052***
	(0.003)	(0.005)	(0.004)
College	0.052***	-0.003	0.091***
	(0.004)	(0.006)	(0.006)
Constant	-0.017*	-0.168***	0.142***
	(0.010)	(0.014)	(0.017)
Observations	392,068	173,462	218,606

Note: Each regression includes a quadratic trend and LLM dummy variables. Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by LLM.

Table 9: Difference-in-differences regressions. Dependent variable: private sector employment. Full sample and by age group.

	(1)	(2)	(3)
	Full sample	Sub-sample of men aged 25-39	Sub-sample of men aged 40-55
Post 2008.3	-0.014***	-0.014**	-0.014**
	(0.004)	(0.005)	(0.005)
(Post 2008.3)*Treated	0.007	-0.008	0.019**
	(0.006)	(0.008)	(0.008)
Native	-0.073***	-0.068***	-0.080***
	(0.007)	(0.007)	(0.009)
Has children	-0.020***	-0.032***	-0.001
	(0.004)	(0.005)	(0.006)
Age	-0.004***	0.000	-0.006***
	(0.000)	(0.001)	(0.000)
Married	0.083***	0.069***	0.076***
	(0.005)	(0.006)	(0.006)
Lower secondary education	0.031***	0.070***	0.013*
	(0.008)	(0.016)	(0.008)
Upper secondary education	-0.081***	-0.043**	-0.099***
	(0.008)	(0.016)	(0.008)
College	-0.059***	-0.025	-0.075***
	(0.012)	(0.020)	(0.013)
Constant	0.767***	0.741***	0.760***
	(0.020)	(0.030)	(0.029)
Observations	368,604	162,948	205,656

Note: Each regression includes a quadratic trend and LLM dummy variables. Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by LLM.

Table 10: Difference-in-differences regressions. Dependent variable: unemployed or inactive. Full sample and by age group.

	(1)	(2)	(3)
	Full sample	Sub-sample of men aged 25-39	Sub-sample of men aged 40-55
Post 2008.3	0.013***	0.019***	0.008**
	(0.003)	(0.004)	(0.004)
(Post 2008.3)*Treated	0.004	0.006	0.001
	(0.003)	(0.005)	(0.004)
Native	-0.038***	-0.026***	-0.064***
	(0.004)	(0.004)	(0.005)
Has children	0.028***	0.036***	-0.005*
	(0.002)	(0.003)	(0.003)
Age	0.001***	-0.010***	0.006***
	(0.000)	(0.000)	(0.000)
Married	-0.130***	-0.103***	-0.102***
	(0.003)	(0.004)	(0.004)
Lower secondary education	-0.100***	-0.092***	-0.080***
	(0.005)	(0.011)	(0.006)
Upper secondary education	-0.125***	-0.105***	-0.119***
	(0.006)	(0.012)	(0.006)
College	-0.079***	-0.019	-0.127***
	(0.009)	(0.014)	(0.007)
Constant	0.211***	0.461***	-0.015
	(0.011)	(0.019)	(0.016)
Observations	368,604	162,948	205,656

Note: Each regression includes a quadratic trend and LLM dummy variables. Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by LLM.

Table 11: 'Difference - in differences' estimates. Dependent variable: dummy equal to 1 if the individual is self employed with employees, to 0 otherwise.

	(1)	(2)	(3)
	With LLM trends	No movers	Random assignment
Post 2008.3	-0.000	0.002	-0.004
	(0.004)	(0.004)	(0.003)
(Post 2008.3)*Treated	-0.007	-0.009**	0.002
	(0.007)	(0.005)	(0.002)
Native	0.081***	0.082***	0.081***
	(0.004)	(0.004)	(0.004)
Has children	0.012***	0.012***	0.011***
	(0.003)	(0.003)	(0.003)
Age	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Married	0.030***	0.030***	0.030***
	(0.003)	(0.003)	(0.003)
Lower secondary education	0.035***	0.035***	0.035***
	(0.004)	(0.003)	(0.004)
Upper secondary education	0.054***	0.055***	0.054***
	(0.004)	(0.004)	(0.004)
College	0.097***	0.099***	0.097***
	(0.006)	(0.006)	(0.006)
Constant	1.959***	0.143***	0.123***
	(0.009)	(0.018)	(0.018)
Observations	205,656	200,687	205,656

Note: Each regression includes a quadratic trend and LLM dummy variables. Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered by LLM.