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Abstract: We examine whether organized crime affects firms' performance (defined using Total Factor Productivity growth) both directly and indirectly, by downsizing the positive externalities arising from the geographic concentration of (intra- and inter-industry) market-related firms. The analysis uses a large sample of Italian small- and medium-sized manufacturing firms over the period 2010-2013. The results highlight the negative direct effects of organized crime on firms' productivity growth. Any positive effect derived from industrial clustering is thoroughly debilitated by a strong presence of organized crime, and the negative moderation effect of organized crime on productivity growth is greater for smaller than for larger firms.

Keywords: Total Factor Productivity; Organized crime; Industrial clustering; Externalities; Italy.

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1. INTRODUCTION

How the local environment where Italian firms operate affects their economic performance and behavior has been the object of great scrutiny. Research has focused on issues such as local institutional quality (Lasagni, Nifo, & Vecchione, 2015), financial development (Moretti, 2014), the presence of innovative *milieux* (Belussi, Sammarra, & Sedita, 2010), or industrial agglomeration (Cainelli, Ganau, & Iacobucci, 2016), among others. Most of this literature tends to point towards the idea that, as firms interact with local actors (e.g. neighboring firms, banks, local institutions, research centers), their capacity to get and assimilate knowledge, their competitiveness, and their economic performance are positively or negatively affected by the socio-economic context in which they are located. Firms operating in different environments are likely to gain from both tangible (e.g. local availability of inputs and intermediate goods, reduction of transportation costs) and intangible (e.g. the reduction of transaction costs favored by repeated interactions and increasing trust among local actors) agglomeration externalities that reduce the costs of the economic activity, thus fostering their efficiency and growth (Baldwin, Brown, & Rigby, 2010; Martin, Mayer, & Mayneris, 2011).

This paper builds on this idea and, while providing additional insights on the role played by the context where a firm operates on its performance – defined in terms of Total Factor Productivity (TFP) growth –, it particularly focuses on what is widely regarded as an important negative externality: organized crime in Italy.

Organized crime (namely, *mafia*-type criminality) represents an Italian symbol. Italy is often identified as a country with pervasive organized crime. From its places of origin – Sicily, Campania, Calabria, and Apulia – *mafia*-type activities have spread to many other parts of the country (Buonanno and Pazzona, 2014). A widespread presence of criminality is likely to affect the economic activity and therefore the performance of individual firms. Criminal organizations reduce the level of legality and security of the places where they operate (La Spina and Lo Forte, 2006), undermining both the socio-economic environment and the local firms' performance. Organized crime makes the business environment less secure and dynamic and increases uncertainty, reducing trust and reciprocity among agents. Criminal organizations function in the market through controlled "illicit" firms, altering competition and market rules. It can be said that organized crime acts as a tax on the local economic system (Detotto and Otranto, 2010): it increases the costs and reduces the returns of economic activity, undermining firms' efficiency (Albanese and Marinelli, 2013). Yet, despite its expansion beyond its place of origin, the presence of organized crime across Italy remains extremely uneven. Areas of the country completely ravaged by crime coexist, often in close proximity, with regions where organized criminality is almost absent.

This paper empirically investigates the extent to which a firm's productivity benefits in terms of agglomeration and industrial clustering are erased by the presence of organized crime in the firm's region. The hypothesis driving the research is that organized crime will dent a firm's growth potential by reducing trust and reciprocity in the local system and weakening the traditional market-based linkages among firms, increasing transaction costs and diluting any positive externalities arising from location in highly agglomerated areas.

The empirical analysis covers a large sample of Italian manufacturing small- and medium-sized firms (SME) over the period 2010-2013. The identification strategy is based on a sample-selection model which allows accounting for firm exit over the three-year growth period considered, and the robustness of the results is tested controlling for the potential endogeneity of the variables capturing organized crime and industrial clustering, as well as by estimating the firm's TFP through three different approaches. Overall, empirical results support the theoretical hypotheses: while agglomeration and clustering foster firms' productivity growth, organized crime has a direct negative effect on it as well as a harmful indirect impact, offsetting any benefits of agglomeration.

The rest of the paper is structured as follows. Section 2 presents the literature on organized crime and agglomeration and the theoretical predictions derived from it. Section 3 describes the data and introduces the econometric methodology. Section 4 discusses the empirical results. Section 5 concludes.

2. CLUSTERING, ORGANIZED CRIME AND PRODUCTIVITY

2.1. Industrial clustering and productivity

Agglomeration and industrial clustering are generally regarded as beneficial for the development and growth of firms. From the pioneering work of Marshall (1890), it has been often posited that firms operating in spatially-bounded, high-density areas may benefit from tangible and intangible externalities which spread across local actors, favoring the economic performance of both the local system and the individual agents within it (Glaeser, Kallal, Scheinkman, & Shleifer, 1992; Puga, 2010; Rosenthal and Strange, 2004).

Benefits of agglomeration are realized through two fundamental types of externalities: localization and diversification economies. Localization economies date back to Marshall (1890) and refer to the spatial concentration of firms operating in the same industry (Glaeser et al., 1992). The presence of firms sharing a common competence base facilitates intra-industry transmission of knowledge and technological spillovers (Nooteboom, 2000), as well as benefits from reduced transport costs, external-scale economies, and the availability of specialized workers and suppliers (Duranton and Puga, 2004; Martin et al., 2011). Diversification economies arise from the geographic concentration of firms operating in different industries (Jacobs, 1969). They favor the cross-fertilization of existing ideas and technologies in a diversified local economic environment as well as tangible positive externalities related to the availability of specialized business services providers and the presence of intermediate goods' suppliers operating at different stages of the production chain (Cainelli et al., 2016; Caragliu et al., 2016).

There is no shortage of cross-country literature on the agglomeration-productivity relationship at the firm level (e.g. Cainelli and Lupi, 2010; Cainelli et al., 2016; Cingano and Schivardi, 2004; Ganau, 2016; Henderson, 2003; Lee, Jang, & Hong, 2010; Martin et al., 2011). This literature distinguishes between static (short-run) and dynamic (long-run) effects of localization and diversification economies. The static component of the agglomeration phenomenon concerns tangible and intangible externalities arising from market-based relationships (e.g. availability of specialized inputs' suppliers, reduced transport and transaction costs). The dynamic component involves intangible externalities derived from knowledge and information flows and technological spillovers (Ganau, 2016; Martin et al., 2011).

In this paper we explicitly consider tangible and intangible market-based externalities, by building on the distinction between localization and diversification economies. We synthesize intra- and inter-industry market-based externalities by means of a concept of industrial clustering which refers to the geographic concentration of horizontally and vertically market-related firms. Akin to Porter's (1990) notion of cluster, the concept of industrial clustering captures the spatial agglomeration of firms operating at different stages of the production chain, allowing to simultaneously account for static localization- and diversification-type externalities. Industrial clustering thus encompasses tangible – related to the availability of intra- and inter-industry inputs' suppliers, as well as to the reduction of transport costs (Cainelli et al., 2016) – and intangible effects – related to the reduction of transaction costs, resulting from face-to-face interactions, repeated and long-lasting market relationships, and increasing trust among business partners (Cainelli, 2008; Mistri and Solari, 2003). The combination of tangible and intangible effects will spur firm-level growth by reducing the costs of the economic activity, either through lowering the costs of local inputs and intermediate goods or through reduced transaction costs resulting from long-lasting production linkages among local firms. Therefore, existing literature tends to underline that the geographic concentration of (intra- and inter-industry) market-related firms is expected to raise firm-level productivity.

2.2. Organized crime and productivity

The effect of organized crime on productivity has featured in economic literature since, at least, the work of Schelling (1971). Organized crime is widely regarded to have both direct and indirect negative effects on the economic activity. First, the presence of criminal organizations weakens legality and security (Daniele and Marani, 2011; La Spina and Lo Forte, 2006). Such a situation makes the business environment less secure and dynamic, increases uncertainty and the risks associated with new investment opportunities, and reduces trust and reciprocity among economic agents. In these circumstances the formation and development of economic networks is jeopardized, as firms are less willing to establish solid and long-lasting production linkages. Second, organized crime increases the costs and reduces the returns of the economic activity (Buonanno, Montolio, & Vanin, 2009; Powell, Manish, & Nair, 2010; Huggins and Thompson, 2016), acting like a tax on the economic system (Detotto and Otranto, 2010). Organized crime influences the allocation of public resources, alters market rules, and reduces competition among firms, e.g. in terms of inputs' procurement, distribution channels, as well as public contracts (Felli and Tria, 2000; Netti, 1999). Finally, firms may be also coerced by criminal organizations, for instance, into acquiring inputs from suppliers controlled by the criminal organization (Albanese and Marinelli, 2013) or into directly paying the organization itself in order to be able to operate and stay in market. Overall, these conditions damage economic performance and are translated into reduced investments, higher costs, and lower efficiency (Daniele, 2009; Detotto and Otranto, 2010).

Only a limited number of contributions have empirically analyzed the economic effects of organized crime. Some works have focused on its macroeconomic implications in terms of labor productivity (e.g. Centorrino and Ofria, 2008; Felli and Tria, 2000), GDP growth (e.g. Pinotti, 2015; Tullio and Quarella, 1999), employment rates (e.g. Peri, 2004), inward foreign direct investments (e.g. Daniele and Marani, 2011), and public transfers (Barone and Narciso, 2015). The microeconomic effects of organized crime and, specifically, the effects on an average firm economic activity have, by contrast, drawn much less attention. Among these limited contributions, Albanese and Marinelli (2013), Ofria (2000) and Netti (1999) can be highlighted. Albanese and Marinelli (2013) explicitly focus on the effect of organized crime on the productivity of Italian firms. They find that organized crime reduces firm-level productivity regardless of firm size and sector. This negative effect is robust to the potential endogeneity of the organized crime variable, even though their instrumental-variable (IV) estimations refer only to a sub-sample of firms from selected Southern regions, i.e. those historically affected by criminal (*mafia*-type) organizations.

Based on the theoretical relationship between organized crime and economic performance, as well as on previous empirical evidence, the presence of *mafia*-type activity is expected to negatively affect productivity growth at firm level. Organized crime increases the costs of economic exchanges by increasing uncertainty, operating a monopolistic control over the local market, altering the rules of competition among firms, as well as imposing protection rackets to local business actors. In addition to these negative direct effects, organized crime is further likely to cancel out any potential positive relationships between industrial clustering and firm-level productivity growth. Criminal organizations tend to operate in the market through firms they control which may impose the acquisition of inputs or business services to other local firms, altering normal production linkages along the supply chain. The presence of criminal organizations also reduces trust and reciprocity in the local system, increasing transaction costs among local actors. Therefore, organized crime is likely to break established local-level market relationships among firms and prevent the emergence of new ones, thus downsizing the positive externalities arising from the spatial concentration of market-related firms.

3. DATA AND METHODOLOGY

3.1. The dataset

The empirical analysis employs balance sheet data drawn from the *AIDA* databank (Bureau Van Dijk). The dataset has been constructed considering only SMEs – i.e. firms with less than 250 employees – in the manufacturing industry with a positive turnover and value added over at least three consecutive years during the period 2009-2013. In addition, firms included in the analysis have to report a value added-to-turnover ratio ≥ 0 and ≤ 1.[1] Firms with missing or inconsistent value added, total labor cost, tangible assets, and intermediate inputs data have been removed from the dataset. This leaves an unbalanced panel including 51,398 firms (for a total of 146,556 observations over the period 2009-2013), which is used to estimate firm-level TFP. The sample is further cleaned by removing firms with missing information about location at province level (NUTS-3 level of the European Union territorial classification – *Nomenclature des Unités Territoriales Statistiques*), year of establishment, and amount of investments in 2010. The final sample covers 26,812 firms for the period 2010-2013, conditional on being observed in 2010. The 26,812 firms are used to analyze the effects of industrial clustering and organized crime on productivity growth. Tables A1 and A2 in the Appendix display the sample distribution taking into account industry and geographic location, respectively.[2]

3.2. Econometric modeling

In order to investigate whether and how (i) industrial clustering fosters TFP growth at the level of the firm and whether and how (ii) organized crime affects TFP growth both directly and indirectly, moderating the expected (positive) causal relationship between industrial clustering and growth, we specify the following empirical productivity growth equation:

$$\begin{aligned}\Delta TFP_{ipg} = \beta_0 + \beta_1 TFP_{ipg}^{2010} + \beta_2 AGE_{ipg}^{2010} + \beta_3 SIZE_{ipg}^{2010} + \beta_4 IC_{pg}^{2010} + \beta_5 OC_p^{2010} \\ + \beta_6 \left(IC_{pg}^{2010}\right) \times \left(OC_p^{2010}\right) + \boldsymbol{\gamma}_g + \boldsymbol{\delta}_m + \varepsilon_{ipg}, \qquad (1)\end{aligned}$$

where $\Delta TFP_{ipg} = TFP_{ipg}^{2013} - TFP_{ipg}^{2010}$ denotes the productivity growth of firm i, operating in industry $g = 1, \ldots, 18$, located in province $p = 1, \ldots, 103$, over the three-year period 2010-2013; and TFP_{ipg}^{2010} and TFP_{ipg}^{2013} denote the natural logarithms of a firm's TFP in 2010 and 2013, respectively.

The TFP of a firm is estimated as the residual of a Cobb-Douglas production function specified as follows in logarithmic form:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \varepsilon_{it}, \qquad (2)$$

where β_0 represents the mean efficiency level across firms and over time; y_{it} denotes the value added of firm i at time t; the terms k_{it} and l_{it} denote, respectively, capital and labor inputs; the term ω_{it} represents productivity shocks potentially observed or that can be predicted by the firm when making inputs' decisions, and thus influencing its decision process; and the term ε_{it} is an independent and identically distributed component which represents productivity shocks not affecting a firm's decision process (Ackerberg, Caves, & Frazer, 2015; Olley and Pakes, 1996; Van Beveren, 2012). Hence, the estimated firm-level productivity can be computed solving for ω_{it} as follows:

$$\widehat{\omega}_{it} = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it}.$$

Firm-level TFP is firstly estimated through the two-step semi-parametric approach proposed by Levinsohn and Petrin (2003). This approach allows the possibility of correcting for the simultaneity bias, referring to some form of endogeneity in the inputs due to the correlation between the level of inputs chosen by the firm, based on its prior beliefs on productivity levels, and unobservable productivity shocks (Syverson, 2011; Van Beveren, 2012). Levinsohn and Petrin (2003) use intermediate inputs (m_{it}) to proxy for unobserved productivity, solving the simultaneity problem between input choices and productivity shocks. By specifying $m_{it} = m_t(k_{it}, \omega_{it})$ and under the assumptions of monotonicity and intermediate inputs strictly increasing in productivity, Equation (2) can be re-specified as follows:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + s_t(k_{it}, m_{it}) + \varepsilon_{it},$$

where $\omega_{it} = s_t(k_{it}, m_{it})$ expresses the unobserved productivity as a function of observables, and the term $s_t(k_{it}, m_{it}) = m_t^{-1}(k_{it}, \omega_{it})$ denotes the inversion of the intermediate inputs function.

Although the simultaneity bias can be corrected using Levinsohn and Petrin's (2003) approach, potential collinearity of the labor coefficient is likely to emerge in the first-stage estimation (Van Beveren, 2012). This collinearity may be the consequence of choosing labor and intermediate inputs simultaneously. In this case, both factors are assumed to be allocated in a similar way by the firm, as a function of productivity and capital input and, therefore, depend on the same state variables, i.e. $m_{it} = f_t(\omega_{it}, k_{it})$ and $l_{it} = h_t(\omega_{it}, k_{it})$. As shown by Ackerberg et al. (2015), the labor coefficient results not identified in the first-stage because it is not possible to estimate the non-parametric function of productivity and capital input with the labor variable's coefficient simultaneously, as the labor input is a function of productivity and capital input.

According to Wooldridge (2009), the estimator proposed by Levinsohn and Petrin (2003) can be implemented using a Generalized Method of Moments (GMM) approach where β_k and β_l are estimated in one step, addressing the possible collinearity between labor and intermediate inputs. This approach consists in the simultaneous estimation of two equations with the same dependent variable and the same set of input variables, while different sets of instruments are specified so that the coefficients of the input variables in the first equation are identified exploiting information in the second equation. Given a production function (2), and assuming absence of correlation of ε_{it} with current and past values of capital, labor and intermediate inputs as well as restriction of the dynamics of the unobserved productivity component ω_{it}, Wooldridge (2009) proposes to identify β_k and β_l estimating the following two equations:

$$\begin{cases} y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + f(k_{it}, m_{it}) + \varepsilon_{it} \\ y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + h[f(k_{it-1}, m_{it-1})] + \varepsilon_{it} + a_{it}' \end{cases}$$

where a_{it} denotes productivity innovations and correlates with l_{it} and m_{it}, while it is uncorrelated with k_{it}, and all past values of k_{it}, l_{it}, and m_{it}. The function $f(\cdot)$ can be specified as a low-degree polynomial of order up to three, while the function $h(\cdot)$ (i.e. the productivity process) can be defined as a random walk with drift, such that $\omega_{it} = \tau + \omega_{it-1} + a_{it}$. Equation (2) can thus be re-specified as follows (Galuščák and Lízal, 2011):

$$y_{it} = (\beta_0 + \tau) + \beta_k k_{it} + \beta_l l_{it} + f(k_{it-1}, m_{it-1}) + \eta_{it} + a_{it},$$

and can be estimated through an IV approach, using polynomials in k_{it-1} and m_{it-1} of order up to three approximating for $f(\cdot)$, and k_{it}, k_{it-1}, l_{it-1}, m_{it-1} and polynomials containing m_{it-1} and k_{it-1} of order up to three, as instruments for l_{it} (Petrin and Levinsohn, 2012).

Finally, firm-level TFP is estimated following Ackerberg et al. (2015) when responding to Levinsohn and Petrin's (2003) approach. The two-step semi-parametric approach proposed by Ackerberg et al. (2015) differs from that of Levinsohn and Petrin (2003) in offering to specify an intermediate inputs function for m_{it} to control for unobserved productivity, which is conditional on the labor input (l_{it}). Under the same assumption of strict monotonicity of intermediate inputs in productivity, Ackerberg et al. (2015) specify $m_{it} = m_t(k_{it}, l_{it}, \omega_{it})$, such that unobserved productivity can be expressed as a function of observables through the inverted inputs demand function $\omega_{it} = s_t(k_{it}, l_{it}, m_{it})$. Then, Equation (2) can be re-specified as follows:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + s_t(k_{it}, l_{it}, m_{it}) + \varepsilon_{it},$$

with $s_t(k_{it}, l_{it}, m_{it}) = m_t^{-1}(k_{it}, l_{it}, \omega_{it})$.

Eighteen production functions are estimated at the industry level using the three different estimation approaches.[3] Table A3 in the Appendix reports some descriptive statistics and the correlation matrix of the variables entering the production function, while Table A4 reports the estimated elasticities of the capital and labor inputs.[4]

The key explanatory variables entering the productivity growth equation are those capturing organized crime and industrial clustering. The variable capturing organized crime (OC_p^{2010}) is defined considering three main types of crime: (i) *mafia*-type association ($association_p^{2010}$), (ii) *mafia*-murders ($murder_p^{2010}$), and (iii) extortions ($extortion_p^{2010}$). The variable is operationalized as follows (e.g. Gibbons, 2004):

$$OC_p^{2010} = \ln\left(\frac{association_p^{2010} + murder_p^{2010} + extortion_p^{2010}}{Surface_p}\right), \tag{3}$$

where $Surface_p$ denotes the area of province p. Data on criminality are drawn from the Istat online databank *Territorial Information System on Justice*. The province is used as the geographic unit of analysis. No finer geographical scale can be employed, as crime geographic data are only provided at the level of the 103 Italian provinces. Figure A1 in the Appendix displays the quartile map of the organized crime variable. As expected there is a concentration of reported organized crime in the South of Italy (the *Mezzogiorno*) and, particularly, in the regions of Apulia, Calabria, Campania, and Sicily. However, parts of the *Mezzogiorno*, such as Sardinia, are relatively organized-crime-free, while *mafia*-type activities are strong in some Northern and Central Italian provinces, such as Milan, Prato, Rome, Trieste, Varese, Rimini, or Biella.

The variable capturing industrial clustering (IC_{pg}^{2010}) is defined considering input-output relationships among industries and, specifically, it is constructed to account for both horizontal (i.e. intra-industry) and vertical (i.e. inter-industry) market relationships as follows (Cainelli et al., 2016):

$$IC_{pg}^{2010} = \ln\left\{\frac{\left[\left(N_{pg}^{2010} - 1\right) \cdot w_{gg}^{2010}\right] + \sum_{\substack{j=1 \\ j\neq g}}^{J}\left(N_{pj}^{2010} \cdot w_{gj}^{2010}\right)}{Surface_p}\right\}, \tag{4}$$

where N_{pg}^{2010} denotes the number of active firms operating in industry g and located in province p; N_{pj}^{2010} represents the number of active firms in industry j, with $j \neq g$; w_{gg}^{2010} and w_{gj}^{2010} are the weights capturing the share of inputs that firms in industry g may acquire from, respectively, the same industry and other industries. The reference firm is subtracted from the computation in order to consider the effective number of local potential suppliers.[5] Data on the number of active firms are drawn from the *Movimprese* database, provided by the Italian Chamber of Commerce. The weighting components are derived from the 2010 use table of the Italian input-output matrix provided by Istat.[6]

A cluster can be defined as a geographic concentration of related firms (as well as organizations and institutions) in a given territory (Delgado et al., 2016; Porter, 1990). The industrial clustering variable defined in Equation (4) represents both a measure of geographic concentration of the economic activity and a proxy of the intensity of the input-output relationships among firms. The value of the variable increases as the density of market-interconnected firms grows. From an agglomeration literature perspective, this variable captures the effects of both localization and (vertically-)related diversification economies (Cainelli et al., 2016; Frenken, Van Oort, & Verburg, 2007). With respect to a standard agglomeration measure capturing a mass effect of either localization or diversification economies, the industrial clustering variable proposed in Equation (4) has the advantage of simultaneously accounting for horizontal and vertical market-based relationships. In fact, it weights the number of neighboring local firms by the effective contribution to the reference firm's inputs procurement. For this reason, it represents a better proxy for industrial clustering forces.

Equation (1) also includes the interaction term between the industrial clustering and organized crime variables. The introduction of the interaction is aimed at evaluating whether organized crime plays an indirect negative effect on a firm's productivity growth by limiting the (potential) positive effects of industrial clustering through the reduction of trust among economic actors, the increase of transaction costs, as well as the alteration of competition/cooperation mechanisms across firms at the local level.

The right-hand side of the productivity growth equation includes a set of firm-level control variables: the log-transformed, beginning-of-the period TFP (TFP_{ipg}^{2010}); a measure of firm age (AGE_{ipg}^{2010}), defined as the log-transformed difference between the year 2010 and the year the firm was set up; a size dummy variable for larger firms ($SIZE_{ipg}^{2010}$), defined around the median value of the 2010 employment distribution.[7] Equation (1) includes also a set of industry dummy variables ($\boldsymbol{\gamma}_g$) to capture industry fixed effects, and a set of geographic dummy variables ($\boldsymbol{\delta}_m$) defined at NUTS-1 level to take into account structural differences among Italian macro-areas in terms of socio-economic conditions, industrial development, and infrastructure endowment. Tables A5 to A8 in the Appendix report the descriptive statistics and correlation matrices of the dependent and main explanatory variables.

3.3. Identification strategy

As the simple Ordinary Least Squares (OLS) estimation of Equation (1) may be affected by sample selection – the productivity growth is observed only for the sub-sample of firms surviving over the growth period (e.g. Sleutjes, Van Oort, & Schutjens, 2012) –, we resort to a two-step sample-selection model *à la* Heckman (1979). This model is estimated to account for firm exit over the period 2010-2013. Specifically, a first-stage reduced-form selection equation is estimated by Maximum Likelihood specifying a dummy as dependent variable. The dummy equals one if the firm observed in 2010 is still accounted for in 2013, and zero otherwise. The selection equation is identified by including on its right-hand side all the explanatory variables specified in Equation (1), plus an exclusion restriction which is defined, following Griffith, Redding, and Simpson (2009), as a third-order polynomial expansion $\varphi(\cdot)$ in firm age, capital stock, and investment – all variables are log-transformed and refer to the beginning of the growth period (see also Olley and Pakes, 1996). The selection equation is estimated on the whole sample of firms through a Probit model. Then, the inverse Mills ratio (λ) is computed from the estimated selection equation and is included as an additional regressor in the productivity growth equation to correct for sample selection bias.

The augmented Equation (1) is thus estimated via OLS on the sub-sample of firms surviving over the growth period 2010-2013 (Wooldridge, 2010).

A second critical issue which may affect the OLS estimation of Equation (1) – after correction for the sample selection bias – concerns the potential endogeneity of the variables for industrial clustering (e.g. Graham, Melo, Jiwattanakulpaisarn, & Noland, 2010; Martin et al., 2011; Rosenthal and Strange, 2004) and organized crime (e.g. Albanese and Marinelli, 2013). Endogeneity can occur in the context of Equation (1) for several reasons: (i) shocks at province level may affect the productivity growth of firms, as well as the local industrial structure and the level of criminality; (ii) measuring industrial relationships among firms and the criminal activity is not an easy task; (iii) the most productive firms may self-select into the most agglomerated areas, or move towards more secure business environments.

Therefore, Equation (1) is estimated by applying an IV approach and, specifically, a two-stage least squares (TSLS) estimator. As the identification of a good instrument – i.e. one correlated with the endogenous variable without affecting the dependent variable (Greene, 2003) – may be a hard task, previous research on both the agglomeration economics and crime literature has proposed alternative approaches. Often, current values of agglomeration variables are instrumented using their long-lagged values (e.g. Ciccone and Hall, 1996), while measures of organized crime have been instrumented using geographic or historical variables to capture the institutional, socio-economic, and environmental features of the places where organized crime originally emerged (e.g. Albanese and Marinelli, 2013; Barone and Narciso, 2015). However, as the aim of our research is to investigate whether industrial clustering and organized crime influence firm-level productivity growth across Italian provinces, both in the areas where organized crime originated (parts of the *Mezzogiorno*) as well as in those where it has appeared more recently (Northern and Central provinces), our identification strategy does not rely on geographic or historical factors. Instead, it follows Autor and Duggan's (2003) modification to the shift-share approach originally proposed by

Bartik (1991) and largely employed in different fields (e.g. Ascani and Gagliardi, 2015; Buonanno and Pazzona, 2014; Faggio and Overman, 2014; Moretti, 2010).

The proposed IV approach considers industry and crime shares, respectively, defined at the province level for the year 2007, as well as changes at the national level over the 2007-2010 period, to instrument the 2010 variables capturing industrial clustering and organized crime. The rationale underlying the instruments is that each province would have observed a change of its industrial structure and criminality level over the 2007-2010 period which is proportional to its beginning-of-the period conditions in absence of province-specific shocks. The IV constructed to instrument the industrial clustering variable (IV_p^{IC}) takes into account industry variations and is defined as follows:

$$IV_p^{IC} = \sum_{g=1}^{G} \left\{ \left(\frac{N_{pg}^{2007}}{\sum_{g=1}^{G} N_{pg}^{2007}} \right) \cdot \left[\ln\left(N_{(-p)g}^{2010}\right) - \ln\left(N_{(-p)g}^{2007}\right) \right] \right\},$$

where N_{pg}^{2007} denotes the number of firms operating in industry g and located in province p in 2007, while the terms $N_{(-p)g}^{2007}$ and $N_{(-p)g}^{2010}$ denote the number of firms operating in industry g at the national level, excluding the province p, in 2007 and 2010, respectively. All industries are considered in constructing the IV. The objective is to capture changes in the industrial structure of a province which would affect a firm's current possibility for inputs' procurement. The IV constructed to instrument the organized crime variable (IV_p^{OC}) accounts for crime variations and is defined as follows:

$$IV_p^{OC} = \sum_{c=1}^{C} \left\{ \left(\frac{S_{pc}^{2007}}{\sum_{c=1}^{C} S_{pc}^{2007}} \right) \cdot \left[\ln\left(S_{(-p)c}^{2010}\right) - \ln\left(S_{(-p)c}^{2007}\right) \right] \right\},$$

where S_{pc}^{2007} denotes the number of crimes of type c recorded in province p in 2007, while the terms $S_{(-p)c}^{2007}$ and $S_{(-p)c}^{2010}$ denote the number of crimes of type c at the national level, excluding the province

p, in 2007 and 2010, respectively. As the organized crime variable defined in Equation (3) represents only a proxy for the real phenomenon (e.g. Calderoni, 2011), all crimes classified by Istat – beyond *mafia*-type ones – are considered when constructing the IV. The aim is to better capture changes in criminal activity at the province level.[8]

The intuition behind the identification strategy relies on the pre-crisis composition of the local industrial and crime structures, together with their national changes over the crisis, to exploit the geographic variability of the effects induced by the crisis in Italy. Looking at the industrial dimension, the economic downturn could have been more severe in provinces where the local, pre-crisis industrial structure was driven by sectors more exposed to international interactions. This scenario, in turn, could have induced a process of re-configuration of the local industrial structure during the crisis driven by national sectoral dynamics, with consequences on firm-level opportunity for local market transactions in the post-crisis period. Looking at the crime dimension, previous empirical contributions suggest that economic-related crimes tend to increase in periods of economic downturn (e.g. de Blasio, Maggio, & Menon, 2016; Edmark, 2005). In absence of province-specific shocks related to the crisis, crime-specific variations at the national level during the crisis would have been allocated proportionally to the pre-crisis local shares. By contrast, individuals living in provinces that suffered more the effects of the crisis could have had higher incentives to engage in criminal activities. Similarly, businesses run in provinces recording a higher downturn during the crisis could have more easily fallen prey to criminal organizations. Furthermore, local industrial and crime dynamics may have observed a certain degree of correlation as a consequence of the economic downturn; provinces more deeply affected on the industrial side could have also witnessed an escalation in criminal activity resulting, for example, from increased unemployment and the financial weakness or bankruptcy of local firms – which, in turn, could have eased the path for criminal organizations to take control over the local market.

In addition to the relevance of the IVs, it is crucial that neither the nationwide shocks nor the pre-crisis shares are directly correlated with firms' TFP growth over the 2010-2013 period. The exclusion of the province-specific contribution to the national changes during the crisis reduces this risk (e.g. Faggio and Overman, 2014). Moreover, as in Ascani and Gagliardi (2015) and Faggio and Overman (2014) in the context of cross-sectional analyses, the exogeneity of the IVs is further strengthened by the use of lagged (and pre-crisis) shares − see also de Blasio et al. (2016) in the context of panel data.

The issues of sample selection and endogenous regressors have been addressed simultaneously following Wooldridge (2010, pp. 809−813). Specifically, the right-hand side of the first-stage, reduced-form selection equation is specified including all the exogenous variables entering the second-stage equation, plus the instruments identified for the endogenous variables instead of the endogenous variables themselves. Consequently, the structural (i.e. the productivity growth) equation is estimated via TSLS including the inverse Mills ratio derived from the selection equation as additional regressor.

4. EMPIRICAL RESULTS

4.1. Main results

Table 1 reports results of the OLS estimation of Equation (1), corrected for sample selection. The null hypothesis testing the exclusion restriction $\varphi(\cdot)$ in the selection equation is always rejected, and the parameter λ (i.e. the inverse Mills ratio computed from the selection equation) is statistically significant in all specifications. This indicates the need to correct for sample selection and the validity of the adopted strategy. Moreover, the mean variance inflation factor (VIF) is lower than the conservative cut-off value of 10 in all specifications, suggesting the absence of multicollinearity problems.

The results of specification (1) – estimated without including the interaction term between the variables for industrial clustering and organized crime – point to, as hypothesized, a negative effect of organized crime on firm-level productivity growth. They also highlight the presence of a positive link between industrial clustering and productivity growth. In this respect, the results confirm previous findings on both the relationship between organized crime and firm productivity (e.g. Albanese and Marinelli, 2013) and on the relationship between industrial clustering and productivity (e.g. Cainelli et al., 2016). Regarding the controls, the beginning-of-the period TFP variable has negative coefficients, as do the age and size variables.

[place Table 1 here]

Specification (2) complements specification (1) by identifying a negative indirect effect of organized crime on the relationship between industrial clustering and productivity growth. The coefficients of the interaction term are negative and statistically significant, implying that any positive effect arising from the geographic concentration of (intra- and inter-industry) market-related firms decreases as the incidence of local organized crime increases. Table 2 allows discerning the dimension of the moderation effect of organized crime on the industrial clustering-productivity growth relationship, as it reports the TFP growth elasticity of industrial clustering estimated at selected percentiles of the organized crime variable. The estimated elasticity decreases as the level of organized crime increases. Following Ackerberg et al.'s (2015) approach to TFP estimation, the results reveal that a 1 percent increase in the level of industrial clustering is associated with a 4.4 percent increase of productivity growth, when the value of organized crime is in the 1st percentile of its distribution; with a 2.8 percent increase of productivity growth, when the value of organized crime is in the 50th percentile of its distribution; and with a non-statistically significant 1.1 percent increase of productivity growth, when the value of organized crime is in the 99th percentile of its distribution.

[place Table 2 here]

The results of the analysis thus confirm the theoretical predictions. On the one hand, firms located in local systems characterized by a high density of market-related firms (i.e. surrounded by a high number of potential suppliers) benefit from agglomeration externalities related to the local availability of suppliers, the reduction of transport costs, as well as the reduction of transaction costs associated with increasing trust among local business partners. On the other hand, organized crime reduces trust among individuals, alters competition, and undermines the established local industrial structure, causing a weakening of existing market relationships among local firms. Organized crime therefore leads to an increase in the costs of the economic activity and to a significant reduction of the advantages related to economics of agglomeration, producing a clear decrease in firm-level efficiency.

The robustness of the results is tested by controlling for the potential endogeneity of the variables capturing industrial clustering and organized crime. Re-location processes of the most productive firms towards the most agglomerated areas, or towards areas characterized by lower levels of criminality, may cause biases in the estimated coefficients due to reverse causality. Table 3 reports results of the TSLS estimation of Equation (1) aimed at controlling for the potential endogeneity. Similarly to the exogenous analysis, the null hypothesis testing the exclusion restriction $\varphi(\cdot)$ in the selection equation is always rejected, and the parameter λ is statistically significant. First-stage F statistics on the endogenous variables are higher than the conservative cut-off value of 10 in all specifications and, as before, the mean VIF is lower than the cut-off value of 10.

[place Table 3 here]

Overall, the findings reported above are confirmed when controlling for endogeneity. There is a negative direct effect of organized crime on productivity growth and a positive one of industrial clustering. The results also confirm an indirect negative effect of organized crime on the positive relationship between industrial clustering and productivity growth. As Table 4 shows, the dimensions of this effect are quite high: a 1 percent increase in the level of industrial clustering is associated with a 19.2 percent increase of productivity growth, when the value of organized crime is in the 1st percentile of its distribution; with a 4.9 percent increase of productivity growth, when the value of organized crime is in the 50th percentile of its distribution; and with a non-statistically significant 3.4 percent increase of productivity growth, when the value of organized crime is in the 75th percentile of its distribution – see Ackerberg et al.'s (2015) approach to TFP estimation.

[place Table 4 here]

Once endogeneity is controlled for, the negative indirect effect of organized crime increases, making the positive marginal effect of industrial clustering on productivity growth negligible for high levels of organized crime. The presence of criminal organizations alters the local industrial structure and the established market relationships among firms, meaning that the positive agglomeration externalities stemming from the geographic concentration of suppliers disappear in areas characterized by a high incidence of organized crime. Negligible agglomeration externalities are a consequence of the presence of protection rackets, high extortion, and "illicit" firms in the local productive cluster, which leads to increasing costs (e.g. higher acquisition costs, higher transaction costs, as well as the imposition of taxes to stay in the market) for "legal" firms.

Furthermore, Equation (1) is modified to test whether the negative moderation effect of organized crime on the industrial clustering-productivity growth relationship differs for firms of different sizes. The idea is that the effects of organized crime are likely to be greater for smaller firms because they have less available resources and less market power with respect to larger firms. Smaller firms may have more difficulties for competing in a market dominated by criminal organizations, which operate imposing protection rackets and the acquisition of inputs from controlled "illicit" firms. Moreover, violent actions towards employers and firms' assets in order to gain the control of the local market may act as a greater deterrent for smaller firms, simply by virtue of their size.

Table 5 reports the results of the TSLS estimation of the augmented version of Equation (1), which includes both two-way interactions of the industrial clustering and organized crime variables with the size dummy variable, and a three-way interaction term among the three variables. Diagnostics on the sample selection issue confirm the empirical approach adopted, and the first-stage F statistics are larger than the conservative cut-off value of 10 in all specifications.

[place Table 5 here]

Table 6 reports the TFP growth elasticities of industrial clustering and organized crime corresponding to specifications (1) in Table 5. These elasticities estimate the direct effects by size class. The results indicate that, first, smaller firms benefit more from the local availability of input suppliers than larger ones. Second, their growth seems to be negatively affected by organized crime more than that of larger firms, although this result is marginally reversed when firm-level TFP is estimated following Ackerberg et al. (2015).

[place Table 6 here]

The above results are further confirmed by Table 7, which shows that the indirect negative effect of organized crime is higher for smaller than for larger firms. For example, following Ackerberg et al.'s (2015) TFP estimation approach, a 21 percent decline in agglomeration benefits for smaller firms is evident when moving from the 1^{st} to the 25^{th} percentile of the organized crime variable's distribution, while a 5.1 percent decline emerges for larger firms. Similarly, smaller firms suffer a 5.1 percent decline moving from the 25^{th} to the 50^{th} percentile, while larger firms suffer a 1.2 percent decline. Moreover, the estimated elasticity is positive but non-significant at the 75^{th}

percentile for smaller firms, while positive and statistically significant for larger firms. Finally, negative agglomeration externalities arise for smaller firms when the value of organized crime variables is in the 99th percentile of its distribution, while the effect becomes negligible for larger firms at the same value of the organized crime variable.

[place Table 7 here]

4.2. Robustness tests

A series of tests has been performed to assess the role of some potential drawbacks related to the empirical analysis and, thus, to check the robustness of the main findings. All the Tables presenting these results are reported in the Appendix.

First, the OLS and TSLS estimations of Equation (1) are replicated using an alternative measure of firm-level performance, i.e. labor productivity – computed as deflated value added per employee. The rationale of this exercise is that firm-level TFP estimation presents several drawbacks. As shown in Tables A9 and A10, the main findings obtained using the three alternative measures of TFP are confirmed.

Second, as Table A5 in the Appendix reports, the mean value of the TFP growth variables is negative. This negative average firm-level growth could be a consequence of the post-crisis period investigated. Therefore, the TSLS estimation of Equation (1) is replicated using the 2013 productivity level as dependent variable. As Tables A11 and A12 show, the results confirm the previous findings both using a measure of TFP and a measure of labor productivity to proxy for firm-level performance.

Third, the TSLS estimation of Equation (1) is reproduced using an alternative proxy to capture local agglomeration forces. Following Cainelli et al. (2016), the industrial clustering variable is replaced by a simple measure of geographic concentration of industries (GC_{pg}^{2010}) defined as follows:

$$GC_{pg}^{2010} = \ln\left(\frac{N_{pg}^{2010} - 1}{Surface_p}\right),$$

where all terms are defined as in Equation (4). Although the geographic concentration variable does not represent a proxy for the whole dynamics of market-based relationships among firms, as it does not take into account inter-industry transactions, it may be useful to check the robustness of the results under the rationale that inputs' procurement in manufacturing industries is manly driven by horizontal (i.e. intra-industry) transactions.[9] As shown in Tables A13 and A14, the results confirm the previous findings obtained using the industrial clustering variable, which captured both intra- and inter-industry market-based transactions.

Fourth, the robustness of the results is tested using an alternative variable for organized crime which accounts for attacks and criminal conspiracy, besides the *mafia*-association, the *mafia*-murder and the extortion crimes. The rationale underlying this alternative specification of the organized crime variable refers to the complexity of properly reflecting such an ample and varied phenomenon, which official statistics on criminal activity can hardly capture (Calderoni, 2011). As Tables A15 and A16 suggest, the previous findings are once again confirmed, although this alternative organized crime variable still represents a poor proxy for the organized crime phenomenon.

Fifth, the TSLS estimation of Equation (1) is reproduced without controlling for the sample selection bias, i.e. without including the estimated inverse Mills ratio as additional regressor. This exercise aims at verifying that the results on the coefficients of interest are not driven by the arbitrary exclusion restriction identifying the selection equation. The results reported in Tables A17 and A18, once again, confirm the main ones.

Finally, the robustness of the results is tested using an alternative approach to estimate firms' TFP. The Levinsohn and Petrin's (2003) approach has been modified to account for endogenous firm exit in a similar fashion to Olley and Pakes (1996): specifically, a firm's probability of exiting the sample is modeled through a third-order polynomial function in intermediate inputs and capital input. As Tables A19 and A20 show, the results are robust to this different TFP estimation approach.

5. CONCLUSIONS

This paper makes inroads into the understanding of the mechanisms underlying the relationship between the local environment where firms operate and their economic performance. Specifically, it has focused on whether and to which extent organized crime (*mafia*-type criminality) affects a firm's performance (defined in terms of TFP growth) both directly and indirectly, by downsizing any positive externalities arising from the geographic concentration of (intra- and inter-industry) market-related firms.

The analysis is conducted using a large sample of Italian manufacturing SMEs over the period 2010-2013, on which a two-step sample-selection model has been estimated to control for a potential selection bias of the surviving firms. The robustness of the results has been tested through an IV approach to control for the endogeneity of the variables capturing organized crime and industrial clustering. Three different approaches have also been employed to estimate firm-level TFP and several robustness exercises have been performed.

The empirical results demonstrate the presence of a negative (direct) effect of organized crime on firm-level productivity growth. The negative influence of organized crime is also indirect, as *mafia*-type associations, extortions, and murders create local conditions that undermine the positive effect of industrial clustering on productivity growth. Moreover, this negative moderation effect is more detrimental for smaller than for larger firms. The positive impact of industrial clustering decreases as the level of organized crime at the local level increases, to the extent that it becomes negative in those areas with particularly high levels of criminality – specifically, for small firms.

These results can be interpreted considering two interrelated consequences of criminal activity. On the one hand, criminal organizations gain from the economic control of specific productions and, therefore, may influence their dynamics. On the other hand, the presence of criminal organizations also reduces trust and reciprocity among individuals, increasing transaction costs, thus contributing to make the local business environment less competitive. This produces negative externalities on local market-based relationships among firms: market transactions become more expensive, in particular if the criminal organization imposes, as is normally the case, protection rackets and other illegal payments on the local firms. Hence, high levels of organized crime destabilize traditional competition/cooperation relationships existing among firms within a locality. Smaller firms and businesses are the greatest victims. These aspects contribute to determine the negative (indirect) effect which can be ascribed to the presence of criminal organizations: they influence firms' performance increasing the costs of the economic activity, as well as altering the mechanisms which determine the positive effect of industrial agglomeration on firm-level growth.

The results underline the importance of the local context on firm-level performance, beyond the traditional firm-specific characteristics (Fitjar and Rodríguez-Pose, 2015). In particular, they highlight the relevance of accounting for different dimensions of the local environment where firms operate, as well as how these local-level factors interact with one another in order to determine the economic behavior of firms. From a theoretical and an empirical point of view, the results of the analysis open new questions concerning the dynamics of the relationship between agglomeration forces and the performance of firms. They hint at the fact that the local context – and at how different factors external to the firm combine in the local environment – alters the way in which firms behave, innovate, perform, and benefit from spatial agglomeration. From a policy perspective, the results point to the need of targeting industrial policies not only at the level of the firm but addressing local bottlenecks that may limit the capacity of firms to be created, operate, and thrive in particular areas of Italy or elsewhere in the world. Organized crime is one of these bottlenecks and tackling it would represent a significant boost to productivity and, consequently, to the economic dynamism of firms, cities, and territories.

ENDNOTES

1. The analysis focuses only on manufacturing industries because the balance sheet data available for services firms are less complete and reliable than those available for manufacturing firms. The analysis focuses on firms' TFP (growth), which is estimated using balance sheet data.
2. Firms are ascribed to different industries and sectors following the Ateco 2007 classification of economic activities. All two-digit manufacturing sectors are considered, except for the sectors "12 – Tobacco products" and "33 – Repair and installation of machinery and equipment", due to the absence of firms after the cleaning procedure.
3. Deflated balance sheet data on value added, total labor cost, intermediate inputs and tangible assets are used to estimate the industry-specific production functions. Value added (VA_{it}) is deflated with the corresponding production price index and is used as output in the production functions; total labor cost (L_{it}) is deflated with the corresponding wage index and is used as labor input; total tangible assets (K_{it}) are deflated with the corresponding capital deflator and are used as capital input; intermediate inputs (M_{it}) are defined (at current prices) as the sum of services, raw materials and consumptions. They are deflated with an intermediate consumptions index. Deflators are calculated using Istat (Italian National Institute of Statistics) data and the reference year for depreciation is 2006. TFP is estimated at the industry level, rather than at the two-digit sector level. This is done in order to maintain the same industrial level of aggregation, as the 2010 input-output data used to construct the variable capturing industrial clustering are only available for the 19 industries specified in Table A1.
4. The estimated inputs' elasticities reported in Table A4 indicate low returns to scale independently of the estimation approach considered. These results could be explained considering two different aspects. First, the estimation of firm-level TFP presents several drawbacks as different estimation techniques tend to take into account only one or two issues simultaneously. This is despite the fact that the literature has emphasized several problems other than endogeneity and input choice – e.g. omitted price bias and optimal level of analysis (firm,

plant or product) – that also need to be addressed (Van Beveren, 2012). Second, these results could depend on the firm-level balance sheet data used in the estimation procedure, as they are close to results obtained in other research using the same (e.g. Ganau, 2016; Lasagni et al., 2015) or similar (e.g. Albanese and Marinelli, 2013; Di Giacinto, Gomellini, Micucci, & Pagnini, 2014) data sources.

5. The literature has focused on different dimensions of the cluster phenomenon. For instance, Feser (2005) and Feser and Bergman (2000) analyze the input-output component of industrial clusters, while Feldman and Audretsch (1999) and Koo (2005) focus on knowledge-based clusters. Delgado, Porter, and Stern (2016) propose a measure of inter-industry linkages which is based on the co-location pattern of employment and establishments, input-output linkages and shared jobs, and which allows for the comparison of clustering phenomena across regions.
6. The weighting scheme has been defined excluding public services (e.g. defense, public administration, public infrastructures, etc.), domestic services, education, restaurants and leisure activities, construction, real estate, and commercial activities. These industries have not been considered because their supplied inputs are not directly employed in the production processes by manufacturing firms. In particular, commercial firms have been excluded because they act as intermediaries and they are not specific with regard to the inputs sold (Cainelli et al., 2016).
7. The dummy variable for large size firms equals one if the firm has a minimum of 15 employees, while it equals zero if the firm has 14 employees or less. The choice of splitting the sample around the median value is driven by the highly skewed nature of the 2010 employment distribution (see Figure A2 in the Appendix).
8. The correlation coefficient between organized crime and non-organized crime per square kilometer in 2010 is equal to 0.798. 7 percent of Italian provinces lie in the 90th percentile of both distributions.
9. According to the 2010 Italian use table, the highest pairwise share of inputs acquired by all but four manufacturing industries refers to intra-industry inputs' procurement.

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TABLE 1: OLS results

Dependent variable	$\Delta\text{TFP}_{\text{ipg}}$ (LP)		$\Delta\text{TFP}_{\text{ipg}}$ (W)		$\Delta\text{TFP}_{\text{ipg}}$ (ACF)	
Specification	(1)	(2)	(1)	(2)	(1)	(2)
$\text{TFP}_{\text{ipg}}^{2010}$	-0.394****	-0.394****	-0.398****	-0.398****	-0.416****	-0.416****
	(0.020)	(0.020)	(0.020)	(0.020)	(0.018)	(0.018)
$\text{AGE}_{\text{ipg}}^{2010}$	-0.044****	-0.044****	-0.044****	-0.044****	-0.030****	-0.031****
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
$\text{SIZE\_CLASS}_{\text{ipg}}^{2010}$	-0.056***	-0.057***	-0.060***	-0.061***	-0.038**	-0.039**
	(0.020)	(0.020)	(0.020)	(0.020)	(0.019)	(0.019)
$\text{IC}_{\text{pg}}^{2010}$	0.043****	0.016	0.042****	0.015	0.027***	0.008
	(0.009)	(0.013)	(0.009)	(0.013)	(0.009)	(0.013)
$\text{OC}_{\text{p}}^{2010}$	-0.029****	-0.033****	-0.028****	-0.033****	-0.015**	-0.019**
	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)
$\text{IC}_{\text{pg}}^{2010}\times\text{OC}_{\text{p}}^{2010}$	…	-0.007***	…	-0.007***	…	-0.005*
		(0.003)		(0.003)		(0.003)
λ	-0.707****	-0.710****	-0.692****	-0.695****	-0.280****	-0.283****
	(0.075)	(0.074)	(0.073)	(0.073)	(0.058)	(0.058)
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
NUTS-1 Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	17,961	17,961	17,961	17,961	17,961	17,961
R^2	0.11	0.11	0.12	0.12	0.14	0.14
Adjusted R^2	0.11	0.11	0.12	0.12	0.14	0.14
Model F statistic [p-value]	19.61 [0.000]	19.07 [0.000]	19.93 [0.000]	19.39 [0.000]	24.06 [0.000]	23.36 [0.000]
Mean VIF	3.88	4.48	3.86	4.46	3.65	4.26
Elasticity of $\text{IC}_{\text{pg}}^{2010}$	0.043****	0.044****	0.042****	0.043****	0.027***	0.027***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Selection Equation						
Number of Firms	26,812	26,812	26,812	26,812	26,812	26,812
Pseudo R^2	0.06	0.06	0.06	0.06	0.06	0.06
Model Wald χ^2 [p-value]	1,915.26 [0.000]	1,922.50 [0.000]	1,909.69 [0.000]	1,917.20 [0.000]	1,914.24 [0.000]	1,919.73 [0.000]
H_0: $\varphi(\cdot) = 0$	216.85 [0.000]	217.59 [0.000]	221.85 [0.000]	222.58 [0.000]	278.14 [0.000]	278.87 [0.000]

Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$; $****p < 0.001$. Bootstrapped (1,000 replications) standard errors are shown in parentheses, and they are clustered at the province-industry level. All specifications include a constant term. LP denotes Levinsohn and Petrin's (2003) approach, W denotes Wooldridge's (2009) approach, while ACF denotes Ackerberg et al.'s (2015) approach to firms' TFP estimation. λ denotes the inverse Mills ratio from the first-stage selection equations. $\varphi(\cdot)$ denotes the third-order polynomial included on the right-hand side of the selection equation as exclusion restriction.

TABLE 2: TFP growth elasticity of industrial clustering (OLS results)

Dependent Variable	$\Delta\mathrm{TFP_{ipg}}$ (LP)	$\Delta\mathrm{TFP_{ipg}}$ (W)	$\Delta\mathrm{TFP_{ipg}}$ (ACF)
Distribution of Organized Crime ($\mathrm{OC_p^{2010}}$)			
1st Percentile	0.068**** (0.013)	0.067**** (0.013)	0.044**** (0.013)
25th Percentile	0.049**** (0.009)	0.048**** (0.009)	0.031*** (0.009)
50th Percentile	0.044**** (0.009)	0.043**** (0.009)	0.028*** (0.009)
75th Percentile	0.042**** (0.009)	0.041**** (0.009)	0.026*** (0.009)
99th Percentile	0.021** (0.012)	0.019 (0.012)	0.011 (0.012)

Notes: The estimated elasticities of the industrial clustering variable (IC_{pg}^{2010}) refer to specifications (2) in Table 1.

TABLE 3: TSLS results

Dependent variable	ΔTFP_{ipg} (LP)		ΔTFP_{ipg} (W)		ΔTFP_{ipg} (ACF)	
Specification	(1)	(2)	(1)	(2)	(1)	(2)
TFP_{ipg}^{2010}	-0.399****	-0.394****	-0.402****	-0.398****	-0.418****	-0.417****
	(0.020)	(0.020)	(0.020)	(0.020)	(0.018)	(0.018)
AGE_{ipg}^{2010}	-0.047****	-0.047****	-0.046****	-0.046****	-0.031****	-0.032****
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
$SIZE\_CLASS_{ipg}^{2010}$	-0.057***	-0.058***	-0.061***	-0.063***	-0.039**	-0.040**
	(0.020)	(0.020)	(0.020)	(0.020)	(0.018)	(0.018)
IC_{pg}^{2010}	0.133****	-0.173	0.130****	-0.172	0.062**	-0.121
	(0.036)	(0.126)	(0.036)	(0.125)	(0.026)	(0.075)
OC_{p}^{2010}	-0.093***	-0.095***	-0.091***	-0.094***	-0.039*	-0.055***
	(0.033)	(0.031)	(0.032)	(0.031)	(0.023)	(0.021)
$IC_{pg}^{2010} \times OC_{p}^{2010}$	…	-0.068**	…	-0.068**	…	-0.045**
		(0.029)		(0.029)		(0.018)
λ	-0.719****	-0.711****	-0.703****	-0.698****	-0.285****	-0.284****
	(0.073)	(0.074)	(0.072)	(0.072)	(0.057)	(0.057)
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
NUTS-1 Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	17,961	17,961	17,961	17,961	17,961	17,961
Model F statistic [p-value]	19.82 [0.000]	17.93 [0.000]	20.14 [0.000]	18.26 [0.000]	23.52 [0.000]	22.64 [0.000]
Mean VIF	3.05	3.67	3.05	3.67	3.02	3.64
First-stage F statistic [p-value]						
IC_{pg}^{2010}	105.81 [0.000]	101.25 [0.000]	105.86 [0.000]	101.29 [0.000]	106.28 [0.000]	101.54 [0.000]
OC_{p}^{2010}	127.71 [0.000]	110.56 [0.000]	127.78 [0.000]	110.58 [0.000]	128.28 [0.000]	110.71 [0.000]
$IC_{pg}^{2010} \times OC_{p}^{2010}$	…	146.32 [0.000]	…	146.32 [0.000]	…	146.47 [0.000]
Elasticity of IC_{pg}^{2010}	0.133****	0.080**	0.130****	0.078**	0.062**	0.044**
	(0.036)	(0.034)	(0.036)	(0.034)	(0.026)	(0.020)
Selection Equation						
Number of Firms	26,812	26,812	26,812	26,812	26,812	26,812
Pseudo R^2	0.06	0.06	0.06	0.06	0.06	0.06
Model Wald χ^2 [p-value]	1,852.28 [0.000]	1,844.58 [0.000]	1,846.65 [0.000]	1,838.79 [0.000]	1,854.11 [0.000]	1,850.27 [0.000]
H_0: $\varphi(\cdot) = 0$	218.39 [0.000]	215.23 [0.000]	223.46 [0.000]	220.29 [0.000]	280.18 [0.000]	277.20 [0.000]

Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$; $****p < 0.001$. Bootstrapped (1,000 replications) standard errors are shown in parentheses, and they are clustered at the province-industry level. All specifications include a constant term. LP denotes Levinsohn and Petrin's (2003) approach, W denotes Wooldridge's (2009) approach, while ACF denotes Ackerberg et al.'s (2015) approach to firms' TFP estimation. λ denotes the inverse Mills ratio from the first-stage selection equations. $\varphi(\cdot)$ denotes the third-order polynomial included on the right-hand side of the selection equation as exclusion restriction.

TABLE 4: TFP growth elasticity of industrial clustering (TSLS results)

Dependent Variable	$\Delta\mathrm{TFP}_{\mathrm{ipg}}$ (LP)	$\Delta\mathrm{TFP}_{\mathrm{ipg}}$ (W)	$\Delta\mathrm{TFP}_{\mathrm{ipg}}$ (ACF)
Distribution of Organized Crime ($\mathrm{OC}_{\mathrm{p}}^{2010}$)			
1^{st} Percentile	0.304**** (0.088)	0.301**** (0.087)	0.192**** (0.059)
25^{th} Percentile	0.129**** (0.032)	0.128**** (0.032)	0.077**** (0.022)
50^{th} Percentile	0.086*** (0.033)	0.085*** (0.033)	0.049** (0.020)
75^{th} Percentile	0.063* (0.038)	0.062* (0.037)	0.034 (0.022)
99^{th} Percentile	-0.134 (0.110)	-0.124 (0.109)	-0.096 (0.065)

Notes: The estimated elasticities of the industrial clustering variable (IC_{pg}^{2010}) refer to specifications (2) in Table 3.

TABLE 5: TSLS results by size class

Dependent variable	ΔTFP_{ipg} (LP)		ΔTFP_{ipg} (W)		ΔTFP_{ipg} (ACF)	
Specification	(1)	(2)	(1)	(2)	(1)	(2)
TFP_{ipg}^{2010}	-0.395****	-0.391****	-0.397****	-0.394****	-0.416****	-0.416****
	(0.020)	(0.020)	(0.020)	(0.020)	(0.018)	(0.018)
AGE_{ipg}^{2010}	-0.044****	-0.046****	-0.043****	-0.046****	-0.030****	-0.032****
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
$SIZE\_CLASS_{ipg}^{2010}$	0.033	0.038	0.026	0.026	-0.054	-0.013
	(0.073)	(0.089)	(0.073)	(0.088)	(0.057)	(0.072)
IC_{pg}^{2010}	0.183****	-0.321	0.179****	-0.321	0.082**	-0.238*
	(0.045)	(0.206)	(0.045)	(0.204)	(0.034)	(0.132)
OC_{p}^{2010}	-0.109***	-0.138***	-0.106***	-0.135***	-0.038	-0.078**
	(0.040)	(0.046)	(0.040)	(0.045)	(0.030)	(0.034)
$IC_{pg}^{2010} \times OC_{p}^{2010}$	...	-0.119**	...	-0.118**	...	-0.082**
		(0.051)		(0.050)		(0.034)
$IC_{pg}^{2010} \times SIZE\_CLASS_{ipg}^{2010}$	-0.132****	0.255*	-0.130****	0.258*	-0.053**	0.203*
	(0.031)	(0.155)	(0.031)	(0.154)	(0.025)	(0.109)
$OC_{p}^{2010} \times SIZE\_CLASS_{ipg}^{2010}$	0.058**	0.062**	0.057**	0.059*	0.009	0.028
	(0.027)	(0.031)	(0.027)	(0.031)	(0.021)	(0.025)
$IC_{pg}^{2010} \times OC_{p}^{2010} \times SIZE\_CLASS_{ipg}^{2010}$	...	0.086**	...	0.086**	...	0.062**
		(0.040)		(0.040)		(0.029)
λ	-0.667****	-0.684****	-0.650****	-0.669****	-0.262****	-0.274****
	(0.070)	(0.074)	(0.069)	(0.073)	(0.055)	(0.057)
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
NUTS-1 Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	17,961	17,961	17,961	17,961	17,961	17,961
Model F statistic [p-value]	18.39 [0.000]	16.11 [0.000]	18.64 [0.000]	16.36 [0.000]	22.04 [0.000]	20.69 [0.000]
Mean VIF	5.02	8.32	5.01	8.31	4.90	8.18
First-stage F statistic [p-value]						
IC_{pg}^{2010}	54.43 [0.000]	51.41 [0.000]	54.43 [0.000]	51.44 [0.000]	54.31 [0.000]	51.57 [0.000]
OC_{p}^{2010}	65.34 [0.000]	55.42 [0.000]	65.36 [0.000]	55.44 [0.000]	65.52 [0.000]	55.50 [0.000]
$IC_{pg}^{2010} \times OC_{p}^{2010}$	...	74.05 [0.000]	...	74.06 [0.000]	...	74.12 [0.000]
$IC_{pg}^{2010} \times SIZE\_CLASS_{ipg}^{2010}$	54.37 [0.000]	105.32 [0.000]	54.28 [0.000]	105.35 [0.000]	54.43 [0.000]	105.38 [0.000]
$OC_{p}^{2010} \times SIZE\_CLASS_{ipg}^{2010}$	80.74 [0.000]	82.09 [0.000]	80.87 [0.000]	82.18 [0.000]	80.64 [0.000]	82.06 [0.000]
$IC_{pg}^{2010} \times OC_{p}^{2010} \times SIZE\_CLASS_{ipg}^{2010}$	...	70.01 [0.000]	...	70.01 [0.000]	...	69.96 [0.000]
Selection Equation						
Number of Firms	26,812	26,812	26,812	26,812	26,812	26,812

Pseudo R^2	0.06	0.06	0.06	0.06	0.06	0.06
Model Wald χ^2 [p-value]	1,994.55 [0.000]	1,866.84 [0.000]	1,987.33 [0.000]	1,860.54 [0.000]	1,989.05 [0.000]	1,875 [0.000]
H_0: $\varphi(\cdot) = 0$	217.68 [0.000]	214.44 [0.000]	222.61 [0.000]	219.63 [0.000]	279.81 [0.000]	275.86 [0.000]

Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$; $****p < 0.001$. Bootstrapped (1,000 replications) standard errors are shown in parentheses, and they are clustered at the province-industry level. All specifications include a constant term. LP denotes Levinsohn and Petrin's (2003) approach, W denotes Wooldridge's (2009) approach, while ACF denotes Ackerberg et al.'s (2015) approach to firms' TFP estimation. λ denotes the inverse Mills ratio from the first-stage selection equations. $\varphi(\cdot)$ denotes the third-order polynomial included on the right-hand side of the selection equation as exclusion restriction.

TABLE 6: TFP growth elasticity of industrial clustering and organized crime by size class (TSLS, two-way interactions)

Dependent Variable	ΔTFP_{ipg} (LP)		ΔTFP_{ipg} (W)		ΔTFP_{ipg} (ACF)	
Size Class	Small	Large	Small	Large	Small	Large
IC_{pg}^{2010}	0.183****	0.051*	0.179****	0.049*	0.055****	0.039***
	(0.045)	(0.026)	(0.045)	(0.026)	(0.016)	(0.014)
OC_{p}^{2010}	-0.109***	-0.051**	-0.106***	-0.049**	-0.025**	-0.027**
	(0.040)	(0.024)	(0.040)	(0.024)	(0.012)	(0.013)

Notes: The estimated elasticities of the industrial clustering variable (IC_{pg}^{2010}) and the organized crime variable (OC_{p}^{2010}) refer to specifications (1) in Table 5.

TABLE 7: TFP growth elasticity of industrial clustering by size class (TSLS, three-way interaction)

Dependent Variable	ΔTFP_{ipg} (LP)		ΔTFP_{ipg} (W)		ΔTFP_{ipg} (ACF)	
Size Class	Small	Large	Small	Large	Small	Large
Distribution of Organized Crime (OC_p^{2010})						
1st Percentile	0.513****	0.164***	0.507****	0.162***	0.333***	0.104**
	(0.159)	(0.063)	(0.157)	(0.062)	(0.113)	(0.045)
25th Percentile	0.207****	0.080***	0.203****	0.079***	0.123****	0.053***
	(0.048)	(0.026)	(0.048)	(0.026)	(0.036)	(0.018)
50th Percentile	0.132***	0.059**	0.129***	0.059**	0.072**	0.041***
	(0.043)	(0.025)	(0.043)	(0.024)	(0.028)	(0.030)
75th Percentile	0.092*	0.048*	0.089*	0.048*	0.044	0.034**
	(0.050)	(0.026)	(0.039)	(0.026)	(0.030)	(0.016)
99th Percentile	-0.253	-0.047	-0.253	-0.045	-0.192*	-0.024
	(0.178)	(0.070)	(0.176)	(0.068)	(0.113)	(0.045)

Notes: The estimated elasticities of the industrial clustering variable (IC_{pg}^{2010}) refer to specifications (2) in Table 5.

APPENDIX

TABLE A1: Sample distribution by industry and two-digit sector

Industry	Ateco 2007 Two-Digit Sector	Number of Firms	
		a. v.	%
1	10 - Food products	2,215	8.26
1	11 - Beverages	392	1.46
1	12 - Tobacco products	0	0.00
2	13 - Textiles	1,140	4.25
2	14 - Wearing apparel	1,008	3.76
2	15 - Leather and related products	961	3.58
3	16 - Wood, wood and cork products, except furniture; straw articles, plaiting materials	836	3.12
4	17 - Paper and paper products	644	2.40
5	18 - Printing and reproduction of recorded media	855	3.19
6	19 - Coke and refined petroleum products	81	0.30
7	20 - Chemicals and chemical products	1,009	3.76
8	21 - Basic pharmaceutical products and pharmaceutical preparations	157	0.59
9	22 - Rubber and plastic products	1,469	5.48
10	23 - Other non-metallic mineral products	1,538	5.74
11	24 - Basic metals	626	2.33
12	25 - Fabricated metal products, except machinery and equipment	5,929	22.11
13	26 - Computer, electronic, and optical products	935	3.49
14	27 - Electrical equipment	1,228	4.58
15	28 - Machinery and equipment N.E.C.	3,010	11.23
16	29 - Motor vehicles, trailers and semi-trailers	400	1.49
17	30 - Other transport equipment	298	1.11
18	31 - Furniture	1,120	4.18
18	32 - Other manufacturing	961	3.58
19	33 - Repair and installation of machinery and equipment	0	0.00
	Total Sample	26,812	100.00

Notes: Firms are classified according to the Ateco 2007 classification of economic activities adopted by Istat, which corresponds to the NACE Rev. 2 classification. Industries are defined according to the input-output system adopted by Istat.

TABLE A2: Sample distribution by NUTS-1 geographic area

NUTS-1 Geographic Area	Number of Firms	
	a. v.	%
North West	10,367	38.67
North East	8,607	32.10
Centre	4,447	16.59
South	2,603	9.71
Islands	788	2.94
Total Sample	26,812	100.00

Notes: North West includes Liguria, Lombardy, Piedmont and Aosta Valley; North East includes Emilia Romagna, Friuli-Venezia Giulia, Trentino-Alto Adige and Veneto; Centre includes Lazio, Marche, Tuscany and Umbria; South includes Abruzzi, Basilicata, Calabria, Campania, Molise and Apulia; Islands are Sicily and Sardinia.

TABLE A3: Descriptive statistics and correlation matrix of the variables entering the production function

		Mean	Std. Dev.	Min.	Max.	va_{igpt}	k_{igpt}	l_{igpt}	m_{igpt}
	overall	6.136	1.422	-2.085	12.083				
va_{igpt}	between		1.372	0.806	12.011	1			
	within		0.281	0.331	9.147				
	overall	5.585	2.129	-7.028	12.660				
k_{igpt}	between		2.091	-4.158	12.622	0.693	1		
	within		0.335	-0.780	11.108				
	overall	5.718	1.395	-1.761	9.775				
l_{igpt}	between		1.363	-0.181	9.680	0.946	0.661	1	
	within		0.202	1.677	8.303				
	overall	6.962	1.667	-2.188	14.293				
m_{igpt}	between		1.628	0.017	13.978	0.848	0.655	0.807	1
	within		0.225	2.785	10.458				

Notes: All variables are log-transformed. va_{igpt} denotes value added; k_{igpt} denotes the capital input; l_{igpt} denotes the labor input; m_{igpt} denotes intermediate inputs. Descriptive statistics and the correlation matrix refer to a sample of 51,398 firms, i.e. 146,556 observations over the period 2009-2013.

TABLE A4: Estimated inputs' elasticities of the production functions

Industry	LP (2003)		W (2009)		ACF (2015)		No. of Observations
	k_{igpt}	l_{igpt}	k_{igpt}	l_{igpt}	k_{igpt}	l_{igpt}	
1	0.077**** (0.012)	0.656**** (0.010)	0.073**** (0.012)	0.658**** (0.010)	0.140**** (0.008)	0.774**** (0.023)	13,916
2	0.091**** (0.007)	0.742**** (0.006)	0.092**** (0.008)	0.744**** (0.007)	0.089**** (0.005)	0.828**** (0.012)	17,777
3	0.039** (0.017)	0.695**** (0.014)	0.041** (0.016)	0.702**** (0.015)	0.086**** (0.008)	0.774**** (0.022)	4,919
4	0.027 (0.033)	0.719**** (0.022)	0.029 (0.033)	0.731**** (0.022)	0.115**** (0.019)	0.781**** (0.104)	3,171
5	0.039** (0.018)	0.728**** (0.014)	0.040** (0.016)	0.744**** (0.017)	0.071**** (0.008)	0.813**** (0.021)	5,128
6	0.084 (0.153)	0.740**** (0.067)	0.133 (0.166)	0.727**** (0.074)	0.121 (0.094)	0.858**** (0.137)	398
7	0.076**** (0.018)	0.708**** (0.016)	0.081**** (0.018)	0.721**** (0.018)	0.071**** (0.009)	0.928**** (0.017)	4,938
8	0.061 (0.056)	0.558**** (0.042)	0.062 (0.051)	0.579**** (0.047)	0.059* (0.032)	0.806**** (0.180)	798
9	0.069**** (0.021)	0.692**** (0.011)	0.069*** (0.022)	0.702**** (0.013)	0.110**** (0.011)	0.829**** (0.020)	7,638
10	0.087**** (0.016)	0.671**** (0.012)	0.086**** (0.015)	0.683**** (0.013)	0.096**** (0.008)	0.810**** (0.016)	8,845
11	0.026 (0.034)	0.739**** (0.017)	0.048** (0.024)	0.730**** (0.021)	0.107**** (0.016)	0.886**** (0.039)	3,077
12	0.064**** (0.006)	0.757**** (0.005)	0.062**** (0.006)	0.772**** (0.005)	0.086**** (0.003)	0.852**** (0.008)	32,410
13	0.072**** (0.013)	0.769**** (0.011)	0.071**** (0.013)	0.786**** (0.013)	0.052**** (0.005)	0.898**** (0.011)	5,246
14	0.071**** (0.012)	0.705**** (0.014)	0.066**** (0.011)	0.726**** (0.015)	0.081**** (0.011)	0.846**** (0.023)	6,582
15	0.070**** (0.009)	0.711**** (0.009)	0.070**** (0.009)	0.735**** (0.009)	0.077**** (0.005)	0.888**** (0.010)	15,924
16	0.051*** (0.017)	0.771**** (0.019)	0.051*** (0.019)	0.795**** (0.019)	0.068**** (0.010)	0.906**** (0.019)	2,149
17	0.019 (0.018)	0.756**** (0.019)	0.029 (0.018)	0.763**** (0.021)	0.050**** (0.011)	0.886**** (0.019)	1,928
18	0.059**** (0.011)	0.693**** (0.010)	0.059**** (0.012)	0.710**** (0.011)	0.093**** (0.006)	0.770**** (0.019)	11,712

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; **** $p < 0.001$. LP denotes Levinsohn and Petrin's (2003) approach, W denotes Wooldridge's (2009) approach, while ACF denotes Ackerberg et al.'s (2015) approach to firms' TFP estimation. k_{igpt} denotes the capital input, while l_{igpt} denotes the labor input. TFP is estimated on a sample of 51,398 firms, i.e. 146,556 observations over the period 2009-2013. Standard errors are shown in parentheses.

TABLE A5: Descriptive statistics of the dependent and main explanatory variables

	No. Obs.	Mean	Std. Dev.	Min.	Max.
$\Delta \mathrm{TFP}_{\mathrm{ipg}}$ (LP)	17,961	-0.047	0.411	-7.446	5.973
$\Delta \mathrm{TFP}_{\mathrm{ipg}}$ (W)	17,961	-0.048	0.411	-7.444	5.977
$\Delta \mathrm{TFP}_{\mathrm{ipg}}$ (ACF)	17,961	-0.057	0.410	-7.407	5.990
$\mathrm{TFP}_{\mathrm{ipg}}^{2010}$ (LP)	26,812	1.748	0.523	-4.637	5.028
$\mathrm{TFP}_{\mathrm{ipg}}^{2010}$ (W)	26,812	1.673	0.517	-4.752	4.955
$\mathrm{TFP}_{\mathrm{ipg}}^{2010}$ (ACF)	26,812	0.887	0.423	-5.649	4.178
$\mathrm{AGE}_{\mathrm{ipg}}^{2010}$	26,812	2.780	0.815	0.693	4.890
$\mathrm{SIZE\_CLASS}_{\mathrm{ipg}}^{2010}$	26,812	0.469	0.499	0.000	1.000
$\mathrm{IC}_{\mathrm{pg}}^{2010}$	26,812	-1.084	1.150	-4.745	2.467
$\mathrm{OC}_{\mathrm{p}}^{2010}$	26,812	-3.699	1.107	-6.992	-0.572

Notes: LP denotes Levinsohn and Petrin's (2003) approach, W denotes Wooldridge's (2009) approach, while ACF denotes Ackerberg et al.'s (2015) approach to firms' TFP estimation. Δ denotes the log difference between time T and $(T - t)$.

TABLE A6: Correlation matrix of the dependent variables

		[1]	[2]	[3]
ΔTFP_{ipg} (LP)	[1]	1		
ΔTFP_{ipg} (W)	[2]	0.9999	1	
ΔTFP_{ipg} (ACF)	[3]	0.9916	0.9928	1

Notes: LP denotes Levinsohn and Petrin's (2003) approach, W denotes Wooldridge's (2009) approach, while ACF denotes Ackerberg et al.'s (2015) approach to firms' TFP estimation.

TABLE A7: Correlation matrix of the main explanatory variables

		[1]	[2]	[3]	[4]	[5]	[6]	[7]
$\mathrm{TFP}_{\mathrm{ipg}}^{2010}$ (LP)	[1]	1						
$\mathrm{TFP}_{\mathrm{ipg}}^{2010}$ (W)	[2]	0.995	1					
$\mathrm{TFP}_{\mathrm{ipg}}^{2010}$ (ACF)	[3]	0.759	0.779	1				
$\mathrm{AGE}_{\mathrm{ipg}}^{2010}$	[4]	0.181	0.173	-0.010	1			
$\mathrm{SIZE\_CLASS}_{\mathrm{ipg}}^{2010}$	[5]	0.400	0.379	0.091	0.269	1		
$\mathrm{IC}_{\mathrm{pg}}^{2010}$	[6]	-0.014	0.016	0.048	0.065	-0.012	1	
$\mathrm{OC}_{\mathrm{p}}^{2010}$	[7]	-0.033	-0.038	-0.027	0.031	-0.035	0.661	1

Notes: LP denotes Levinsohn and Petrin's (2003) approach, W denotes Wooldridge's (2009) approach, while ACF denotes Ackerberg et al.'s (2015) approach to firms' TFP estimation.

TABLE A8: Sample distribution by size

Size Class	Number of Firms	
	a. v.	%
Small (≤ 14 employees)	14,234	53.09
Large (> 14 employees)	12,578	46.91
Total Sample	26,812	100.00

Notes: The sample is split around the median value, which is defined on the 2010 employment distribution and is equal to 14.

TABLE A9: OLS and TSLS results on labor productivity growth

Dependent variable	$\Delta \text{Labor Productivity}_{\text{ipg}}$			
Estimation Method	OLS		TSLS	
Specification	(1)	(2)	(1)	(2)
$\text{Labor Productivity}_{\text{ipg}}^{2010}$	-0.455****	-0.455****	-0.463****	-0.454****
	(0.015)	(0.015)	(0.016)	(0.016)
$\text{AGE}_{\text{ipg}}^{2010}$	-0.035****	-0.036****	-0.038****	-0.038****
	(0.007)	(0.007)	(0.007)	(0.007)
$\text{SIZE\_CLASS}_{\text{ipg}}^{2010}$	-0.103****	-0.104****	-0.107****	-0.103****
	(0.026)	(0.026)	(0.026)	(0.026)
$\text{IC}_{\text{pg}}^{2010}$	0.061****	0.034**	0.164****	-0.109
	(0.010)	(0.014)	(0.034)	(0.156)
$\text{OC}_{\text{p}}^{2010}$	-0.033****	-0.037****	-0.108****	-0.112***
	(0.009)	(0.010)	(0.031)	(0.037)
$\text{IC}_{\text{pg}}^{2010} \times \text{OC}_{\text{p}}^{2010}$	…	-0.007**	…	-0.061
		(0.003)		(0.038)
λ	-0.893****	-0.898****	-0.912****	-0.891****
	(0.083)	(0.082)	(0.084)	(0.083)
Industry Dummies	Yes	Yes	Yes	Yes
NUTS-1 Dummies	Yes	Yes	Yes	Yes
Number of Firms	17,961	17,961	17,961	17,961
R^2	0.17	0.17	...	...
Adjusted R^2	0.17	0.17	...	...
Model F statistic [p-value]	48.50 [0.000]	47.83 [0.000]	49.45 [0.000]	46.99 [0.000]
Mean VIF	3.94	4.55	3.01	3.64
First-stage F statistic [p-value]				
$\text{IC}_{\text{pg}}^{2010}$	...	...	106.94 [0.000]	101.57 [0.000]
$\text{OC}_{\text{p}}^{2010}$	...	...	127.30 [0.000]	110.56 [0.000]
$\text{IC}_{\text{pg}}^{2010} \times \text{OC}_{\text{p}}^{2010}$	...	...	…	146.02 [0.000]
Elasticity of $\text{IC}_{\text{pg}}^{2010}$	0.061****	0.061****	0.164****	0.118***
	(0.010)	(0.010)	(0.034)	(0.040)
Selection Equation				
Number of Firms	26,812	26,812	26,812	26,812
Pseudo R^2	0.06	0.06	0.06	0.06
Model Wald χ^2 [p-value]	1,950.46 [0.000]	1,962.02 [0.000]	1,890.81 [0.000]	1,886.17 [0.000]
H_0: $\varphi(\cdot) = 0$	196.11 [0.000]	196.47 [0.000]	198.56 [0.000]	195.07 [0.000]

Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$; $****p < 0.001$. Bootstrapped (1,000 replications) standard errors are shown in parentheses, and they are clustered at the province-industry level. All specifications include a constant term. λ denotes the inverse Mills ratio from the first-stage selection equations. $\varphi(\cdot)$ denotes the third-order polynomial included on the right-hand side of the selection equation as exclusion restriction.

TABLE A10: Labor productivity growth elasticity of industrial clustering

Dependent Variable	$\Delta\text{Labor Productivity}_{\text{ipg}}$	
Estimation Method	OLS	TSLS
Distribution of Organized Crime		
1^{st} Percentile	0.086****	0.320***
	(0.014)	(0.121)
25^{th} Percentile	0.068****	0.162****
	(0.010)	(0.042)
50^{th} Percentile	0.062****	0.124***
	(0.010)	(0.039)
75^{th} Percentile	0.060****	0.103**
	(0.010)	(0.043)
99^{th} Percentile	0.038***	-0.074
	(0.013)	(0.135)

Notes: The estimated elasticities of the industrial clustering variable (IC_{pg}^{2010}) refer to specifications (2) in Table A9.

TABLE A11: TSLS results on 2013 productivity level

ependent variable	$\mathrm{TFP}^{2013}_{\mathrm{ipg}}$ (LP)		$\mathrm{TFP}^{2013}_{\mathrm{ipg}}$ (W)		$\mathrm{TFP}^{2013}_{\mathrm{ipg}}$ (ACF)		Labor $\mathrm{Productivity}^{2013}_{\mathrm{ipg}}$	
pecification	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$\mathrm{FP}^{2010}_{\mathrm{ipg}}$	0.601****	0.606****	0.598****	0.602****	0.582****	0.583****	...	...
	(0.020)	(0.020)	(0.020)	(0.020)	(0.018)	(0.018)		
abor $\mathrm{Productivity}^{2010}_{\mathrm{ipg}}$	...	...	...	...	...	...	0.537****	0.546****
							(0.016)	(0.016)
$\mathrm{GE}^{2010}_{\mathrm{ipg}}$	-0.047****	-0.047****	-0.046****	-0.046****	-0.031****	-0.032****	-0.038****	-0.038****
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)	(0.007)
$\mathrm{IZE\_CLASS}^{2010}_{\mathrm{ipg}}$	-0.057***	-0.058***	-0.061***	-0.063***	-0.039**	-0.040**	-0.107****	-0.103****
	(0.020)	(0.020)	(0.020)	(0.020)	(0.018)	(0.018)	(0.026)	(0.026)
$^{2010}_{\mathrm{pg}}$	0.133****	-0.173	0.130****	-0.172	0.062**	-0.121	0.164****	-0.109
	(0.036)	(0.126)	(0.036)	(0.125)	(0.026)	(0.075)	(0.034)	(0.156)
$\mathrm{C}^{2010}_{\mathrm{p}}$	-0.093***	-0.095***	-0.091***	-0.094***	-0.039*	-0.055***	-0.108****	-0.112***
	(0.033)	(0.031)	(0.032)	(0.031)	(0.023)	(0.021)	(0.031)	(0.037)
$^{2010}_{\mathrm{pg}}\times\mathrm{OC}^{2010}_{\mathrm{p}}$	…	-0.068**	…	-0.068**	…	-0.045**	…	-0.061
		(0.029)		(0.029)		(0.018)		(0.038)
	-0.719****	-0.711****	-0.703****	-0.698****	-0.285****	-0.284****	-0.912****	-0.891****
	(0.073)	(0.074)	(0.072)	(0.072)	(0.057)	(0.057)	(0.084)	(0.083)
ndustry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
UTS-1 Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
umber of Firms	17,961	17,961	17,961	17,961	17,961	17,961	17,961	17,961
odel F statistic [p-value]	520.07 [0.000]	449.85 [0.000]	500.85 [0.000]	428.48 [0.000]	209.23 [0.000]	198.34 [0.000]	249.50 [0.000]	218.94 [0.000]
ean VIF	3.05	3.67	3.05	3.67	3.02	3.64	3.01	3.64
irst-stage F statistic [p-value]								
$^{2010}_{\mathrm{pg}}$	105.81 [0.000]	101.25 [0.000]	105.86 [0.000]	101.29 [0.000]	106.28 [0.000]	101.54 [0.000]	106.94 [0.000]	101.57 [0.000]
$\mathrm{C}^{2010}_{\mathrm{p}}$	127.71 [0.000]	110.56 [0.000]	127.78 [0.000]	110.58 [0.000]	128.28 [0.000]	110.71 [0.000]	127.30 [0.000]	110.56 [0.000]
$^{2010}_{\mathrm{pg}}\times\mathrm{OC}^{2010}_{\mathrm{p}}$	…	146.32 [0.000]	…	146.32 [0.000]	…	146.47 [0.000]	…	146.02 [0.000]
lasticity of $\mathrm{IC}^{2010}_{\mathrm{pg}}$	0.133****	0.080**	0.130****	0.078**	0.062**	0.044**	0.164****	0.118***
	(0.036)	(0.034)	(0.036)	(0.034)	(0.026)	(0.020)	(0.034)	(0.040)
Selection Equation								
umber of Firms	26,812	26,812	26,812	26,812	26,812	26,812	26,812	26,812
seudo R^2	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
odel Wald χ^2 [p-value]	1,852.28 [0.000]	1,844.58 [0.000]	1,846.65 [0.000]	1,838.79 [0.000]	1,854.11 [0.000]	1,850.27 [0.000]	1,890.81 [0.000]	1,886.17 [0.000]
$_0$: $\varphi(\cdot) = 0$	218.39 [0.000]	215.23 [0.000]	223.46 [0.000]	220.29 [0.000]	280.18 [0.000]	277.20 [0.000]	198.56 [0.000]	195.07 [0.000]

otes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$; $****p < 0.001$. Bootstrapped (1,000 replications) standard errors are shown in parentheses, and they are clustered at the province-industry level. A pecifications include a constant term. LP denotes Levinsohn and Petrin's (2003) approach, W denotes Wooldridge's (2009) approach, while ACF denotes Ackerberg et al.'s (2015) approach to firms' TF stimation. λ denotes the inverse Mills ratio from the first-stage selection equations. $\varphi(\cdot)$ denotes the third-order polynomial included on the right-hand side of the selection equation as exclusion restriction.

TABLE A12: 2013 productivity elasticity of industrial clustering (TSLS results)

Dependent Variable	$\mathrm{TFP}_{\mathrm{ipg}}^{2013}$ (LP)	$\mathrm{TFP}_{\mathrm{ipg}}^{2013}$ (W)	$\mathrm{TFP}_{\mathrm{ipg}}^{2013}$ (ACF)	Labor $\mathrm{Productivity}_{\mathrm{ipg}}^{2013}$
Distribution of Organized Crime ($\mathrm{OC}_{\mathrm{p}}^{2010}$)				
1st Percentile	0.304**** (0.088)	0.301**** (0.087)	0.192**** (0.059)	0.320*** (0.121)
25th Percentile	0.129**** (0.033)	0.127**** (0.032)	0.077**** (0.022)	0.162**** (0.042)
50th Percentile	0.086*** (0.033)	0.085*** (0.033)	0.049** (0.020)	0.124*** (0.039)
75th Percentile	0.063* (0.038)	0.062* (0.037)	0.034 (0.022)	0.103** (0.043)
99th Percentile	-0.134 (0.110)	-0.134 (0.109)	-0.096 (0.065)	-0.074 (0.135)

Notes: The estimated elasticities of the industrial clustering variable (IC_{pg}^{2010}) refer to specifications (2) in Table A11.

TABLE A13: TSLS results using a geographic concentration measure

ependent variable	ΔTFP$_{ipg}$ (LP)		ΔTFP$_{ipg}$ (W)		ΔTFP$_{ipg}$ (ACF)		ΔLabor Productivity$_{ipg}$	
pecification	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
FP^{2010}_{ipg}	-0.400****	-0.398****	-0.403****	-0.401****	-0.418****	-0.418****	...	...
	(0.020)	(0.020)	(0.020)	(0.020)	(0.018)	(0.018)		
abor Productivity$^{2010}_{ipg}$	...	...	...	...	...	...	-0.463****	-0.458****
							(0.016)	(0.015)
GE^{2010}_{ipg}	-0.047****	-0.047****	-0.047****	-0.046****	-0.032****	-0.032****	-0.038****	-0.038****
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)	(0.007)
IZE_CLASS$^{2010}_{ipg}$	-0.062***	-0.067***	-0.067***	-0.071****	-0.042**	-0.045**	-0.114****	-0.115****
	(0.020)	(0.021)	(0.020)	(0.021)	(0.018)	(0.019)	(0.027)	(0.027)
C^{2010}_{pg}	0.107****	-0.091	0.105****	-0.091	0.050***	-0.067	0.132****	-0.036
	(0.027)	(0.072)	(0.027)	(0.071)	(0.019)	(0.041)	(0.026)	(0.094)
C^{2010}_{p}	-0.072***	-0.067***	-0.070***	-0.066***	-0.029*	-0.038**	-0.082****	-0.077***
	(0.025)	(0.022)	(0.025)	(0.022)	(0.017)	(0.015)	(0.024)	(0.026)
$\text{C}^{2010}_{pg}\times\text{OC}^{2010}_{p}$	-0.039**	...	-0.039**	...	-0.026***	...	-0.033	...
	(0.016)		(0.016)		(0.010)		(0.022)	
	-0.737****	-0.744****	-0.721****	-0.728****	-0.293****	-0.300****	-0.933****	-0.928****
	(0.075)	(0.075)	(0.074)	(0.074)	(0.055)	(0.058)	(0.086)	(0.086)
ndustry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
UTS-1 Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
umber of Firms	17,961	17,961	17,961	17,961	17,961	17,961	17,961	17,961
odel F statistic [p-value]	19.36 [0.000]	18.29 [0.000]	19.71 [0.000]	18.61 [0.000]	23.36 [0.000]	22.69 [0.000]	48.82 [0.000]	48.49 [0.000]
ean VIF	3.05	3.77	3.05	3.77	3.02	3.73	3.01	3.73
irst-stage F statistic [p-value]								
C^{2010}_{pg}	109.73 [0.000]	128.90 [0.000]	109.80 [0.000]	128.93 [0.000]	110.16 [0.000]	129.05 [0.000]	110.47 [0.000]	128.92 [0.000]
C^{2010}_{p}	127.71 [0.000]	110.56 [0.000]	127.78 [0.000]	110.58 [0.000]	128.28 [0.000]	110.71 [0.000]	127.30 [0.000]	110.56 [0.000]
$\text{C}^{2010}_{pg}\times\text{OC}^{2010}_{p}$	…	136.66 [0.000]	…	136.67 [0.000]	…	136.73 [0.000]	…	136.70 [0.000]
lasticity of GC^{2010}_{pg}	0.107****	0.055**	0.105****	0.054**	0.050***	0.030**	0.132****	0.086****
	(0.027)	(0.022)	(0.027)	(0.021)	(0.019)	(0.013)	(0.026)	(0.026)
Selection Equation								
umber of Firms	26,812	26,812	26,812	26,812	26,812	26,812	26,812	26,812
seudo R^2	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
odel Wald χ^2 [p-value]	1,852.28 [0.000]	1,844.58 [0.000]	1,846.65 [0.000]	1,838.79 [0.000]	1,854.11 [0.000]	1,850.27 [0.000]	1,890.81 [0.000]	1,886.17 [0.000]
$_0$: $\varphi(\cdot) = 0$	218.39 [0.000]	215.23 [0.000]	223.46 [0.000]	220.29 [0.000]	280.18 [0.000]	277.20 [0.000]	198.56 [0.000]	195.07 [0.000]

lotes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$; $****p < 0.001$. Bootstrapped (1,000 replications) standard errors are shown in parentheses, and they are clustered at the province-industry level. A pecifications include a constant term. LP denotes Levinsohn and Petrin's (2003) approach, W denotes Wooldridge's (2009) approach, while ACF denotes Ackerberg et al.'s (2015) approach to firms' TF stimation. λ denotes the inverse Mills ratio from the first-stage selection equations. $\varphi(\cdot)$ denotes the third-order polynomial included on the right-hand side of the selection equation as exclusion restriction.

TABLE A14: Growth elasticity of geographic concentration (TSLS results)

Dependent Variable	ΔTFP_{ipg} (LP)	ΔTFP_{ipg} (W)	ΔTFP_{ipg} (ACF)	$\Delta \text{Labor Productivity}_{ipg}$
Distribution of Organized Crime (OC_p^{2010})				
1st Percentile	0.185****	0.182****	0.116****	0.195***
	(0.046)	(0.045)	(0.031)	(0.068)
25th Percentile	0.084****	0.082****	0.049****	0.110****
	(0.019)	(0.019)	(0.013)	(0.025)
50th Percentile	0.059***	0.057***	0.032***	0.089****
	(0.021)	(0.057)	(0.012)	(0.025)
75th Percentile	0.045*	0.044*	0.023*	0.078**
	(0.024)	(0.023)	(0.013)	(0.028)
99th Percentile	-0.069	-0.069	-0.052	-0.017
	(0.063)	(0.062)	(0.036)	(0.082)

Notes: The estimated elasticities of the geographic concentration variable (GC_{pg}^{2010}) refer to specifications (2) in Table A13.

TABLE A15: TSLS results using an extended organized crime variables

ependent variable	$\Delta\mathrm{TFP}_{ipg}$ (LP)		$\Delta\mathrm{TFP}_{ipg}$ (W)		$\Delta\mathrm{TFP}_{ipg}$ (ACF)		$\Delta\mathrm{Labor\ Productivity}_{ipg}$	
pecification	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
FP_{ipg}^{2010}	-0.399****	-0.393****	-0.402****	-0.397****	-0.418****	-0.417****	…	…
	(0.020)	(0.020)	(0.020)	(0.020)	(0.018)	(0.018)		
$\mathrm{abor\ Productivity}_{ipg}^{2010}$	…	…	…	…	…	…	-0.464****	-0.453****
							(0.016)	(0.016)
GE_{ipg}^{2010}	-0.047****	-0.047****	-0.047****	-0.047****	-0.032****	-0.032****	-0.038****	-0.038****
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)	(0.007)
$\mathrm{IZE\_CLASS}_{ipg}^{2010}$	-0.057***	-0.059***	-0.062***	-0.063***	-0.039**	-0.040**	-0.108****	-0.104****
	(0.020)	(0.020)	(0.020)	(0.020)	(0.017)	(0.018)	(0.026)	(0.026)
C_{pg}^{2010}	0.137****	-0.193	0.134****	-0.192	0.064**	-0.133*	0.169****	-0.130
	(0.040)	(0.133)	(0.039)	(0.132)	(0.026)	(0.079)	(0.038)	(0.163)
C_{p}^{2010}	-0.098***	-0.096***	-0.095***	-0.094***	-0.041*	-0.055**	-0.114***	-0.113***
	(0.037)	(0.034)	(0.036)	(0.033)	(0.023)	(0.022)	(0.035)	(0.039)
$\mathrm{C}_{pg}^{2010}\times\mathrm{OC}_{p}^{2010}$	...	-0.076**	...	-0.076**	...	-0.050**	...	-0.069*
		(0.032)		(0.032)		(0.020)		(0.041)
	-0.722****	-0.713****	-0.707****	-0.699****	-0.286****	-0.285****	-0.917****	-0.892****
	(0.074)	(0.074)	(0.072)	(0.073)	(0.054)	(0.057)	(0.084)	(0.083)
ndustry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
UTS-1 Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
umber of Firms	17,961	17,961	17,961	17,961	17,961	17,961	17,961	17,961
odel F statistic [p-value]	19.77 [0.000]	17.80 [0.000]	20.09 [0.000]	18.14 [0.000]	23.35 [0.000]	22.60 [0.000]	49.46 [0.000]	46.85 [0.000]
ean VIF	3.08	3.69	2.08	3.69	3.05	3.66	3.04	3.65
irst-stage F statistic [p-value]								
C_{pg}^{2010}	105.81 [0.000]	101.25 [0.000]	105.86 [0.000]	101.29 [0.000]	106.26 [0.000]	101.54 [0.000]	106.94 [0.000]	101.57 [0.000]
C_{p}^{2010}	129.30 [0.000]	108.61 [0.000]	129.37 [0.000]	108.63 [0.000]	129.84 [0.000]	108.76 [0.000]	129.27 [0.000]	108.67 [0.000]
$\mathrm{C}_{pg}^{2010}\times\mathrm{OC}_{p}^{2010}$	…	149.07 [0.000]	…	149.63 [0.000]	…	149.22 [0.000]	…	148.79 [0.000]
lasticity of IC_{pg}^{2010}	0.137****	0.075**	0.134****	0.074**	0.064**	0.041*	0.169****	0.114***
	(0.040)	(0.036)	(0.039)	(0.036)	(0.026)	(0.021)	(0.038)	(0.042)
Selection Equation								
umber of Firms	26,812	26,812	26,812	26,812	26,812	26,812	26,812	26,812
seudo R^2	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
odel Wald χ^2 [p-value]	1,852.28 [0.000]	1,844.58 [0.000]	1,846.65 [0.000]	1,838.79 [0.000]	1,854.11 [0.000]	1,850.27 [0.000]	1,890.81 [0.000]	1,886.17 [0.000]
$_0$: $\varphi(\cdot) = 0$	218.39 [0.000]	215.23 [0.000]	223.46 [0.000]	220.29 [0.000]	280.18 [0.000]	277.20 [0.000]	198.56 [0.000]	195.07 [0.000]

otes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$; $****p < 0.001$. Bootstrapped (1,000 replications) standard errors are shown in parentheses, and they are clustered at the province-industry level. A pecifications include a constant term. LP denotes Levinsohn and Petrin's (2003) approach, W denotes Wooldridge's (2009) approach, while ACF denotes Ackerberg et al.'s (2015) approach to firms' TF stimation. λ denotes the inverse Mills ratio from the first-stage selection equations. $\varphi(\cdot)$ denotes the third-order polynomial included on the right-hand side of the selection equation as exclusion restriction.

TABLE A16: Growth elasticity of industrial clustering (TSLS results)

Dependent Variable	ΔTFP_{ipg} (LP)	ΔTFP_{ipg} (W)	ΔTFP_{ipg} (ACF)	$\Delta \text{Labor Productivity}_{ipg}$
Distribution of Organized Crime (OC_p^{2010})				
1st Percentile	0.341**** (0.103)	0.337**** (0.102)	0.215*** (0.069)	0.356*** (0.137)
25th Percentile	0.146**** (0.036)	0.143**** (0.036)	0.087**** (0.025)	0.178**** (0.047)
50th Percentile	0.098*** (0.033)	0.096*** (0.033)	0.056*** (0.021)	0.134**** (0.039)
75th Percentile	0.072* (0.037)	0.070* (0.037)	0.039* (0.022)	0.110*** (0.042)
99th Percentile	-0.149 (0.115)	-0.148 (0.114)	-0.105 (0.068)	-0.090 (0.140)

Notes: The estimated elasticities of the industrial clustering variable (IC_{pg}^{2010}) refer to specifications (2) in Table A15.

TABLE A17: TSLS results without correcting for sample selection

Dependent variable	$\Delta\text{TFP}_{\text{ipg}}$ (LP)		$\Delta\text{TFP}_{\text{ipg}}$ (W)		$\Delta\text{TFP}_{\text{ipg}}$ (ACF)	
Specification	(1)	(2)	(1)	(2)	(1)	(2)
$\text{TFP}_{\text{ipg}}^{2010}$	-0.282****	-0.319****	-0.290****	-0.327****	-0.386****	-0.399****
	(0.015)	(0.017)	(0.016)	(0.017)	(0.017)	(0.017)
$\text{AGE}_{\text{ipg}}^{2010}$	0.009*	-0.009**	0.009**	-0.009**	-0.004	-0.016****
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\text{SIZE\_CLASS}_{\text{ipg}}^{2010}$	0.117****	0.133****	0.113****	0.127****	0.044****	0.046****
	(0.008)	(0.009)	(0.009)	(0.009)	(0.006)	(0.006)
$\text{IC}_{\text{pg}}^{2010}$	0.082***	-0.078	0.082****	-0.079	0.057***	-0.083*
	(0.026)	(0.048)	(0.020)	(0.048)	(0.018)	(0.046)
$\text{OC}_{\text{p}}^{2010}$	-0.094****	-0.039**	-0.094****	-0.038**	-0.059****	-0.033**
	(0.021)	(0.017)	(0.017)	(0.017)	(0.015)	(0.016)
$\text{IC}_{\text{pg}}^{2010}\times\text{OC}_{\text{p}}^{2010}$	...	-0.029**	...	-0.029**	...	-0.029**
		(0.013)		(0.013)		(0.012)
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
NUTS-1 Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms	17,961	17,961	17,961	17,961	17,961	17,961
Model F statistic [p-value]	41.89 [0.000]	17.64 [0.000]	27.58 [0.000]	17.95 [0.000]	39.92 [0.000]	23.36 [0.000]
Mean VIF	3.12	3.76	3.12	3.76	3.09	3.73
First-stage F statistic [p-value]						
$\text{IC}_{\text{pg}}^{2010}$	110.07 [0.000]	104.37 [0.000]	110.07 [0.000]	104.37 [0.000]	109.98 [0.000]	104.30 [0.000]
$\text{OC}_{\text{p}}^{2010}$	133.27 [0.000]	112.51 [0.000]	133.28 [0.000]	112.52 [0.000]	133.27 [0.000]	112.51 [0.000]
$\text{IC}_{\text{pg}}^{2010}\times\text{OC}_{\text{p}}^{2010}$	...	148.30 [0.000]	...	148.30 [0.000]	...	148.31 [0.000]
Elasticity of $\text{IC}_{\text{pg}}^{2010}$	0.082***	0.031**	0.082****	0.030**	0.057***	0.026**
	(0.026)	(0.013)	(0.020)	(0.013)	(0.018)	(0.013)

Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$; $****p < 0.001$. Bootstrapped (1,000 replications) standard errors are shown in parentheses, and they are clustered at the province-industry level. All specifications include a constant term. LP denotes Levinsohn and Petrin's (2003) approach, W denotes Wooldridge's (2009) approach, while ACF denotes Ackerberg et al.'s (2015) approach to firms' TFP estimation.

TABLE A18: Growth elasticity of industrial clustering without correcting for sample selection (TSLS results)

Dependent Variable	ΔTFP_{ipg} (LP)	ΔTFP_{ipg} (W)	ΔTFP_{ipg} (ACF)
Distribution of Organized Crime (OC_p^{2010})			
1st Percentile	0.127***	0.127***	0.122***
	(0.047)	(0.047)	(0.044)
25th Percentile	0.052***	0.051***	0.047***
	(0.018)	(0.018)	(0.017)
50th Percentile	0.033**	0.033**	0.028**
	(0.014)	(0.014)	(0.013)
75th Percentile	0.023*	0.023*	0.018
	(0.013)	(0.013)	(0.013)
99th Percentile	-0.061	-0.062	-0.066*
	(0.041)	(0.041)	(0.039)

Notes: The estimated elasticities of the industrial clustering variable (IC_{pg}^{2010}) refer to specifications (2) in Table A17.

TABLE A19: TSLS results controlling for endogenous exit in TFP estimation

Dependent Variables	$\Delta\mathrm{TFP_{ipg}}$ (LP - endogenous exit)	
Specification	(1)	(2)
$\mathrm{TFP_{ipg}^{2010}}$	-0.399****	-0.394****
	(0.020)	(0.020)
$\mathrm{AGE_{ipg}^{2010}}$	-0.046****	-0.046****
	(0.006)	(0.006)
$\mathrm{SIZE\_CLASS_{ipg}^{2010}}$	-0.053***	-0.055***
	(0.020)	(0.020)
$\mathrm{IC_{pg}^{2010}}$	0.130****	-0.171
	(0.036)	(0.124)
$\mathrm{OC_{p}^{2010}}$	-0.090***	-0.093***
	(0.032)	(0.030)
$\mathrm{IC_{pg}^{2010}}\times\mathrm{OC_{p}^{2010}}$	...	-0.067**
		(0.029)
λ	-0.701****	-0.694****
	(0.073)	(0.073)
Industry Dummies	Yes	Yes
NUTS-1 Dummies	Yes	Yes
Number of Firms	17961	17961
Model F statistic [p-value]	19.93 [0.000]	18.04 [0.000]
Mean VIF	3.05	3.67
First-stage F statistic [p-value]		
$\mathrm{IC_{pg}^{2010}}$	105.80 [0.000]	101.24 [0.000]
$\mathrm{OC_{p}^{2010}}$	127.69 [0.000]	110.56 [0.000]
$\mathrm{IC_{pg}^{2010}}\times\mathrm{OC_{p}^{2010}}$	...	146.32 [0.000]
Elasticity of $\mathrm{IC_{pg}^{2010}}$	0.130****	0.078**
	(0.036)	(0.034)
Selection Equation		
Number of Firms	26,812	26,812
Pseudo R^2	0.06	0.06
Model Wald χ^2 [p-value]	1,854.49 [0.000]	1,846.84 [0.000]
$\mathrm{H_0}$: $\varphi(\cdot) = 0$	220.35 [0.000]	217.16 [0.000]

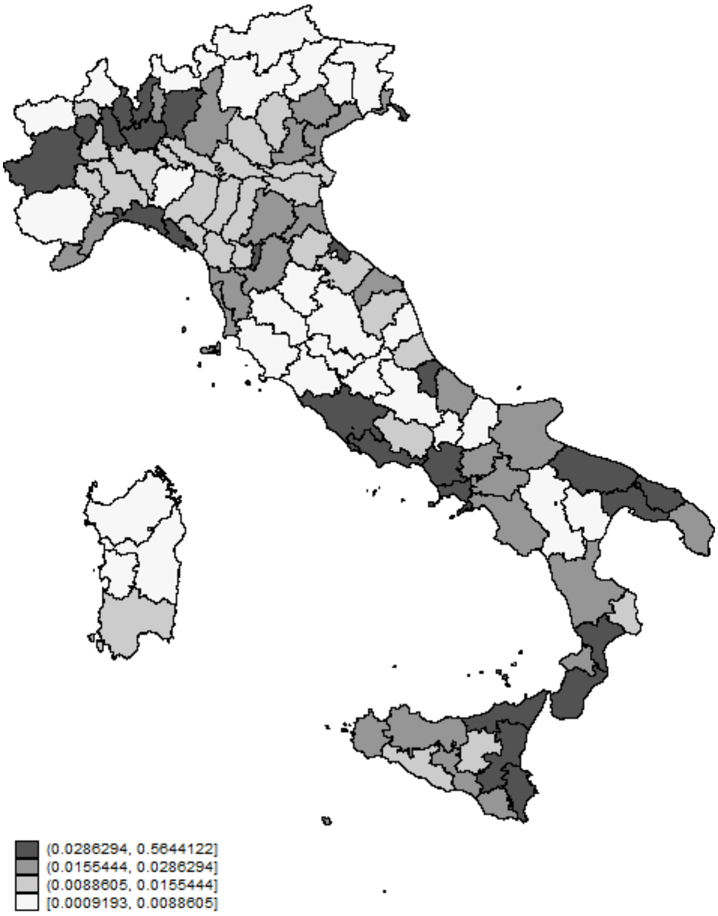
Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$; $****p < 0.001$. Bootstrapped (1,000 replications) standard errors are shown in parentheses, and they are clustered at the province-industry level. All specifications include a constant term. LP denotes Levinsohn and Petrin's (2003) approach, which is modified to account for endogenous exit following Olley and Pakes' (1996) approach. λ denotes the inverse Mills ratio from the first-stage selection equations. $\varphi(\cdot)$ denotes the third-order polynomial included on the right-hand side of the selection equation as exclusion restriction.

TABLE A20: Growth elasticity of industrial clustering controlling for endogenous exit in TFP estimation (TSLS results)

Dependent Variable	ΔTFP_{ipg} (LP - endogenous exit)
Distribution of Organized Crime (OC_p^{2010})	
1^{st} Percentile	0.300**** (0.086)
25^{th} Percentile	0.127**** (0.032)
50^{th} Percentile	0.085*** (0.033)
75^{th} Percentile	0.062* (0.037)
99^{th} Percentile	-0.133 (0.108)

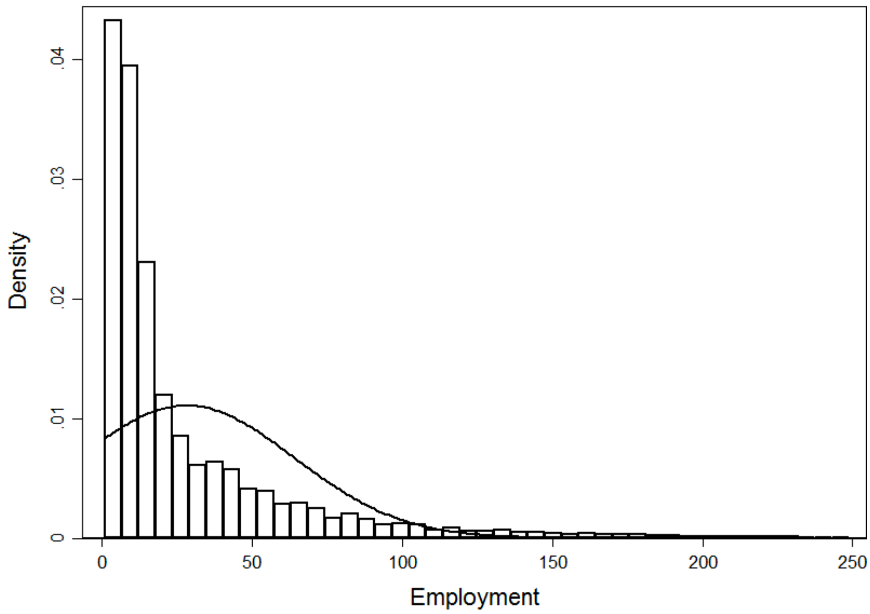
Notes: The estimated elasticities of the industrial clustering variable (IC_{pg}^{2010}) refer to specification (2) in Table A19.

FIGURE A1: Spatial distribution of the organized crime variable



Notes: Quartile distribution of the organized crime variable ($e(OC_p^{2010})$).

FIGURE A2: Distribution of firm-level employment in 2010



Notes: The solid line refers to the normal curve. The 2010 employment variable ranges in the interval [1, 249], and it presents mean value equal to 28.02 and standard deviation equal to 36.98. The null hypothesis of normality is rejected with p-value equal to 0.000.