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Three Essays on Spatial Agglomeration and Firm Performance

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Introduction

Does regional science matter nowadays? Several researchers have tried - and are still trying - to answer this question at the light of the fact that fast connections and communication technologies allow economic actors to easily interact and do business with global partners. Anyhow, the local and global dimensions seem to play a complementary role in influencing firms' economic performance and behaviour rather than being substitute factors. In fact, there are many cases of excellence among Italian industrial districts, high-tech clusters, and innovative milieus which suggest the relevance of the local dimension for firms to grow and compete.

The analysis of the local economic dimension dates back to the pioneering contribution of MARSHALL on the industrial district concept (*Principles of Economics*, 1890, Macmillan, London), which highlights the peculiar advantages for a firm from being located in an industrially specialised local system. According to MARSHALL's (1890) analysis, firms operating in a spatially bounded - and specialised - area can benefit from both tangible and intangible effects. Tangible effects are mainly related to the local availability of inputs' suppliers and specialised workers, the reduction of transportation costs, and the emerging of external-scale economies. On the contrary, intangible effects are related to the reduction of transaction costs (favoured by face-to-face and repeated interactions which increase trust, reputation, and reciprocity among the local actors), and the spread of knowledge and (tacit) information flows concerning production processes, technologies, and innovation practices.

Moving from these intuitions, economists started to analyse the role played by local forces in influencing the economic performance of regional systems and individual actors (i.e. firms). Attention has also been paid to local-based phenomena other than specialised agglomerated areas. Among these, the role of urban areas and the advantages related to the location in large and industrially diversified cities have been deeply analysed by geographers and regional economists.

In particular, agglomeration forces concerning - and arising from - the spatial concentration of the economic activity received great attention in both the theoretical and the empirical literature. The contribution of GLAESER, KALLAL, SCHEINKMAN and SHLEIFER ("Growth in Cities", *Journal of Political Economy*, 1992, Vol. 100, No. 6, pp. 1126-1152) represented the first attempt to empirically analyse the causal relationship between agglomeration externalities and local economic performance, and it began a wide cross-county literature on the topic.

This Thesis moves in this direction and tries to contribute to the debate concerning the relationship between spatial agglomeration forces and firms' economic performance. Specifically, it comes as a collection of three empirical papers dealing with this topic from very different perspectives.

The first chapter of the Thesis is entitled "Productivity, Credit Constraints and the Role of Short-Run Localization Economies: Micro-Evidence from Italy". This chapter is single-authored and is forthcoming in *Regional Studies* (doi:10.1080/00343404.2015.1064883). This paper investigates whether Italian manufacturing firms' productivity is affected by credit constraints, and whether short-run localisation economies foster productivity both directly and indirectly, moderating the negative effects of credit rationing via inter-firm credit relationships. The empirical exercise is based on a sample of 12,524 firms observed over the period 1999-2007 and drawn from the *AIDA* databank (Bureau Van Dijk), and it is carried out in three steps. First, Total Factor Productivity is estimated at the firm level through the approach proposed by WOOLDRIDGE ("On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables", *Economics Letters*, 2009, Vol. 104, No. 3, pp. 112-114). Second, dynamic investment equations are estimated to investigate whether firms are credit constrained, and to test the potential moderation effect of short-run localisation economies on the investment-to-cash flow sensitivity. Third, an instrumental-variable approach is employed to test whether firms' productivity is negatively affected by credit constraints (i.e. the marginal effect of cash flow on investments), and whether short-run localisation economies positively affect productivity both directly and indirectly, downsizing the negative effects of credit rationing. The results suggest that firms are affected by credit rationing, and that localisation economies positively moderate the investment-to-cash flow sensitivity favouring inter-firm trade credit. It emerges a negative effect of credit rationing on firms' productivity, while localisation economies have both a direct and an indirect positive effect on productivity. In fact, short-run localisation economies seem to reduce the negative credit constraints-productivity relationship by about 4.5%. Finally, the results suggest a complementary effect between localisation economies and the local banking structure: the positive moderation effect of localisation economies on both firms' investment-to-cash flow sensitivity and the credit constraints-productivity relationship increases as the density of bank branches in the local system increases.

The second chapter is entitled "Industrial Clusters, Organised Crime and Productivity Growth in Italian SMEs" and is co-authored with Andrés Rodríguez-Pose (LSE). This paper empirically investigates whether organised crime (namely, *mafia*-type criminality) affects a firm's performance (defined in terms of Total Factor Productivity growth) both directly and indirectly, downsizing positive externalities arising from the geographic concentration of (intra- and inter-industry) market-related firms. Therefore, this paper investigates the simultaneous role played by - and the interplay of - market-based agglomeration economies and organised crime in influencing manufacturing small and medium sized firms' productivity growth. On the one hand, firms operating in a local system characterised by a high density of horizontally- and vertically-interconnected firms (in terms of input-output relationships) may benefit from both tangible (e.g. the reduction of transportation costs, the local availability of inputs' suppliers) and intangible (e.g. the reduction of transaction costs) agglomeration externalities which are likely to foster their productivity growth. On the other hand, organised crime is likely to negatively affect both the socio-economic environment and firms' performance, for instance imposing protection rackets, altering market rules and competition processes. In particular, criminal organisations may break established economic networks among firms, for instance imposing to local firms the acquisition of inputs from "illicit" firms controlled by the criminal organisation itself. The empirical analysis covers a large sample of Italian manufacturing small and medium sized firms observed over the period 2008-2011, and it employs a two-step sample-selection model to control for firm exit over the three-year growth period. The robustness of the results is tested controlling for potential endogeneity of the variables capturing industrial clustering and organised crime, as well as using two different approaches to estimate Total Factor Productivity. The results suggest a negative direct effect of organised crime on firms' productivity growth, while location in a dense local industrial system fosters productivity growth. Moreover, the positive effect of industrial clustering on productivity growth decreases as the level of organised crime increases in the local system, and that this negative moderation effect of organised crime is greater for smaller than for larger firms. Finally, the results suggest that the extortion crime has a very strong incidence in weakening a firm's performance.

The third chapter is entitled "Agglomeration, Heterogeneity and Firm Productivity" and is co-authored with Giulio Cainelli (University of Padova). This paper analyses the relationship between agglomeration (i.e. localisation- vs. diversification-type) economies and firms' short-run productivity growth using Italian manufacturing firm-level data. The analysis deals with two key issues. First, it deals with the Modifiable Areal Unit Problem (MAUP) using distance-based agglomeration measures computed for each firm in the sample over a continuous space, thus avoiding the use of pre-defined spatial units of analysis. Second, it explicitly tests the hypothesis of firm heterogeneity in the context of agglomeration phenomena, i.e. it considers the firms located within a given geographic area as heterogeneous units which may contribute to the production of the agglomeration externalities in different ways, and with a different intensity, according to their specific characteristics (defined in terms of size and Total Factor Productivity). This means that firms can be seen both as receivers of the agglomeration externalities, and as producers of these externalities. The results suggest that intra-industry (i.e. localisation-type) externalities have a positive effect on firms' productivity growth at short distances, while a negligible effect at a longer distance (i.e. after 15 km). Moreover, this positive effect seems to decrease as the distance increases. On the contrary, inter-industry (i.e. diversification-type) externalities have a negative effect on firms' productivity growth at a very short distance (i.e. within 5 km), while a positive effect at a longer distance (i.e. after 15 km). Therefore, it emerges a sort of substitution effect between intra- and inter-industry externalities at different distances. It also emerges that firm heterogeneity (in terms of size and productivity) matters in the generation of intra-industry externalities: in fact, the decreasing-with-distance pattern characterising their positive effect changes to an increasing-with-distance pattern when neighbour firms' characteristics are accounted for. It follows an attenuation of the substitution effect between intra- and inter-industry externalities. In fact, they seem to have opposing effects at short distances (i.e. within 15 km), while both types of externalities seem to foster firms' productivity growth at a longer distance (i.e. after 15 km). Moreover, inter-industry externalities seem to have a greater effect on short-run productivity growth than intra-industry externalities.

Introduzione

Quanto contano gli studi regionali oggigiorno? Molti ricercatori hanno cercato - e ancora cercano - di rispondere a questa domanda alla luce dello sviluppo di mezzi e tecnologie di comunicazione che consentono agli attori economici di interagire e condurre affari con partner globali. Ad ogni modo, le dimensioni locale e globale sembrano avere ruoli complementari, anziché sostitutivi, nell'influenzare la performance e le scelte economiche delle imprese. Ciò emerge chiaramente se si considerano casi di successo tra i distretti industriali italiani, i cluster high-tech e i sistemi locali innovativi, che evidenziano la rilevanza della dimensione locale nel promuovere la crescita e la competitività delle imprese.

L'analisi della dimensione economica locale trova origine nello studio pioneristico di MARSHALL (*Principles of Economics*, 1890, Macmillan, London) sul concetto di distretto industriale, in cui sono messi in evidenza i vantaggi peculiari che un'impresa può trarre dall'essere localizzata in un sistema industriale locale altamente specializzato. Nello specifico, MARSHALL (1890) sottolinea come un'impresa che operi in una località geograficamente delimitata - e specializzata in termini di produzione industriale - possa trarre beneficio sia da fattori tangibili, sia da fattori intangibili. I primi riguardano la disponibilità "locale" di fornitori e lavoratori altamente specializzati, la riduzione dei costi di trasporto, e l'emergere di economie di scala esterne. I secondi, al contrario, riguardano la riduzione dei costi di transazione, che risulta facilitata da interazioni dirette e ripetute (tali da accrescere il livello di fiducia, reputazione e reciprocità) tra gli attori economici locali, e la diffusione di conoscenza e flussi di informazioni (tacite) riguardanti processi produttivi, tecnologie e pratiche innovative.

L'analisi di MARSHALL (1890) ha spinto molti economisti ad analizzare la relazione tra fattori legati alla dimensione locale e performance economica, sia a livello di sistemi regionali che di imprese. Nel tempo, diverse tipologie di "forze" locali sono state oggetto di studio, oltre ai conglomerati produttivi altamente specializzati. Ad esempio, economisti regionali e geografi hanno rivolto la loro attenzione verso la dimensione urbana e i vantaggi legati alla localizzazione in città caratterizzate da un'ampia diversificazione della struttura industriale.

In particolare, numerosi contributi teorici ed empirici hanno sottolineato la rilevanza di esternalità agglomerative legate alla concentrazione spaziale delle attività economiche. Il contributo di GLAESER, KALLAL, SCHEINKMAN and SHLEIFER ("Growth in Cities", *Journal of Political Economy*, 1992, Vol. 100, No. 6, pp. 1126-1152) è stato il primo tentativo di analizzare empiricamente la relazione di causalità tra esternalità agglomerative e performance economica locale, dando il via ad un'ampia letteratura sul tema.

Il presente elaborato (Tesi) si basa su questa letteratura, e cerca di contribuire al dibattito avente ad oggetto la relazione tra forze legate all'agglomerazione spaziale delle attività economiche e performance delle imprese. Nello specifico, questa Tesi è costituita da tre capitoli (papers) che analizzano la suddetta relazione da punti di vista molti differenti.

Il primo capitolo della Tesi è intitolato "Productivity, Credit Constraints and the Role of Short-Run Localization Economies: Micro-Evidence from Italy". Questo capitolo è a firma singola, ed è stato accettato per pubblicazione dalla rivista *Regional Studies* (doi:10.1080/00343404.2015.1064883). Questo capitolo analizza la relazione tra produttività di impresa, razionamento creditizio ed economie di localizzazione di breve termine. Nello specifico, analizza gli effetti diretti di razionamento creditizio ed economie di localizzazione sulla produttività di impresa, così come il potenziale effetto di moderazione (positivo) che le economie di localizzazione possono avere sulla relazione (negativa) tra razionamento creditizio e produttività, promuovendo fenomeni di "inter-firm trade credit". L'analisi empirica utilizza dati di fonte *AIDA* (Bureau Van Dijk) relativi ad un campione di 12.524 imprese osservate nel corso del periodo 1999-2007. L'analisi è condotto in tre fasi. In primo luogo, la Produttività Totale dei Fattore è stimata a livella di impresa utilizzando l'approccio proposto da WOOLDRIDGE ("On

Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables", *Economics Letters*, 2009, Vol. 104, No. 3, pp. 112-114). Successivamente, una serie di funzioni di investimento dinamiche sono stimate al fine di analizzare se le imprese del campione siano oggetto di razionamento creditizio, e di testare il potenziale effetto di moderazione delle economie di localizzazione di breve termine sulla relazione tra investimenti e cash flow di impresa. Infine, sono stimati una serie di modelli per variabili strumentali al fine di analizzare se la produttività di impresa sia influenzata negativamente dal razionamento creditizio (definito come effetto marginale del cash flow sugli investimenti), e se le economie di localizzazione di breve termine abbiano sia un effetto positivo diretto sulla produttività, sia un effetto positivo indiretto tale da ridurre gli effetti negativi legati al razionamento creditizio. I risultati empirici suggeriscono che le imprese del campione siano oggetto di razionamento creditizio, e che le economie di localizzazione abbiano un effetto positivo tale da moderare la dipendenza degli investimenti dal cash flow favorendo fenomeni di "inter-firm trade credit". Emerge inoltre un effetto negativo del razionamento creditizio sulla produttività di impresa, mentre le economie di localizzazione sembrano avere un effetto diretto positivo sulla produttività. Allo stesso modo, le economie di localizzazione sembrano avere anche un effetto indiretto positivo sulla produttività: infatti, i risultati mostrano che l'effetto negativo del razionamento creditizio sulla produttività diminuisce del 4,5% quando l'effetto di moderazione delle economie di localizzazione è preso in considerazione. Infine, i risultati mostrano un effetto di complementarietà tra economie di localizzazione e struttura bancaria a livello locale. Infatti, l'effetto indiretto positivo delle economie di localizzazione risulta crescente al crescere della densità di filiali bancarie nel sistema locale di appartenenza dell'impresa.

Il secondo capitolo è intitolato "Industrial Clusters, Organised Crime and Productivity Growth in Italian SMEs", ed è co-autorato con Andrés Rodríguez-Pose (LSE). Questo secondo capitolo analizza il ruolo della criminalità organizzata (di tipo mafioso) sulla performance di impresa (definita in termini di crescita della Produttività Totale dei Fattori), considerando anche il suo potenziale effetto indiretto (negativo) sulla relazione (positiva) tra esternalità agglomerative legate alla co-localizzazione di imprese fornitrici (industrial clustering) e crescita della produttività di un campione di piccole e medie imprese manifatturiere italiane. Pertanto, sono presi in esame due differenti (e contrastanti) fattori definiti a livello locale: la criminalità organizzata e la concentrazione spaziale di imprese connesse da relazioni di mercato. Da una parte, imprese che operano in sistemi locali caratterizzati da un'alta densità di imprese potenzialmente connesse (orizzontalmente e verticalmente) da relazioni di mercato possono beneficiare di esternalità agglomerative sia tangibili (ad esempio, la riduzione dei costi di trasporto, la disponibilità di fornitori a livello locale) che intangibili (ad esempio, la riduzione dei costi di transazione), che tendono a favorire la crescita di impresa. Dall'altra parte, la presenza di organizzazioni criminali tende ad avere conseguenze negative sia per l'ambiente socio-economico, sia per la performance di impresa, ad esempio a causa dell'imposizione del pagamento del pizzo, di azioni lesive delle regole di mercato e dei processi competitivi tra imprese. In particolare, la criminalità organizzata opera nel mercato per mezzo di imprese "illegali" direttamente controllate, la cui presenza ed attività (ad esempio, l'imposizione dell'acquisto di input alle imprese "legali") tendono ad indebolire le relazioni di mercato esistenti tra le imprese locali. L'analisi empirica è basata su un campione di piccole e medie imprese manifatturiere italiane osservate nel periodo 2008-2011. L'analisi è condotta applicando modelli di tipo "sample selection", e la robustezza dei risultati è testata controllando per la potenziale endogeneità delle variabili che catturano i fenomeni di criminalità organizzata e agglomerazione industriale, così come stimando la Produttività Totale dei Fattori a livello di impresa per mezzo di due approcci econometrici differenti. I risultati mostrano un effetto diretto negativo della criminalità organizzata sulla crescita della produttività di impresa. AL contrario, la crescita della produttività trae beneficio da un'alta densità di imprese circostanti potenzialmente connesse da relazioni di mercato. I risultati suggeriscono inoltre un effetto negativo indiretto della criminalità organizzata, la cui presenza nel sistema locale sembra ridurre sensibilmente gli effetti positivi dell'agglomerazione di imprese sulla crescita della produttività. Questo risultato sembra particolarmente accentuato per le imprese di più piccole dimensioni. Inoltre, il crimine di estorsione sembra giocare un ruolo chiave in questo scenario.

Il terzo capitolo è intitolato "Agglomeration, Heterogeneity and Firm Productivity", ed è co-autorato con Giulio Cainelli (Università di Padova). Questo capitolo analizza la relazione tra economie di agglomerazione (nello specifico, economie di localizzazione e di diversificazione) e crescita della produttività di breve periodo utilizzando un campione di imprese manifatturiere italiane. Nello specifico, due aspetti chiave sono presi in considerazione. Il primo riguarda il cosiddetto "Modifiable Areal Unit Problem (MAUP)", che è trattato costruendo variabili di agglomerazione "distance-based" a livello di impresa e assumendo lo spazio come continuo, e cioè evitando l'uso di aree geografiche pre-definite come unità spaziali di analisi. Il secondo riguarda l'ipotesi di eterogeneità di impresa, che nel contesto dei fenomeni agglomerativi si riferisce all'idea che le imprese co-localizzate nello spazio siano unità eterogenee in grado di contribuire alla produzione delle esternalità agglomerative in maniera (e con intensità) differente in base alle loro specifiche caratteristiche (nello specifico, dimensione e Produttività Totale dei Fattori). Assumere eterogeneità di impresa implica assumere che le imprese non solo traggano beneficio dalle esternalità agglomerative, ma anche agiscano come loro "generatori". I risultati suggeriscono che le esternalità intra-industriali (economie di localizzazione) abbiano un effetto positivo sulla crescita della produttività nella breve distanza, mentre un effetto statisticamente non significativo per distanze maggiori (oltre i 15 km). Inoltre, questo effetto positivo risulta inversamente proporzionale rispetto alla distanza. Al contrario, le esternalità inter-industriali (economie di diversificazione) hanno un effetto negativo nella breve distanza (entro i 5 km), mentre un effetto positivo nella lunga distanza (oltre i 15 km). Pertanto, sembra emergere un effetto di sostituzione tra economie di localizzazione e di diversificazione a distanze differenti. I risultano mostrano inoltre l'importanza di considerare l'eterogeneità di impresa (in termini di dimensione e produttività) nel processo di generazione delle esternalità intra-industriali: infatti, quando si tiene conto delle caratteristiche specifiche delle imprese co-localizzate, emerge un effetto positivo delle economie di localizzazione che risulta crescente al crescere della distanza. Emerge quindi un'attenuazione dell'effetto di sostituzione tra esternalità intra- e inter-industriali, che sembrano avere effetti opposti nella breve distanza (entro i 15 km), mentre entrambe sembrano avere un effetto positivo sulla crescita della produttività nella lunga distanza (oltre i 15 km). Inoltre, le economie di diversificazione sembrano avere un effetto maggiore sulla crescita della produttività di breve termine rispetto alle economie di localizzazione.

Chapter 1

Productivity, Credit Constraints and the Role of Short-Run Localization Economies: Micro-Evidence from Italy*

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Abstract: This paper investigates whether Italian manufacturing firms' productivity is affected by credit constraints, and whether short-run localization economies foster productivity both directly and indirectly, moderating the negative effects of credit rationing via inter-firm credit relationships. Results suggest a negative effect of credit rationing on firms' productivity, while a positive relationship exists between short-run localization economies and productivity. It emerges that location in an industrially concentrated area reduces firms' investment-to-cash flow sensitivity, and that it positively moderates the negative effect of credit rationing on productivity. Moreover, the positive moderation effect seems to be increasing in the density of the local banking system.

Keywords: Total Factor Productivity; Credit rationing; Localization economies

JEL classification: C23; D24; G32; R12

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1. INTRODUCTION

The determinants of firms' productivity have been widely investigated (SYVERSON, 2011) and some contributions have also considered, besides traditional factors, the role of financial variables (CARREIRA and SILVA, 2010) and agglomeration economies (ROSENTHAL and STRANGE, 2004). On the one hand, contributions studying the effects of credit rationing on firms' productivity underline a negative credit constraints-productivity relationship. Firms facing difficulties in obtaining credit from banks and institutional markets have to rely on internally generated resources, thus being limited in their investment decisions with negative effects on productivity (CHEN and GUARIGLIA, 2013). On the other hand, the literature on agglomeration economies emphasizes how positive externalities arising from the local economic environment foster firms' productivity. Firms in agglomerated areas benefit from spillover effects in terms of external-scale economies, the reduction of transaction costs, knowledge transmission and, in particular, localization externalities seem to play a key role in enhancing firms' productivity (BEAUDRY and SCHIFFAUEROVA, 2009).

This paper contributes to the literature on the determinants of firms' productivity by linking the abovementioned research streams. It investigates whether Italian manufacturing firms' productivity is sensitive to credit constraints, whether it is fostered by short-run localization externalities, and whether location in industrially concentrated areas downsizes the negative effect of credit constraints on productivity. In fact, the geographic concentration of industries may positively moderate the credit constraints-productivity relationship promoting inter-firm trade credit as an alternative source of funds, which has been found particularly relevant in specialized productive clusters (DEI OTTATI, 1994).

The analysis employs a sample of 11,953 Italian manufacturing firms observed over the period 1999-2007. Results suggest a negative credit constraints-productivity relationship, while a positive relationship exists between localization externalities and productivity. Geographic concentration positively moderates firms' investment-to-cash flow sensitivity, and reduces the negative credit constraints-productivity relationship. Finally, the moderation effect of localization externalities is increasing in the density of bank branches.

The paper is organized as follows. The second section discusses the related literature. The third section describes the dataset and methodology. The fourth section presents the results. The fifth section concludes.

2. RELATED LITERATURE

2.1. Credit constraints and productivity

Many theoretical contributions underline the importance of financial markets in promoting economic growth through the provision of resources necessary to finance productivity-enhancing technological innovations (KING and LEVINE, 1993). Along these lines, several contributions focused on the relationship between finance and firms' investment decisions. The rationale is that financial markets may finance firms to undertake new investment projects, and they may facilitate efficient resources allocation and capital accumulation (AGHION *et al.*, 2010). However, under the assumptions of imperfect financial markets and asymmetric information, firms may face difficulties in raising credit from banks and institutional markets. Consequently, credit-constrained firms have to rely on internal funds, and they cannot allocate efficiently their resources to undertake productivity-enhancing investments (AYYAGARI *et al.*, 2007).

Evidence shows negative effects of credit rationing on firms' investments (FAZZARI *et al.*, 1988; LOVE, 2003; GUARIGLIA, 2008), and since investments represent key sources of productivity, a relationship between financial factors and firms' productivity is likely to emerge (GATTI and LOVE, 2008; CHEN and GUARIGLIA, 2013). Suppose a firm faces two possible scenarios: either it can get the resources needed to finance new productivity-enhancing investments from financial institutions, or financial markets' imperfections are such that a firm cannot raise external funds to finance investments. In the first case, firms will undertake new projects independently of cash flow availability. In the second case, firms willing to make new investments have to rely on internal resources with the consequence that decisions on new investments are subject to cash flow availability. It follows that credit-constrained firms can enhance their productivity only if they have internally the resources required to undertake productivity-enhancing investments. Hence, the more firms are credit constrained, the more their investment decisions depend on cash flow availability and, consequently, the higher it turns to be the sensitivity of productivity to credit rationing.

For the Italian case, ALBARETO and FINALDI RUSSO (2012) underline that the share of manufacturing firms (with at least 50 employees) asking for credit but not receiving it increased by more than 3% over the period 1999-2003, while it decreased from about 6.5% to about 2% over the period 2003-07. Similarly, the total factor productivity (TFP) in the manufacturing industry decreased by 3.51% over the period 1999-2003, while it decreased by 0.90% over period 2003-07. This evidence suggests a relationship between external funds' availability and manufacturing firms' productivity during the period investigated in this paper. Therefore, the following hypothesis is specified:

Hypothesis 1: Firms are credit constrained, and their productivity is negatively affected by credit rationing.

2.2. Localization economies and productivity

The literature on agglomeration economies, which can be defined as local and spatially bounded sources of positive externalities arising from the geographic proximity of economic actors (ROSENTHAL and STRANGE, 2004), builds on the idea that agglomeration induces tangible and intangible benefits for local economic agents, which translate in productivity growth both at firm and local levels (PUGA, 2010).

Localization externalities arising from the spatial concentration of firms operating in the same industry received much attention. GLAESER *et al.* (1992) formalized their role in the Marshall-Arrow-Romer (MAR) model (MARSHALL, 1920; ARROW, 1962; ROMER, 1986), which claims that firms within the same industry and located in a spatially bounded area benefit from intra-industry knowledge and technological spillovers facilitated by the transmission of information: the sharing of a common competence base allows effective learning of new or transmitted knowledge, which requires cognitive proximity among actors (NOOTEBOOM, 2000). Localization economies may also produce advantages concerning the reduction of transportation costs, the emerging of external-scale economies, and the availability of highly specialized workers and inputs' suppliers, all representing sources of higher productivity for firms (DURANTON and PUGA, 2004; MARTIN *et al.*, 2011). The general result of firm-level studies on the agglomeration-productivity relationship is that localization economies tend to foster firms' productivity (see BEAUDRY and SCHIFFAUEROVA, 2009, for a review of empirical works).

The contribution of this paper to the existing literature is twofold. First, it analyses whether localization economies directly affect firms' productivity. Specifically, short-run economies are analysed since the empirical investigation considers yearly levels of firms' productivity. Short-run agglomeration economies tend to capture labour and input markets-related externalities, while knowledge-based spillovers may require a longer time interval to materialize (MARTIN *et al.*, 2011). Therefore, the analysis focuses on the supply-side advantages of agglomeration economies, i.e. those related to the sharing of intermediate inputs' suppliers, the matching between buyers and suppliers, and the sharing of a pool of specialized workers (PUGA, 2010). This leads to the following hypothesis:

Hypothesis 2: Sort-run localization economies foster firms' productivity.

Second, this paper investigates whether localization economies have also an indirect positive effect on productivity by relating the analysis of agglomeration economies to that of credit constraints. Being part of a highly agglomerated area may allow firms (partially) to overcome the negative effects of credit rationing thanks to inter-firm relationships, which materialize on both the productive and the financial sides. Production linkages may entail inter-firm credit relationships (CAINELLI *et al.*, 2012), which represent an alternative, non-institutional channel through which firms can alleviate financial constraints (MENICHINI, 2011; FERRANDO and MULIER, 2013).

Inter-firm credit realizes in a circular way: firms can obtain credit from suppliers through better contracts or delayed payments and, vice versa, they can extend credit to customers (FERRANDO and MULIER, 2013). Inter-firm credit has been found to be particularly relevant in productive clusters, e.g. Italian industrial districts: evidence shows that geographic proximity, reciprocity, and repeated transactions between suppliers and customers increase reputation and trust and reduce asymmetric information problems, thus favouring inter-firm credit relationships (DEI OTTATI, 1994; UGHETTO, 2009; SCALERA and ZAZZARO, 2011).

Geographic concentration of firms within an industry is an industrial district-type source of external economies, and localization externalities diffuse across firms often related by production linkages. Therefore, geographic concentration may alleviate firms' credit constraints promoting inter-firm trade credit (via production linkages, mainly based on input sharing) among firms in the local system, thus favouring a reduction of the negative effects of credit rationing on productivity. Hence, the following hypothesis is specified:

Hypothesis 3: Geographic concentration alleviates firms' credit constraints, thus reducing the negative effects of credit rationing on productivity.

3. DATA AND METHODOLOGY

3.1. The dataset

The analysis employs balance sheet data drawn from the *AIDA* databank (Bureau Van Dijk). The dataset was constructed by considering manufacturing firms with positive values of turnover and value added over seven consecutive years during the period 1998-2007, and reporting a value added-to-turnover ratio ≥ 0 and ≤ 1. Firms in the first and last percentiles of the sales growth distribution have been removed to avoid outlying observations, as well as firms with inconsistent data in terms of value added, total labour costs, tangible assets, production costs, net income and annual depreciation. This first cleaning procedure left an unbalanced panel of 12,524 firms observed over the period 1999-2007, which was used to estimate firm's productivity. The final dataset, resulting in an unbalanced panel of 11,953 firms observed over the period 1999-2007, was obtained by removing firms without information on their year of set up, their location at the provincial level (NUTS-3 level of the European Union territorial classification - Nomenclature des Unités Territoriales Statistiques), and employment. Appendix A describes the structure of the sample and discusses potential drawbacks.

3.2. Econometric methodology

The analysis is conducted in three steps. First, firms' TFP is estimated by employing the approach proposed by WOOLDRIDGE (2009). Second, dynamic investment equations are estimated to investigate whether firms are credit constrained, and to test the potential moderation effect of geographic concentration on the investment-to-cash flow sensitivity. Third, an instrumental-variable approach is employed to test whether productivity is negatively affected by credit constraints (the marginal effect of cash flow on investments), and whether geographic concentration positively affects productivity both directly and indirectly, downsizing the (potential) negative effect of credit rationing.

3.2.1. Productivity estimation

Firms' TFP is estimated as the residual of a Cobb-Douglas production function that, taking logarithms, can be specified as follows:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + u_{it} + \eta_{it} \tag{1}$$

where β_0 represents the mean efficiency level across firms and over time; y_{it}, k_{it} and l_{it} represent, respectively, value added, capital input and labour input of firm i at time t; η_{it} is an independent and identically distributed (i.i.d.) component representing productivity shocks not affecting a firm's decision process; and:

$$\omega_{it} = \beta_0 + u_{it}$$

represents firm-level productivity, assuming that ω_{it} is a state variable-transmitted component affecting a firm's decision process (VAN BEVEREN, 2012). The estimated productivity is then obtained by solving for ω_{it}:

$$\hat{\omega}_{it} = \hat{\beta}_0 + \hat{u}_{it} = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} \tag{2}$$

Ordinary least squares (OLS) or fixed effects (FE) estimation of equation (1) lead to biased productivity estimates due to the "simultaneity bias", which concerns some form of endogeneity in the inputs due to the correlation between the level of inputs chosen by the firm and unobservable productivity shocks. This problem emerges since firms can choose the level of inputs on the base of prior beliefs on productivity levels, which, however, cannot be observed by the econometrician (SYVERSON, 2011).

Building on the two-step semi-parametric approach proposed by LEVINSOHN and PETRIN (2003), which uses intermediate inputs (m_{it}) as proxy variable to control for unobserved productivity, thus solving the simultaneity problem between input choices and productivity shocks, WOOLDRIDGE (2009) proposes to estimate β_k and β_l using a more efficient one-step generalized method of moments (GMM) estimator, thus correcting possible collinearity between labour and intermediate inputs characterizing LEVINSOHN and PETRIN's (2003) approach (ACKERBERG *et al.*, 2006).[1] WOOLDRIDGE (2009) suggests estimating simultaneously 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 by exploiting information in the second equation. Given a production function (1), and assuming absence of correlation of η_{it} with current and past values of capital, labour and intermediate inputs, and restriction of the dynamics of the unobserved productivity component (ω_{it}), β_k and β_l can be identified by estimating the following two equations:

$$\begin{cases} y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + g(k_{it}, m_{it}) + \eta_{it} \\ y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + j[g(k_{it-1}, m_{it-1})] + \eta_{it} + a_{it} \end{cases} \tag{3}$$

where a_{it} denotes productivity innovations and is correlated with l_{it} and m_{it}, while it is uncorrelated with k_{it} and past values of k_{it}, l_{it} and m_{it}; $g(\cdot)$ may be specified as a low-degree polynomial of order up to three; and $j(\cdot)$ (i.e. the productivity process) may be defined as a random walk with drift, such that:

$$\omega_{it} = \tau + \omega_{it-1} + a_{it}$$

Then, equation (1) can be re-specified as follows (GALUŠČÁK and LÍZAL, 2011):

$$y_{it} = (\beta_0 + \tau) + \beta_k k_{it} + \beta_l l_{it} + g(k_{it-1}, m_{it-1}) + \eta_{it} + a_{it} \tag{4}$$

and can be estimated through an instrumental-variable approach using polynomials in k_{it-1} and m_{it-1} of order up to three approximating for $g(\cdot)$; 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). Appendix B describes the variables entering the production function and presents results of the TFP estimation.

3.2.2. Credit constraints and localization economies

The following dynamic investment equation is estimated to evaluate whether firms are affected by credit constraints, and whether geographic concentration reduces the investment-to-cash flow sensitivity (BOND and VAN REENEN, 2007):

$$\left(\frac{I}{Kb}\right)_{igpt} = \beta_0 + \beta_1 \left(\frac{I}{Kb}\right)_{igpt-1} + \beta_2 \left(\frac{CF}{Kb}\right)_{igpt} + \beta_3 \Delta SALES_{igpt} + \beta_4 GC_{gpt} + \beta_5 URB_{pt}$$

$$+\beta_6 \left(\frac{CF}{Kb}\right)_{igpt} \times GC_{gpt} + \beta_7 TFP_{igpt} + \beta_8 SIZE_{igpt} + \beta_9 AGE_{igpt} + \varepsilon_{igpt}$$

$$\varepsilon_{igpt} = v_i + v_t + v_g + v_r + v_{igpt} \tag{5}$$

where $(I/Kb)_{igpt}$ is the logarithm of the ratio between firm investments in real terms (I_{igpt}) and capital stock at the beginning of the period (Kb_{igpt}) of the ith firm operating in the two-digit industrial sector g and located in province p at time t. The right-hand side of equation (5) includes the first-order time-lagged dependent variable; the cash flow variable $(CF/Kb)_{igpt}$ to capture the effect of credit constraints; the term:

$$\Delta SALES_{igpt} = SALES_{igpt} - SALES_{igpt-1}$$

to capture the short-run response of investments to demand shocks (where $SALES_{igpt}$ is the logarithm of deflated sales); the term GC_{gpt} to capture localization economies; the term URB_{pt} to capture urbanization economies; and the interaction term between $(CF/Kb)_{igpt}$ and GC_{gpt} to capture the potential moderation effect of geographic concentration on the investment-to-cash flow sensitivity. The variables TFP_{igpt}, $SIZE_{igpt}$ and AGE_{igpt} capture firms' productivity, size and age. The composite error term, ε_{igpt}, is defined as the sum of five components: v_i captures firm-specific effects; v_t represents time fixed effects defined by a set of year dummies; v_g captures industry-specific effects defined by a set of two-digit industrial sector dummies; v_r represents geographic fixed effects at the NUTS-2 level capturing structural differences across Italian regions; v_{igpt} denotes the error term.

The cash flow variable is defined as the logarithm of the ratio between cash flow (CF_{igpt}) and capital stock at the beginning of the period. Cash flow is generally used in the financial literature to proxy for internal resources availability and to capture the sensitivity of a firm's performance measure to credit constraints (CARREIRA and SILVA, 2010). Since credit constrained firms have to rely on internal resources to finance new investments, additional cash flow allows them to optimize real investments. Hence, a positive coefficient of the cash flow variable means that firms are facing difficulties in raising external capitals, and the higher is the marginal effect of cash flow on investments, the more firms are affected by credit rationing.[2]

Localization externalities are captured by an index of geographic concentration of industries measured as follows (CAINELLI *et al.*, 2015):

$$GC_{gpt} = \ln(N_{gpt}/A_p) \quad (6)$$

where N_{gpt} denotes the number of firms operating in the industrial sector g and located in province p at time t; and A_p is the area of province p (km^2). The variable capturing urbanization externalities is defined as follows (MELO and GRAHAM, 2009):

$$URB_{pt} = \ln(N_{pt}/A_p) \quad (7)$$

where N_{pt} denotes the total number of firms located in province p at time t. The use of density measures to proxy for agglomeration economies has two main advantages: it is robust to differences in land area sizes, and it captures well the benefits arising from the spatial concentration of economic activities (CICCONE and HALL, 1996).[3]

The interaction term between the variables for cash flow and geographic concentration aims at capturing a (potential) moderation effect of the agglomeration on the investment-to-cash flow sensitivity. Firms operating in agglomerated areas and characterized by robust and long-lasting relationships with neighbour firms (suppliers and customers) can benefit from positive externalities which materialize in delayed or long-term payments and better contracts. Hence, increasing trust among entrepreneurs allows inter-firm credit, which may downsize firms' dependence on internal resources, thus alleviating credit constraints. A negative coefficient of the interaction term means a positive moderation effect of geographic concentration, i.e. that dependence on internal resources decreases as the level of geographic concentration increases.

Firm productivity is the residual of the estimated equation (4), firm size is defined as the logarithm of the total number of employees, while firm age is defined as the logarithm of the difference between the year of observation and the year of firm set up.

3.2.3. Productivity, credit constraints and localization economies

Equation (8) is specified to analyse the effect of credit constraints and the direct (and indirect) effect of geographic concentration on productivity:

$$TFP_{igpt} = \beta_0 + \beta_1 GC_{gpt} + \beta_2 URB_{pt} + \beta_3 CC_{igpt} + \beta_4 SIZE_{igpt} + \beta_5 AGE_{igpt} + \beta_6 WAGE_{igpt}$$
$$+\beta_7 VERTICAL_{igpt} + \beta_8 SALES_{igpt} + \beta_9 VA_{pt} + \beta_{10} \Delta VA_{pt} + \alpha_i + \gamma_t + v_{igpt} \qquad (8)$$

where TFP_{igpt} is the estimated productivity from equation (4). The terms GC_{gpt} and URB_{pt} capture the direct effect of localization and urbanization economies. Short-run localization externalities are expected to foster firms' productivity favouring the emerging of external-scale economies, the reduction of transportation costs, and the availability of specialized inputs' suppliers and workers (MARTIN *et al.*, 2011). The urbanization variable allows to control for scale economies arising from the concentration of all economic activities (ROSENTHAL and STRANGE, 2004). Location in large urban areas may benefit firms, increasing the probability to access to specialized business services as well as to public facilities, infrastructures, transportation systems, and knowledge produced by private and public actors (JACOBS, 1969; MELO *et al.*, 2009; PUGA, 2010).

The term CC_{igpt} denotes credit constraints. It is computed as the marginal effect of cash flow on investments from equation (5), and it allows one to test for both the direct credit constraints-productivity relationship and the indirect effect of geographic concentration on productivity. If $\beta_3 < 0$ in equation (8), then productivity is negatively affected by credit rationing. Moreover, by letting β_3^1 and β_3^2 be the estimated coefficients of the CC_{igpt} variable in equation (8) when the CC_{igpt} variable is obtained estimating equation (5), respectively, without and with the inclusion of the interaction term between cash flow and geographic concentration, then $\beta_3^2 < \beta_3^1$ means that geographic concentration has an indirect positive effect since it reduces the negative effect of credit rationing on productivity.

The terms $SIZE_{igpt}$, AGE_{igpt}, $WAGE_{igpt}$, $VERTICAL_{igpt}$ and $SALES_{igpt}$ represent firm-specific time-varying control variables, where $WAGE_{igpt}$ is the logarithm of deflated wages and $VERTICAL_{igpt}$ captures the degree of services outsourcing. The variables VA_{pt} and ΔVA_{pt} denote, respectively, the logarithm of deflated value added in province p at time t and its growth between periods t and $t-1$, and they are included to capture the dynamics of the performance of the province where firms operate. The terms α_i and γ_t capture, respectively, firm and time fixed effects, while v_{igpt} is an error term.

3.2.4. Robustness exercise

The investment equation (5) is modified to control for the role of the local banking system including a measure of operational proximity (OP_{pt}) defined as follows (ALESSANDRINI *et al.*, 2009):

$$OP_{pt} = \ln\left[\left(\frac{BB_{pt}}{POP_{pt}}\right) * 10000\right] \tag{9}$$

where BB_{pt} denotes the number of bank branches located in province p at time t; and POP_{pt} denotes the population living in the corresponding province.[4] This variable allows one to control for the effect of the concentration of the banking system on firms' investment decisions. On the one hand, little physical distance between borrower and lending office allows the bank to supplement "hard" information with "soft" information collected at the local level, which facilitate screening and monitoring activities, and relationship lending. Moreover, firms may easily get access to financial resources as the number of bank branches in the local area increases due to higher competition in the local credit market. On the other hand, little physical distance may have negative effects on investment decisions if local banks charge higher interest rates to the closest borrowers due to information rents or transportation costs (ALESSANDRINI *et al.*, 2009). Finally, a three-way interaction term is included in the investment equation to capture the joint effect of localization externalities and banks' density on the investment-to-cash flow sensitivity. Appendix C reports descriptive statistics, the correlation matrix and the definition of the main variables.

3.2.5. Estimation issues

The estimation of equations (5) and (8) leads to two main econometric issues: unobserved heterogeneity and endogeneity of the explanatory variables.

The two-step system GMM (SYS-GMM) estimator is employed to estimate equation (5) because, in the context of dynamic panel data, a simple instrumental-variable estimator produces a biased coefficient of the time-lagged dependent variable (WOOLDRIDGE, 2002). The SYS-GMM estimator combines a system of first-differenced variables (removing unobserved heterogeneity) instrumented with lagged levels, and a system of variables in level instrumented with lags of their own first differences (ARELLANO and BOVER, 1995; BLUNDELL and BOND, 1998). The variables capturing firm age and industry, geographic, and time fixed effects are treated as exogenous and are used as instruments for themselves only in levels. The time-lagged dependent variable and the variables for cash flow, productivity, size and operational proximity are instrumented using their values lagged 3-6 in both levels and first differences, while the sales growth variable is instrumented using its values lagged 3-6 only in levels. The geographic concentration and urbanization variables are instrumented using their 1971 values, plus the logarithm of a population density measure (population in the province/km^2) dated 1921.

The static nature of equation (8) allows one to employ instrumental-variable FE estimators to deal with unobserved heterogeneity and endogeneity. In particular, reverse causality between firms' productivity and agglomeration economies is likely to emerge: on the one hand, agglomeration economies may foster firms' productivity; on the other hand, firms' location choices could be influenced by high levels of productivity with the consequence that firms could migrate towards the most productive areas, thus reinforcing the agglomeration itself (ROSENTHAL and STRANGE, 2004; GRAHAM *et al.*, 2010). Since the FE estimator prevents the use of time-invariant instruments (e.g. long lags of the agglomeration variables), agglomeration variables are instrumented using the difference between their values at time $t-1$ and in 1971:

$$\Delta GC_{gpt-1} = GC_{gpt-1} - GC_{gp1971}$$

$$\Delta URB_{pt-1} = URB_{pt-1} - URB_{p1971}$$

and the difference between population density at time $t-1$ and in 1921:

$$\Delta PD_{pt-1} = \ln\left(PD_{pt-1}\right) - \ln(PD_{p1921})$$

Besides the two-stage least squares (TSLS) estimator, the GMM estimator with optimal weighting matrix is employed because it is more efficient in case of heteroskedastic errors (CAMERON and TRIVEDI, 2005).

The validity of the estimation methodology is assessed through ARELLANO and BOND's (1991) test of serial correlation for dynamic panel data, HANSEN's (1982) *J*-statistic of over-identifying restrictions, first-stage *F*-statistics to test instruments' relevance in the TFP equation, and the Lagrange Multiplier (LM) KLEIBERGEN and PAAP's (2006) rank statistic to test the null hypothesis of under-identification of the matrix of reduced-form coefficients.[5]

4. EMPIRICAL RESULTS

Table 1 reports results of the investment and TFP equations estimated without controlling for (Model 1) and controlling for (Model 2) the moderation effect of geographic concentration. Diagnostic tests for the investment equations support the estimation strategy: ARELLANO and BOND's (1991) test highlights the absence of third-order serial correlation in the first-differenced residuals, and the null hypothesis of instruments' exogeneity is never rejected since *p*-values of HANSEN's (1982) *J*-statistic are never significant. Similarly, diagnostic tests support the instrumental-variable estimation of the TFP equations: *p*-values of HANSEN's (1982) *J*-statistic are never significant; first-stage *F*-statistics on excluded instruments referring to the agglomeration variables have *p*-values equal to zero in all cases, thus suggesting a good predictive power of the chosen instruments; KLEIBERGEN and PAAP's (2006) rank statistic always rejects the null hypothesis that the matrix of reduced-form coefficients is under-identified, thus maintaining the instruments' relevance. Moreover, the mean variance inflation factor (VIF) is lower than the conservative cut-off value of 10 in all specifications, thus suggesting absence of multicollinearity problems (NETER *et al.*, 1985).

Results of the investment equations show positive and significant coefficients of cash flow, meaning that firms are affected by credit rationing. The coefficient of the interaction term between cash flow and geographic concentration is negative and statistically significant, thus suggesting that localization externalities positively moderate the investment-to-cash flow sensitivity favouring inter-firm trade credit.

Results suggest time persistence of the investment dynamics, while there is no evidence of short-run adjustment in the investment decisions due to demand shocks. The TFP and age variables show negative and significant coefficients, while the size variable has positive and significant coefficients. The coefficients of the agglomeration variables are negative but non-significant in the main terms.

Results of the TFP equations show a positive and significant direct effect of localization externalities on firms' productivity, while the coefficients of the urbanization variable are never significant. This last result may depend on the short-run nature of the analysis, since urbanization economies tend to materialize in the long-run due to the fact that inter-industry spillovers may require longer time to develop in absence of a common competence base among actors (MARTIN *et al.*, 2011). These results are robust to the estimation of the TFP equation in a reduced form, i.e. without controlling for firm-level and further local-level variables (see Appendix D for robustness results).

The credit constraints variable (i.e. the marginal effect of cash flow on investments obtained estimating the investment equation) shows negative and significant coefficients, thus suggesting a negative effect of credit rationing on productivity. However, the comparison of the coefficients of the credit constraints variable from Models (1) and (2) suggests a positive indirect effect of geographic concentration on the credit constraints-productivity relationship. Coefficients from Model (1) (where the investment equation is estimated without including the interaction term between cash flow and geographic concentration) are higher than the corresponding coefficients from Model (2) (where the investment equation is estimated accounting for the moderation effect of geographic concentration): geographic concentration seems to reduce the negative credit constraints-productivity relationship by about 4.5%.

A positive and significant relationship between firms' productivity and both size and wage also emerges, while the coefficients of the other control variables are never significant.

Table 2 reports results of the robustness exercise testing for the role of the local banking system. Diagnostic tests confirm the validity of the adopted estimation methodology for all specifications and, overall, previous results are confirmed.

Results of the investment equations show positive and significant coefficients of the cash flow variable, which provide evidence of credit rationing. The time-lagged dependent variable and the variable for firm size show positive and significant coefficients, while the TFP and age variables show negative and significant coefficients. The coefficients of the geographic concentration and operational proximity variables are not significant. The coefficient of the interaction term between cash flow and geographic concentration is negative and significant, thus confirming a positive moderation effect of geographic concentration on the investment-to-cash flow sensitivity.

The investment equation in Model (3) is estimated including a three-way interaction term between cash flow, geographic concentration and operational proximity. The estimated coefficient is negative and significant, even though it is slightly lower than the coefficient of the two-way interaction term estimated in Model (2). Fig. 1 provides a better understanding of this result. Fig. 1(a) plots the marginal effect of cash flow on investments at the minimum and maximum levels of geographic concentration when the operational proximity variable is kept at its minimum level, while the operational proximity variable is kept at its maximum level in Fig. 1(b). The comparison of the two panels suggests that the positive moderation effect of geographic concentration on the investment-to-cash flow sensitivity is increasing in the density of bank branches. This suggests a sort of complementary effect between geographic concentration and operational proximity. As the local density of bank branches increases, location in a highly agglomerated area favours inter-firm credit, for instance because firms can easily access to "soft" information on (potential or new) business partners collected by their own local bank, or because higher competition in the local credit market allows firms to sign better contracts thanks to easier access to credit.

Results of the TFP equations highlight a positive and statistically significant relationship between localization externalities and productivity, while coefficients of the urbanization variable are never significant. Results confirm a positive and significant relationship between productivity and both size and wage, while coefficients of the other control variables are never significant. The coefficients of the credit constraints variable are negative and significant in all models. The estimated coefficient from Model (1) is slightly higher than the estimated coefficient from Model (2), thus suggesting little gain in terms of reduction of the negative credit constraints-productivity relationship favoured by geographic concentration when operational proximity enters the investment equation. However, the estimated credit constraints coefficient from Model (3) is highly lower than the estimated coefficient from Model (1). This last result confirms the previous finding of a complementary effect between geographic concentration and operational proximity: localization externalities positively moderate the negative credit constraints-productivity relationship, and this positive moderation effect increases as the density of bank branches increases in the local system.

5. CONCLUSIONS

This paper has put forth insights into the determinants of firms' productivity linking the literature on credit constraints to that on agglomeration economies. It has analysed whether Italian manufacturing firms' productivity is affected by credit rationing, while fostered by short-run localization externalities. Moreover, it has investigated whether localization economies moderate firms' investment-to-cash flow sensitivity promoting inter-firm trade credit, thus reducing the negative effect of credit rationing on productivity.

The analysis was conducted in three steps on a sample of 11,953 firms observed over the period 1999-2007. First, firms' TFP was estimated using the approach proposed by WOOLDRDIGE (2009). Second, a two-step system GMM estimator was employed to investigate whether Italian manufacturing firms are credit constrained, and whether localization economies positively moderate the investment-to-cash flow sensitivity. Third, instrumental-variable FE estimators were employed to analyse the credit constraints-productivity relationship, as well as the direct and indirect effect of localization economies on productivity.

Results suggest that firms are affected by credit constraints, and that geographic concentration positively moderates the investment-to-cash flow sensitivity promoting inter-firm trade credit. A positive relationship emerges between productivity and localization externalities, while urbanization externalities seem to have a negligible effect on productivity. Results suggest a negative relationship between credit constraints and productivity, while there is a positive indirect effect of geographic concentration on TFP: the negative effect of credit constraints on productivity decreases when the positive moderation effect of geographic concentration on the investment-to-cash flow sensitivity is accounted for, and this positive indirect effect of geographic concentration increases as the density of bank branches increases.

The fact that Italian manufacturing firms suffer from credit rationing may depend on the severity of the Italian banking system. This could also explain the relevance of inter-firm credit for firms that are unable to provide banks with the required warranties to obtain the credit necessary to finance new projects. Therefore, the importance of promoting inter-firm relationships and the formation of industrial conglomerates emerges, in particular in those areas where the financial system is less developed.

NOTES

1. The "omitted price bias", resulting from possible correlation between input choices and variation in the firm-level prices, characterizes both LEVINSOHN and PETRIN's (2003) and WOOLDRDGE's (2009) methodologies. Since firm-level prices are, in general, not observed, industry-level price indexes are used to deflate firms' balance sheet data. However, if firms have different market power, firm- and industry-level prices may differ and the use of industry-based deflators can lead to biased productivity estimates (VAN BEVEREN, 2012).
2. KAPLAN and ZINGALES (1997) and CHEN and CHEN (2012) provide evidence that investment-to-cash flow sensitivity does not represent a good measure of financing constraints. However, ALESSANDRINI *et al.* (2009, p. 292) provide evidence on a sample of Italian manufacturing firms that "rationed firms report a greater elasticity of investment with respect to cash flow than non-rationed ones". Therefore, firms' investment-to-cash flow sensitivity can be considered a good proxy for credit constraints at least in the context of Italian firms.
3. The use of the Italian provinces to analyse agglomeration economies may lead to the modifiable areal unit problem (MAUP) since they are defined according to administrative criteria rather than to economic ones as the local labour markets (ARBIA, 1989). However, data on Italian local labour markets are not available for the entire period analysed. Moreover, since provinces have policy powers concerning territorial planning, they may represent an appropriate territorial level to characterize firms' business environment (CAINELLI *et al.*, 2015).
4. The variables URB_{pt} and OP_{pt} are not included together in the robustness exercise due to high correlation, i.e. 0.83.
5. Investment equations are estimated using the "xtabond2" Stata routine (ROODMAN, 2009), while TFP equations are estimated using the "xtivreg2" Stata routine (SCHAFFER, 2010).

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TABLES AND FIGURES

Table 1. Results of investment and total factor productivity (TFP) equations

Model	(1)				(2)			
Dependent variable	$(I/Kb)_{igpt}$	TFP_{igpt}			$(I/Kb)_{igpt}$	TFP_{igpt}		
Estimation method	SYS-GMM	FE	FE-TSLS	FE-GMM	SYS-GMM	FE	FE-TSLS	FE-GMM
$(I/Kb)_{igpt-1}$	0.416***	...	...	...	0.422***	...	...	...
	(0.035)				(0.036)			
$(CF/Kb)_{igpt}$	0.289***	...	...	...	0.193***	...	...	...
	(0.044)				(0.071)			
$\Delta SALES_{igpt}$	0.072	...	...	...	0.070	...	...	...
	(0.046)				(0.044)			
GC_{gpt}	-0.002	0.218*	0.572**	0.545**	-0.076**	0.214*	0.570**	0.543**
	(0.021)	(0.119)	(0.230)	(0.230)	(0.036)	(0.121)	(0.232)	(0.231)
URB_{pt}	-0.008	-0.568	0.657	0.468	-0.005	-0.560	0.701	0.513
	(0.024)	(0.417)	(1.708)	(1.705)	(0.022)	(0.420)	(1.715)	(1.711)
$(CF/Kb)_{igpt} \times GC_{gpt}$	...	...	...	...	-0.050**	...	...	...
					(0.020)			
CC_{igpt}	...	-0.164***	-0.164**	-0.167**	...	-0.119***	-0.119*	-0.122**
		(0.048)	(0.076)	(0.076)		(0.043)	(0.062)	(0.062)
TFP_{igpt}	-0.151**	...	...	...	-0.142**	...	...	...
	(0.067)				(0.067)			
$SIZE_{igpt}$	0.188***	0.091**	0.093**	0.094**	0.182***	0.088*	0.090**	0.090**
	(0.056)	(0.045)	(0.040)	(0.040)	(0.055)	(0.045)	(0.040)	(0.040)
AGE_{igpt}	-0.072***	-0.010	-0.023	-0.019	-0.071***	-0.006	-0.019	-0.015
	(0.025)	(0.140)	(0.109)	(0.109)	(0.025)	(0.140)	(0.110)	(0.109)
$WAGE_{igpt}$	...	0.082*	0.085**	0.086**	...	0.081*	0.084**	0.086**
		(0.048)	(0.043)	(0.043)		(0.048)	(0.043)	(0.043)
$VERTICAL_{igpt}$	...	-0.168	-0.156	-0.161	...	-0.150	-0.138	-0.143
		(0.138)	(0.117)	(0.116)		(0.136)	(0.116)	(0.116)
$SALES_{igpt}$	...	0.005	0.005	0.005	...	0.004	0.004	0.004
		(0.003)	(0.004)	(0.004)		(0.003)	(0.004)	(0.004)
VA_{igpt}	...	0.489	-0.199	-0.075	...	0.482	-0.221	-0.098
		(0.576)	(0.900)	(0.897)		(0.576)	(0.903)	(0.901)
ΔVA_{igpt}	...	-0.584	-0.322	-0.388	...	-0.600	-0.331	-0.398
		(0.512)	(0.639)	(0.637)		(0.516)	(0.641)	(0.639)
Number of observations	70,711	70,711	70,711	70,711	70,711	70,711	70,711	70,711
Number of firms	11,953	11,953	11,953	11,953	11,953	11,953	11,953	11,953
Number of instruments	191	...	...	...	192	...	...	...

Table 1 - Continued

AR(1) (*p*-value)	0.000	...	...	...	0.000	...	...	...
AR(2) (*p*-value)	0.000	...	...	...	0.000	...	...	...
AR(3) (*p*-value)	0.645	...	...	...	0.641	...	...	...
Hansen *J*-statistic (*p*-value)	0.237	...	0.154	0.154	0.276	...	0.155	0.155
R^2	...	0.009	...	...	...	0.006	...	...
Kleibergen-Paap rk LM-statistic (*p*-value)	...	...	0.000	0.000	...	...	0.000	0.000
F-statistic on $\mathrm{GC_{gpt}}$ (*p*-value)	...	...	0.000	0.000	...	...	0.000	0.000
F-statistic on $\mathrm{URB_{pt}}$ (*p*-value)	...	...	0.000	0.000	...	...	0.000	0.000
Mean VIF	1.17	1.58	1.58	1.58	1.75	1.58	1.58	1.58

Notes: Bootstrapped standard errors are shown in parentheses and they are clustered at province-industrial sector level (1291 units). Investment equations are estimated using a two-step system GMM estimator, with WINDMEIJER's (2005) correction; they include a constant term, industrial sector, NUTS-2 and year dummies. The dummy and age variables are used as instruments for themselves only in levels. The $\mathrm{GC_{gpt}}$ and $\mathrm{URB_{pt}}$ variables are treated as endogenous and instrumented using their 1971 values, plus the log of a population density measure (population in the province/km^2) dated 1921. The other variables are treated as endogenous and instrumented using their values lagged 3-6 both in levels and first differences (the sales growth variable uses instruments only in levels). TFP equations include year dummies; first-stage *F*-statistics of excluded instruments for $\mathrm{GC_{gpt}}$ and $\mathrm{URB_{pt}}$ equal, respectively, 18.9 and 33.3 in all instrumental-variable specifications. The $\mathrm{GC_{gpt}}$ and $\mathrm{URB_{pt}}$ variables are instrumented using the one-year lag of their growth between 1971 and current periods of observation, plus the one-year lag of the growth of population density between 1921 and current periods of observation. $\mathrm{CC_{igpt}}$ is the measure of credit constraints from the investment equations. The Kleibergen-Paap rk LM-statistic refers to KLEIBERGEN and PAAP's (2006) under-identification test of the instruments.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Table 2. Robustness exercise controlling for operational proximity

Model	(1)				(2)				(3)			
Dependent variable	$(I/Kb)_{igpt}$	TFP_{igpt}			$(I/Kb)_{igpt}$	TFP_{igpt}			$(I/Kb)_{igpt}$	TFP_{igpt}		
Estimation method	SYS-GMM	FE	FE-TSLS	FE-GMM	SYS-GMM	FE	FE-TSLS	FE-GMM	SYS-GMM	FE	FE-TSLS	FE-GMM
$(I/Kb)_{igpt-1}$	0.417***	...	...	...	0.415***	...	...	...	0.418***	...	...	...
	(0.035)				(0.035)				(0.035)			
$(CF/Kb)_{igpt}$	0.295***	...	...	...	0.257***	...	...	...	0.247***	...	...	...
	(0.043)				(0.064)				(0.065)			
$\Delta SALES_{igpt}$	0.046	...	...	...	0.053	...	...	...	0.048	...	...	...
	(0.040)				(0.040)				(0.041)			
GC_{gpt}	-0.011	0.219*	0.574**	0.547**	-0.057**	0.214*	0.569**	0.543**	-0.106**	0.214*	0.570**	0.543**
	(0.014)	(0.119)	(0.231)	(0.230)	(0.024)	(0.120)	(0.231)	(0.230)	(0.049)	(0.120)	(0.230)	(0.230)
URB_{pt}	...	-0.565	0.652	0.465	...	-0.559	0.688	0.498	...	-0.563	0.661	0.476
		(0.419)	(1.711)	(1.708)		(0.420)	(1.713)	(1.710)		(0.420)	(1.713)	(1.709)
OP_{pt}	0.003	...	...	...	0.002	...	...	...	0.045*	...	...	...
	(0.011)				(0.011)				(0.023)			
$(CF/Kb)_{igpt} \times GC_{gpt}$	...	...	...	...	-0.032*	...	...	...	...	...	...	...
					(0.017)							
$(CF/Kb)_{igpt} \times GC_{gpt} \times OP_{pt}$	...	...	...	...	...	...	...	...	-0.013*	...	...	...
									(0.007)			
CC_{igpt}	...	-0.138**	-0.138*	-0.139*	...	-0.137**	-0.137*	-0.138*	...	-0.120**	-0.120*	-0.123*
		(0.055)	(0.075)	(0.075)		(0.059)	(0.077)	(0.076)		(0.053)	(0.068)	(0.068)
TFP_{igpt}	-0.142**	...	...	...	-0.128*	...	...	...	-0.133*	...	...	...
	(0.068)				(0.069)				(0.074)			
$SIZE_{igpt}$	0.215***	0.091**	0.093**	0.093**	0.207***	0.091**	0.093**	0.093**	0.214***	0.090**	0.092**	0.092**
	(0.050)	(0.045)	(0.040)	(0.040)	(0.050)	(0.045)	(0.040)	(0.040)	(0.050)	(0.045)	(0.040)	(0.040)
AGE_{igpt}	-0.081***	-0.009	-0.023	-0.018	-0.076***	-0.008	-0.022	-0.018	-0.081***	-0.007	-0.021	-0.017
	(0.023)	(0.141)	(0.110)	(0.109)	(0.023)	(0.141)	(0.110)	(0.109)	(0.023)	(0.141)	(0.110)	(0.109)
$WAGE_{igpt}$	...	0.082*	0.085**	0.086**	...	0.082*	0.085**	0.086**	...	0.081*	0.084**	0.086**
		(0.048)	(0.043)	(0.043)		(0.048)	(0.043)	(0.043)		(0.048)	(0.043)	(0.043)
$VERTICAL_{igpt}$	...	-0.158	-0.146	-0.150	...	-0.154	-0.142	-0.147	...	-0.151	-0.138	-0.143
		(0.139)	(0.117)	(0.116)		(0.138)	(0.117)	(0.116)		(0.138)	(0.116)	(0.116)
$SALES_{igpt}$	...	0.003	0.004	0.003	...	0.004	0.004	0.004	...	0.003	0.003	0.003
		(0.003)	(0.004)	(0.004)		(0.003)	(0.004)	(0.004)		(0.003)	(0.004)	(0.004)
VA_{igpt}	...	0.484	-0.201	-0.079	...	0.480	-0.217	-0.093	...	0.480	-0.209	-0.088
		(0.576)	(0.901)	(0.898)		(0.576)	(0.903)	(0.900)		(0.574)	(0.902)	(0.899)
ΔVA_{igpt}	...	-0.587	-0.326	-0.393	...	-0.596	-0.330	-0.398	...	-0.595	-0.333	-0.400
		(0.513)	(0.640)	(0.638)		(0.514)	(0.641)	(0.638)		(0.514)	(0.641)	(0.639)

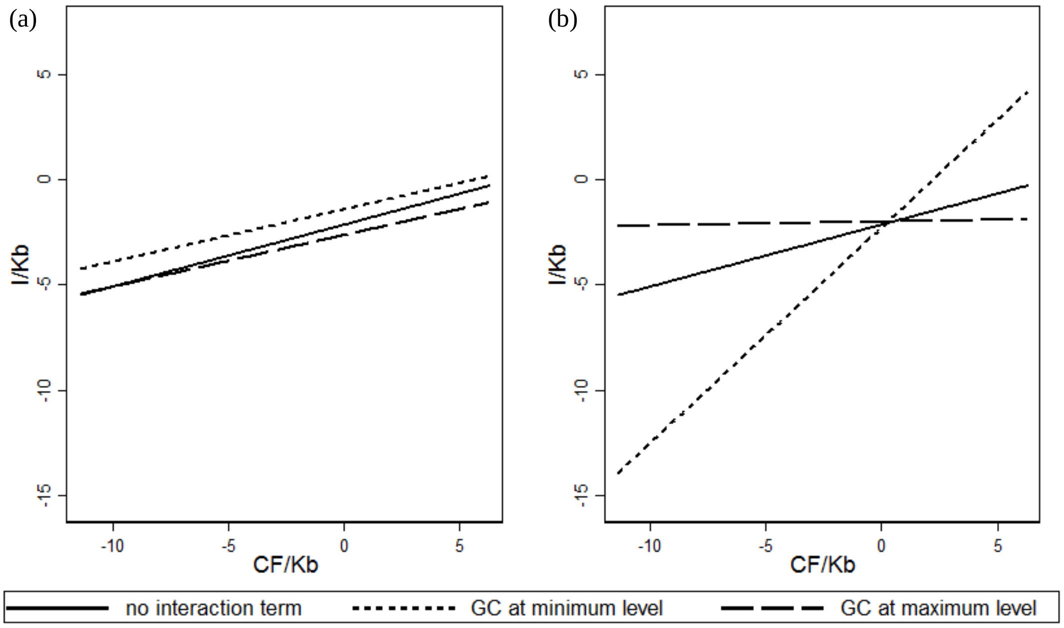
Table 2 - Continued

Number of observations	70,711	70,711	70,711	70,711	70,711	70,711	70,711	70,711	70,711	70,711	70,711	70,711
Number of firms	11,953	11,953	11,953	11,953	11,953	11,953	11,953	11,953	11,953	11,953	11,953	11,953
Number of instruments	193	...	...	...	194	...	...	...	194	...	...	...
AR(1) (p-value)	0.000	...	...	...	0.000	...	...	...	0.000	...	...	...
AR(2) (p-value)	0.000	...	...	...	0.000	...	...	...	0.000	...	...	...
AR(3) (p-value)	0.501	...	...	...	0.561	...	...	...	0.522	...	...	...
Hansen J-statistic (p-value)	0.165	...	0.154	0.154	0.156	...	0.153	0.153	0.165	...	0.159	0.159
R^2	...	0.007	...	...	...	0.006	...	...	...	0.006	...	...
Kleibergen-Paap rk LM-statistic (p-value)	....	....	0.000	0.000	....	....	0.000	0.000	....	....	0.000	0.000
F-statistic on $\mathrm{GC_{gpt}}$ (p-value)	...	...	0.000	0.000	...	...	0.000	0.000	...	...	0.000	0.000
F-statistic on $\mathrm{URB_{pt}}$ (p-value)	...	...	0.000	0.000	...	...	0.000	0.000	...	...	0.000	0.000
Mean VIF	1.15	1.58	1.58	1.58	1.74	1.58	1.58	1.58	1.51	1.58	1.58	1.58

Notes: Bootstrapped standard errors are shown in parentheses and they are clustered at province-industrial sector level (1291 units). Investment equations are estimated using a two-step system GMM estimator, with WINDMEIJER's (2005) correction; they include a constant term, industrial sector, NUTS-2 and year dummies. The dummy and age variables are used as instruments for themselves only in levels. The $\mathrm{GC_{gpt}}$ and $\mathrm{URB_{pt}}$ variables are treated as endogenous and instrumented using their 1971 values, plus the log of a population density measure (population in the province/km^2) dated 1921. The other variables are treated as endogenous and instrumented using their values lagged 3-6 both in levels and first differences (the sales growth variable uses instruments only in levels). TFP equations include year dummies; first-stage F-statistics of excluded instruments for $\mathrm{GC_{gpt}}$ and $\mathrm{URB_{pt}}$ equal, respectively, 18.9 and 33.3 in all instrumental-variable specifications. The $\mathrm{GC_{gpt}}$ and $\mathrm{URB_{pt}}$ variables are instrumented using the one-year lag of their growth between 1971 and current periods of observation, plus the one-year lag of the growth of population density between 1921 and current periods of observation. $\mathrm{CC_{igpt}}$ is the measure of credit constraints from the investment equations. The Kleibergen-Paap rk LM-statistic refers to KLEIBERGEN and PAAP's (2006) under-identification test of the instruments.

$*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

Fig. 1. Investment-to-cash flow sensitivity: three-way interaction



Notes: Solid lines refer to Model (1), while dotted lines refer to Model (3) in Table 2. (a) Marginal effect of cash flow when the operational proximity variable is kept at its minimum level, while it is kept at its maximum level in (b).

APPENDIX A - Sample Description

Table A1 shows the sample distribution in terms of size and geographic area of location. Small sized firms represent more than 60% of the sample, while large firms constitute less than 4% of it. About half of the sample firms is located in the North West of Italy, while less than 9% of the firms is located in a southern region or in an island.

Table A1. Sample distribution by size and geographic area

NUTS-1 Areas	Small (<50)		Medium (50-249)		Large (>249)		Total Firms	
	a. v.	%	a. v.	%	a. v.	%	a. v.	%
North West	3,395	28.40	1,929	16.14	262	2.19	5,586	46.73
North East	2,160	18.07	1,308	10.94	123	1.03	3,591	30.04
Centre	1,159	9.70	536	4.48	56	0.47	1,751	14.65
South & Islands	708	5.92	291	2.43	26	0.22	1,025	8.58
Total Firms	7,422	62.09	4,064	34.00	467	3.91	11,953	100.00

Notes: Percentage values are expressed on the final sample of 11,953 firms. The number of employees defining the size classes is reported in parentheses. North West includes Piemonte, Valle d'Aosta Liguria and Lombardia; North East includes Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia and Emilia-Romagna; Centre includes Toscana, Umbria, Marche and Lazio; South includes Abruzzo, Molise, Campania, Puglia, Basilicata and Calabria; Islands are Sicilia and Sardegna.

Table A2 compares the size distribution of the sample and that of the Italian manufacturing industry (drawn from the 2001 Italian Industry Census conducted by ISTAT) to evaluate the statistical representativeness of the sample. Small sized firms are significantly underrepresented in the sample, although this is not unusual for samples drawn from commercial archives such as the AIDA databank, which consider only limited companies and exclude partnerships - which are instead included in the Industry Census. Therefore, the main empirical limitation of this study is that it considers the "best" small sized firms.

Table A2. A comparison between the sample and the 2001 Italian Industry Census

	Small (<50)		Medium (50-249)		Large (>249)		Total Firms	
	a. v.	%	a. v.	%	a. v.	%	a. v.	%
Sample	6,297	60.96	3,617	35.01	416	4.03	10,330	100.00
Industry Census	530,487	97.72	10,872	2.00	1,517	0.28	542,876	100.00

Notes: Reference year is 2001. Percentage values are expressed on raw totals. The number of employees defining the size classes is reported in parentheses.

Table A3 reports the temporal distribution of the sample, while Table A4 summarises its industrial distribution: all manufacturing sectors are represented in the sample, except for the two-digit sector "33 - Repair and installation of machinery and equipment".

Table A3. Temporal distribution of the sample

Year	No. Firms	%
1999	8,286	9.88
2000	9,402	11.21
2001	10,330	12.32
2002	10,632	12.68
2003	10,388	12.39
2004	10,325	12.31
2005	9,576	11.42
2006	8,695	10.37
2007	6,236	7.44
Total Sample	83,870	100.00

Table A4. Sample distribution according to the Ateco 2007 Industry Classification

Category	Sector	No. Firms	
		a. v.	%
DA	10 - Manufacture of food products	925	7.74
	11 - Manufacture of beverages	190	1.59
	12 - Manufacture of tobacco products	5	0.04
DB	13 - Manufacture of textiles	754	6.31
	14 - Manufacture of wearing apparel	519	4.34
DC	15 - Manufacture of leather and related products	422	3.53
DD	16 - Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	286	2.39
DE	17 - Manufacture of paper and paper products	312	2.61
	18 - Printing and reproduction of recorded media	294	2.46
DF	19 - Manufacture of coke and refined petroleum products	59	0.49
DG	20 - Manufacture of chemicals and chemical products	583	4.88
	21 - Manufacture of basic pharmaceutical products and pharmaceutical preparations	131	1.10
DH	22 - Manufacture of rubber and plastic products	793	6.63
DI	23 - Manufacture of other non-metallic mineral products	620	5.19
DJ	24 - Manufacture of basic metals	436	3.65
	25 - Manufacture of fabricated metal products, except machinery and equipment	1,918	16.05
DL	26 - Manufacture of computer, electronic and optical products	426	3.56
	27 - Manufacture of electrical equipment	536	4.48
DK	28 - Manufacture of machinery and equipment N.E.C.	1,577	13.19
DM	29 - Manufacture of motor vehicles, trailers and semi-trailers	232	1.94
	30 - Manufacture of other transport equipment	114	0.95
DN	31 - Manufacture of furniture	522	4.37
	32 - Other manufacturing	299	2.50
	33 - Repair and installation of machinery and equipment	0	0.00
	Total Sample	11,953	100.00

Notes: Percentage values are expressed on the cleaned total sample. The Ateco 2007 classification of economic activities adopted by Istat is the national version of the European nomenclature Nace Rev. 2 adopted with Regulation (EC) no.1893/2006 of the European Parliament and of the Council of 20th December 2006.

APPENDIX B - Productivity Estimation

Deflated balance sheet data on value added, total labour costs, intermediate inputs, and fixed capital are used to estimate 14 industry-specific production functions. Specifically, value added (VA_{it}) is deflated with the corresponding two-digit production price index, and it is used as output in the production functions. Total labour costs (L_{it}) are deflated with the corresponding two-digit wage index, and they are used as labour input. The capital input (K_{it}) is defined as the real fixed capital stock at the end of the period computed using the Perpetual Inventory Method with a constant depreciation rate equal to 0.085; the capital at the end of the period for future years is defined as $K_t = IK_t + (K_{t-1} - 0.085K_{t-1})$. Intermediate inputs ($M_{it}$) are defined, at current prices, as value of production minus value added, and they are deflated with an intermediate consumptions index. Deflators are calculated using ISTAT data and the reference year for depreciation is 1998. All strictly positive terms enter the production functions in logarithmic form.

Table B1 reports some descriptive statistics and the correlation matrix of the variables used to estimate firms' productivity.

Table B1. Descriptive statistics and correlation matrix of the production function's variables

		Mean	Std. Dev.	Min.	Max.	va_{igpt}	k_{igpt}	l_{igpt}	m_{igpt}
	overall	13.020	1.964	1.792	23.378				
va_{igpt}	between		1.154	8.859	18.760	1			
	within		1.594	1.588	19.365				
	overall	14.455	1.447	6.813	22.242				
k_{igpt}	between		1.407	8.251	21.441	0.407	1		
	within		0.396	7.686	16.996				
	overall	13.857	1.139	3.892	23.020				
l_{igpt}	between		1.112	9.073	19.972	0.492	0.744	1	
	within		0.283	5.600	19.464				
	overall	15.349	1.202	6.871	23.576				
m_{igpt}	between		1.171	11.119	21.718	0.421	0.663	0.742	1
	within		0.307	8.413	20.752				

Notes: All variables are defined in natural logarithm. va_{igpt} denotes value added; k_{igpt} denotes the capital input; l_{igpt} denotes the labour input; m_{igpt} denotes intermediate inputs. Descriptive statistics and the correlation matrix refer to a sample of 12,524 firms, i.e. 104,800 observations over the period 1999-2007.

Table B2 reports results of the 14 estimated industry-specific production functions.

Table B2. TFP estimation: capital elasticity and labour elasticity

Industrial Category	k_{igpt}			l_{igpt}			No. Obs.
DA	0.199	(0.077)	[0.010]	0.590	(0.032)	[0.000]	8,638
DB	0.301	(0.066)	[0.000]	0.525	(0.032)	[0.000]	10,153
DC	0.117	(0.107)	[0.276]	0.643	(0.048)	[0.000]	3,268
DD	0.150	(0.154)	[0.332]	0.562	(0.074)	[0.000]	2,205
DE	0.168	(0.093)	[0.070]	0.640	(0.048)	[0.000]	4,697
DF	-0.019	(0.324)	[0.953]	0.346	(0.160)	[0.030]	463
DG	0.111	(0.089)	[0.211]	0.557	(0.041)	[0.000]	5,493
DH	0.124	(0.089)	[0.163]	0.601	(0.044)	[0.000]	6,065
DI	0.297	(0.103)	[0.004]	0.605	(0.043)	[0.000]	4,642
DJ	0.232	(0.049)	[0.000]	0.641	(0.025)	[0.000]	17,953
DK	0.088	(0.059)	[0.135]	0.613	(0.032)	[0.000]	12,256
DL	0.176	(0.073)	[0.017]	0.685	(0.038)	[0.000]	7,398
DM	0.108	(0.122)	[0.373]	0.383	(0.066)	[0.000]	2,707
DN	0.258	(0.087)	[0.003]	0.597	(0.042)	[0.000]	6,327

Notes: k_{igpt} denotes the capital input, while l_{igpt} denotes the labour input. TFP is estimated on a sample of 12,524 firms, i.e. 104,800 observations over the period 1999-2007. Standard errors are shown in parentheses, and they are clustered at the firm level. P-values are shown in brackets.

APPENDIX C - Variables' Description

Tables C1 and C2 report, respectively, some descriptive statistics and the correlation matrix of the main explanatory variables. Table C3 provides a synthetic description of the main variables.

Table C1. Descriptive statistics of dependent and main explanatory variables

		Mean	Std. Dev.	Min.	Max.
$(\mathrm{I/Kb})_{\mathrm{igpt}}$	overall	-2.080	1.321	-15.698	7.580
	between		0.812	-9.435	0.947
	within		1.082	-12.702	6.273
$\mathrm{TFP}_{\mathrm{igpt}}$	overall	2.005	2.194	-10.644	12.371
	between		1.550	-3.101	10.423
	within		1.558	-9.531	6.687
$(\mathrm{CF/Kb})_{\mathrm{igpt}}$	overall	-1.423	1.061	-11.394	6.284
	between		0.873	-6.829	5.883
	within		0.649	-10.171	4.402
$\mathrm{AGE}_{\mathrm{igpt}}$	overall	3.020	0.592	0	4.771
	between		0.589	0.795	4.754
	within		0.148	1.694	3.774
$\mathrm{SIZE}_{\mathrm{igpt}}$	overall	3.661	1.065	0	9.804
	between		1.033	0.099	9.716
	within		0.314	-1.850	7.647
$\mathrm{SALES}_{\mathrm{igpt}}$	overall	14.358	2.012	0	22.240
	between		1.206	9.483	21.283
	within		1.634	-0.943	19.148
$\mathrm{WAGE}_{\mathrm{igpt}}$	overall	10.234	0.331	3.609	17.478
	between		0.197	8.804	12.001
	within		0.271	5.038	15.838
$\mathrm{VERTICAL}_{\mathrm{igpt}}$	overall	-0.410	0.208	-2.789	0.125
	between		0.185	-2.391	0.073
	within		0.104	-1.845	0.329
$\mathrm{GC}_{\mathrm{gpt}}$	overall	-1.444	1.608	-8.909	2.663
	between		1.610	-8.165	2.626
	within		0.079	-2.909	-0.625
$\mathrm{URB}_{\mathrm{pt}}$	overall	3.364	0.889	0.735	5.236
	between		0.894	1.261	5.235
	within		0.065	2.086	4.755
$\mathrm{OP}_{\mathrm{pt}}$	overall	2.838	1.087	0.023	6.719
	between		1.089	0.084	6.692
	within		0.078	2.433	3.219
$\mathrm{VA}_{\mathrm{pt}}$	overall	10.878	0.259	9.047	12.052
	between		0.248	9.104	12.013
	within		0.068	10.680	11.091

Notes: Descriptive statistics refer to the final sample of 11,953 firms, i.e. 83,870 observations over the period 1999-2007.

Table C2. Correlation matrix of explanatory variables

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
$(I/Kb)_{igpt}$	[1]	1											
TFP_{igpt}	[2]	0.03	1										
$(CF/Kb)_{igpt}$	[3]	0.42	0.12	1									
AGE_{igpt}	[4]	-0.09	-0.01	-0.12	1								
$SIZE_{igpt}$	[5]	0.05	0.06	-0.05	0.21	1							
$SALES_{igpt}$	[6]	0.04	0.06	0.05	0.08	0.38	1						
$WAGE_{igpt}$	[7]	0.03	0.08	0.07	0.09	-0.04	0.11	1					
$VERTICAL_{igpt}$	[8]	0.14	0.06	0.18	-0.13	-0.19	0.11	-0.06	1				
GC_{gpt}	[9]	-0.01	-0.13	0.02	0.02	-0.05	-0.02	0.02	-0.04	1			
URB_{pt}	[10]	0.00	0.03	0.07	0.03	-0.03	0.00	0.10	-0.01	0.55	1		
OP_{pt}	[11]	0.01	0.01	0.08	0.03	-0.02	0.00	0.09	0.02	0.53	0.83	1	
VA_{pt}	[12]	-0.06	0.01	-0.02	0.09	0.02	0.02	0.06	-0.09	0.12	0.19	0.01	1

Notes: The correlation matrix refers to the final sample of 11,953 firms, i.e. 83,870 observations over the period 1999-2007.

Table C3. Construction of main variables

Variable	Acronym	Definition	Data
Total Factor Productivity	$\mathrm{TFP}_{\mathrm{igpt}}$	Residual of a Cobb-Douglas production function estimated using the methodology proposed by WOOLDRIDGE (2009)	*AIDA* databank
Real Investments	$(\mathrm{I/Kb})_{\mathrm{igpt}}$	Scaled investments measure computed as the ratio between investments expressed in real terms and capital stock at the beginning of the period	*AIDA* databank
Nominal Investments	$\mathrm{IC}_{\mathrm{igpt}}$	Investments at current prices defined as $IC_{igpt} = TA_{igpt} - TA_{igpt-1} + AL_{igpt}$., where TA_{igpt} denotes tangible assets, and AL_{igpt} denotes allowances.	*AIDA* databank
Capital stock at the beginning of the period	$\mathrm{Kb}_{\mathrm{igpt}}$	The capital stock at the beginning of the period t is the difference between capital stock at the end of the period t (K_{igpt}) and capital expenditure in the period t.	*AIDA* databank
Cash Flow	$(\mathrm{CF/Kb})_{\mathrm{igpt}}$	Scaled cash flow measure computed as the ratio between cash flow (defined as net income plus annual depreciation) and capital stock at the beginning of the period	*AIDA* databank
Geographic Concentration	$\mathrm{GC}_{\mathrm{gpt}}$	Proxy for localization externalities computed as the ratio between number of firms in industrial sector $g = 10, \dots, 32$ located in province $p = 1, \dots, 103$ and area of the corresponding province in square kilometres	*Movimprese* database (Italian Chamber of Commerce) and ISTAT
Urban Density	$\mathrm{URB}_{\mathrm{pt}}$	Proxy for urbanisation externalities computed as the ratio between total number of firms located in province $p = 1, \dots, 103$ and area of the corresponding province in square kilometres	*Movimprese* database (Italian Chamber of Commerce) and ISTAT
Operation Proximity	$\mathrm{OP}_{\mathrm{pt}}$	Number of bank branches located in province $p = 1, \dots, 103$ *per* 10,000 inhabitants	Bank of Italy and ISTAT
Province Value Added	$\mathrm{VA}_{\mathrm{pt}}$	Deflated value added of province $p = 1, \dots, 103$	ISTAT
Age	$\mathrm{AGE}_{\mathrm{igpt}}$	Age of a firm defined as difference between the year of observation and the year of set up	*AIDA* databank
Size	$\mathrm{SIZE}_{\mathrm{igpt}}$	Firm's number of employees	*AIDA* databank
Sales	$\mathrm{SALES}_{\mathrm{igpt}}$	Firm's deflated sales	*AIDA* databank
Wage	$\mathrm{WAGE}_{\mathrm{igpt}}$	Firm's deflated wages	*AIDA* databank
Vertical Disintegration	$\mathrm{VERTICAL}_{\mathrm{igpt}}$	Proxy for a firm's services outsourcing computed as the ratio between deflated costs to buy services and deflated total costs of production	*AIDA* databank

APPENDIX D - Further Results

Table D1 reports results of the dynamic investment equation estimated including the two-way interaction term between the cash flow variable and the variables for, respectively, urbanisation economies and operational proximity. The estimated coefficients of the interaction terms are not statistically significant.

Table D1. Investment equation with two-way interactions

Dependent variable	$(\mathrm{I/Kb})_{\mathrm{igpt}}$	$(\mathrm{I/Kb})_{\mathrm{igpt}}$
Estimation method	SYS-GMM	SYS-GMM
$(\mathrm{I/Kb})_{\mathrm{igpt-1}}$	0.394***	0.392***
	(0.033)	(0.032)
$(\mathrm{CF/Kb})_{\mathrm{igpt}}$	0.497*	0.297***
	(0.259)	(0.104)
$\Delta\mathrm{SALES}_{\mathrm{igpt}}$	0.083*	0.044
	(0.047)	(0.042)
$\mathrm{GC}_{\mathrm{gpt}}$	0.001	-0.020
	(0.023)	(0.014)
$\mathrm{URB}_{\mathrm{pt}}$	-0.078	...
	(0.107)	
$(\mathrm{CF/Kb})_{\mathrm{igpt}} \times \mathrm{URB}_{\mathrm{pt}}$	-0.040	...
	(0.073)	
$\mathrm{OP}_{\mathrm{pt}}$	...	0.039
		(0.051)
$(\mathrm{CF/Kb})_{\mathrm{igpt}} \times \mathrm{OP}_{\mathrm{pt}}$	...	0.021
		(0.032)
$\mathrm{TFP}_{\mathrm{igpt}}$	-0.135**	-0.140**
	(0.068)	(0.068)
$\mathrm{SIZE}_{\mathrm{igpt}}$	0.162***	0.207***
	(0.057)	(0.050)
$\mathrm{AGE}_{\mathrm{igpt}}$	-0.053**	-0.074***
	(0.026)	(0.023)
Number of Observations	70,711	70,711
Number of Firms	11,953	11,953
AR(3) (*p*-value)	0.802	0.584
Hansen *J*-statistic (*p*-value)	0.185	0.130

Notes: Bootstrapped standard errors are shown in parentheses and they are clustered at province-industrial sector level (1,291 units). Investment equations are estimated using a two-step System GMM estimator, with WINDMEIJER's (2005) correction; they include a constant term, industrial sector, NUTS-2 and year dummies. The dummy and age variables are used as instruments for themselves only in levels. The $\mathrm{GC}_{\mathrm{gpt}}$ and $\mathrm{URB}_{\mathrm{pt}}$ variables are treated as endogenous and instrumented using their 1971 values, plus the log of a population density measure (population in the province per square kilometres) dated 1921. The other variables are treated as endogenous and instrumented using their values lagged 3 to 6 both in levels and first differences (the sales growth variable uses instruments only in levels).

$*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

Table D2 reports results of the TFP equations estimated in a reduced form, i.e. without including firm- and local-level controls, as well as the credit constraints variable (CC_{igpt}). The very low R^2 of the fixed effects (FE) specifications are not an unusual result in the context of agglomeration variables' regression. MARTIN P., MAYER T. and MAYNERIS F. (2011, Spatial concentration and plant-level productivity in France, *Journal of Urban Economics* 69, 182-195) and EHRL P. (2013, Agglomeration economies with consistent productivity estimates, *Regional Science and Urban Economics* 43, 751-763), among others, provide similar results.

Table D2. TFP equations without marginal effects

Dependent variable	$\mathrm{TFP}_{\mathrm{igpt}}$					
Specification		(1)			(2)	
Estimation method	FE	FE-TSLS	FE-GMM	FE	FE-TSLS	FE-GMM
$\mathrm{GC}_{\mathrm{gpt}}$	0.231**	0.555**	0.530**	0.227**	0.587**	0.562**
	(0.096)	(0.224)	(0.224)	(0.109)	(0.232)	(0.231)
$\mathrm{URB}_{\mathrm{pt}}$	-0.482	0.447	0.240	-0.556*	0.619	0.460
	(0.297)	(1.683)	(1.678)	(0.321)	(1.720)	(1.717)
$\mathrm{SIZE}_{\mathrm{igpt}}$	...	...	...	0.080**	0.082**	0.082**
				(0.040)	(0.040)	(0.040)
$\mathrm{AGE}_{\mathrm{igpt}}$	...	...	...	0.004	-0.010	-0.006
				(0.110)	(0.110)	(0.110)
$\mathrm{WAGE}_{\mathrm{igpt}}$	...	...	...	0.079*	0.082*	0.084*
				(0.043)	(0.043)	(0.043)
$\mathrm{VERTICAL}_{\mathrm{igpt}}$	...	...	...	-0.114	-0.102	-0.106
				(0.114)	(0.115)	(0.115)
$\mathrm{SALES}_{\mathrm{igpt}}$	...	...	...	0.002	0.002	0.002
				(0.004)	(0.004)	(0.004)
$\mathrm{VA}_{\mathrm{igpt}}$	...	...	...	0.460	-0.212	-0.106
				(0.447)	(0.903)	(0.901)
$\Delta\mathrm{VA}_{\mathrm{igpt}}$	...	...	...	-0.609	-0.354	-0.417
				(0.538)	(0.645)	(0.642)
Number of Observations	70,711	70,711	70,711	70,711	70,711	70,711
Number of Firms	11,953	11,953	11,953	11,953	11,953	11,953
R^2	0.0004	...	...	0.001	...	...
Hansen *J*-statistic (*p*-value)	...	0.182	0.182	...	0.168	0.168
Kleibergen-Paap rk LM-statistic (*p*-value)	...	0.000	0.000	...	0.000	0.000
F-statistic on $\mathrm{GC}_{\mathrm{gpt}}$ (*p*-value)	...	0.000	0.000	...	0.000	0.000
F-statistic on $\mathrm{URB}_{\mathrm{pt}}$ (*p*-value)	...	0.000	0.000	...	0.000	0.000
Mean VIF	1.73	1.73	1.73	1.61	1.61	1.61

Notes: Standard errors are shown in parentheses and they are clustered at province-industrial sector level (1,291 units). All specifications include a set of year dummies. First-stage F statistics of excluded instruments for $\mathrm{GC}_{\mathrm{gpt}}$ and $\mathrm{URB}_{\mathrm{pt}}$ equal, respectively, to 17 and 31.7 in specifications (2) and (3), while they equal to, respectively, 18.9 and 33.3 in specifications (5) and (6). The $\mathrm{GC}_{\mathrm{gpt}}$ and $\mathrm{URB}_{\mathrm{pt}}$ variables are instrumented using the one-year lag of their growth between 1971 and current periods of observation, plus the one-year lag of the growth of population density between 1921 and current periods of observation. The Kleibergen-Paap rk LM-statistic refers to the KLEIBERGEN-PAAP's (2006) under-identification test of instruments.

$*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

Table D3 reports results of reduced-form TFP equations corresponding to the specifications reported in Table 1 in the main text.

Table D3. Reduced-form TFP equations

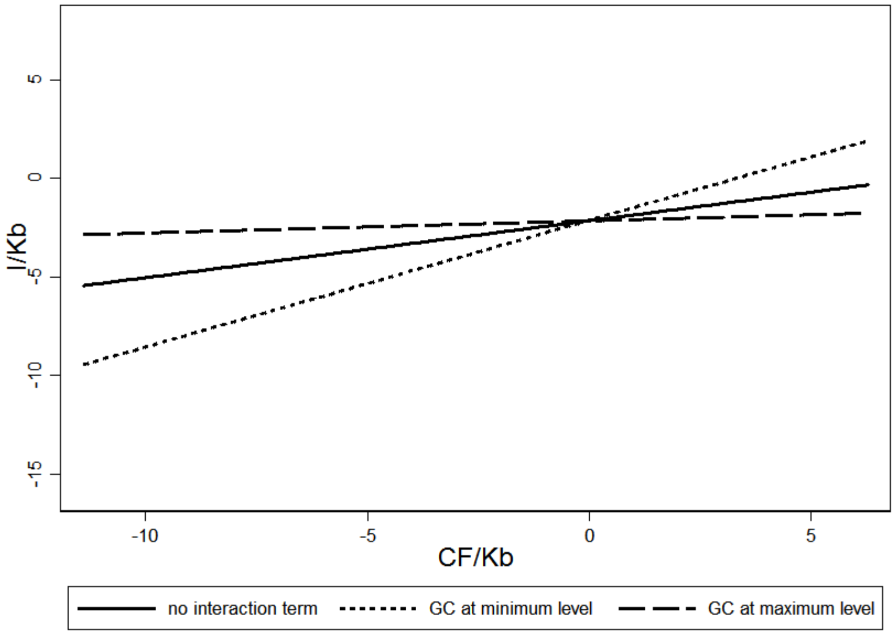
Dependent variable	$\mathrm{TFP}_{\mathrm{igpt}}$					
Specification		(1)			(2)	
Estimation method	FE	FE-TSLS	FE-GMM	FE	FE-TSLS	FE-GMM
$\mathrm{GC}_{\mathrm{gpt}}$	0.225*	0.538**	0.511**	0.220*	0.537**	0.510**
	(0.120)	(0.224)	(0.223)	(0.121)	(0.224)	(0.224)
$\mathrm{URB}_{\mathrm{pt}}$	-0.491	0.475	0.232	-0.484	0.520	0.279
	(0.390)	(1.673)	(1.667)	(0.392)	(1.678)	(1.673)
$\mathrm{CC}_{\mathrm{igpt}}$ [Model (1)]	-0.163***	-0.163**	-0.166**	...	...	...
	(0.047)	(0.076)	(0.075)			
$\mathrm{CC}_{\mathrm{igpt}}$ [Model (2)]	...	...	...	-0.118***	-0.118*	-0.121**
				(0.043)	(0.062)	(0.062)
Number of Observations	70,711	70,711	70,711	70,711	70,711	70,711
Number of Firms	11,953	11,953	11,953	11,953	11,953	11,953
R^2	0.008	...	...	0.006	...	...
Hansen *J*-statistic (*p*-value)	...	0.164	0.164	...	0.166	0.166
Kleibergen-Paap rk LM-statistic (*p*-value)	...	0.000	0.000	...	0.000	0.000
F-statistic on $\mathrm{GC}_{\mathrm{gpt}}$ (*p*-value)	...	0.000	0.000	...	0.000	0.000
F-statistic on $\mathrm{URB}_{\mathrm{pt}}$ (*p*-value)	...	0.000	0.000	...	0.000	0.000

Notes: Bootstrapped standard errors are shown in parentheses and they are clustered at province-industrial sector level (1,291 units). All specifications include a set of year dummies. First-stage F statistics of excluded instruments for $\mathrm{GC}_{\mathrm{gpt}}$ and $\mathrm{URB}_{\mathrm{pt}}$ equal, respectively, to 16.9 and 31.7 in all instrumental-variable specifications. The $\mathrm{GC}_{\mathrm{gpt}}$ and $\mathrm{URB}_{\mathrm{pt}}$ variables are instrumented using the one-year lag of their growth between 1971 and current periods of observation, plus the one-year lag of the growth of population density between 1921 and current periods of observation. The Kleibergen-Paap rk LM-statistic refers to the KLEIBERGEN-PAAP's (2006) under-identification test of instruments.

$*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

Figure D1 refers to the results of the dynamic investment equations reported in Table 1 in the main text, and it plots the marginal effects of cash flow on investments. The investment-to-cash flow sensitivity turns to be decreasing in the level of geographic concentration, and the slope of the clash flow variable computed without accounting for a moderation effect is steeper than the slope computed when the geographic concentration variable is kept at its maximum level. This suggests that localization externalities positively moderate the investment-to-cash flow sensitivity by favouring inter-firm trade credit.

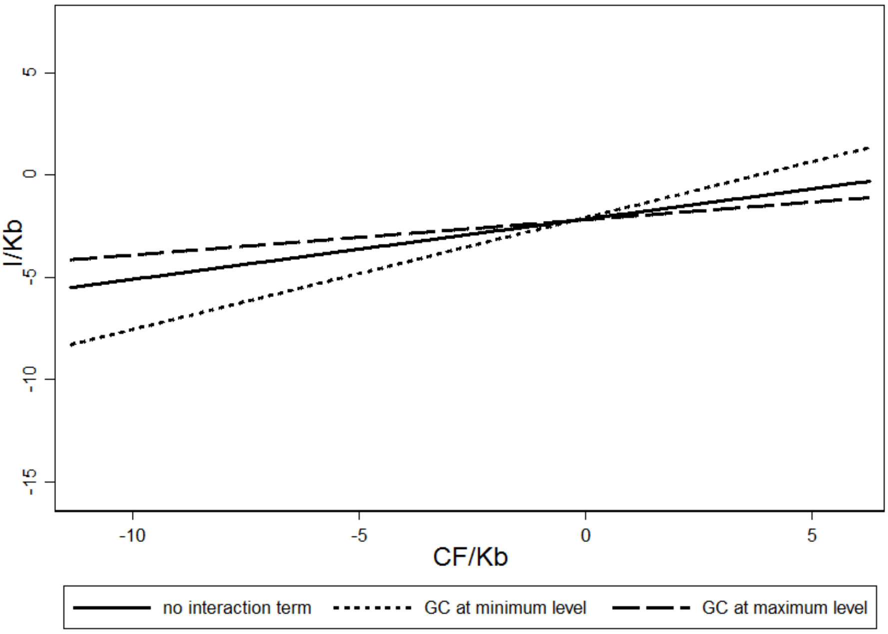
Figure D1. Investment-to-cash flow sensitivity



Notes: The solid line refers to Model (1), while the dotted lines refer to Model (2) in Table 1 in the paper.

Figure D2 refers to the results of Models (1) and (2) reported in Table 2 in the main text. The plot clearly shows that the marginal effect of cash flow on investments decreases as the level of geographic concentration in the local system increases.

Figure D2. Investment-to-cash flow sensitivity: controlling for operational proximity



Notes: The solid line refers to Model (1), while the dotted lines refer to Model (2) in Table 2 in the paper.

Table D4 reports results of a robustness exercise which replicates the main model (which results are reported in Table 1 in the main text) using firms' TFP estimated through the semi-parametric approach proposed by LEVINSOHN J. and PETRIN A. (2003, Estimating production functions using inputs to control for unobservables, *Review of Economic Studies* 70, 317-341).

Table D4. Investment and TFP equations using LEVINSOHN and PETRIN (2003)

Model	(1)				(2)			
Dependent variable	$(I/Kb)_{igpt}$	TFP_{igpt}			$(I/Kb)_{igpt}$	TFP_{igpt}		
Estimation method	SYS-GMM	FE	FE-TSLS	FE-GMM	SYS-GMM	FE	FE-TSLS	FE-GMM
$(I/Kb)_{igpt-1}$	0.416***	...	...	...	0.421***	...	...	...
	(0.035)				(0.035)			
$(CF/Kb)_{igpt}$	0.287***	...	...	...	0.196***	...	...	...
	(0.044)				(0.071)			
$\Delta SALES_{igpt}$	0.073*	...	...	...	0.071	...	...	...
	(0.044)				(0.044)			
GC_{gpt}	-0.001	0.203*	0.537**	0.508**	-0.074**	0.198	0.536**	0.505**
	(0.021)	(0.121)	(0.237)	(0.236)	(0.037)	(0.123)	(0.238)	(0.237)
URB_{pt}	-0.009	-0.552	0.639	0.444	-0.006	-0.543	0.682	0.487
	(0.024)	(0.420)	(1.708)	(1.704)	(0.022)	(0.423)	(1.713)	(1.709)
$(CF/Kb)_{igpt} \times GC_{gpt}$	...	...	...	...	-0.049**	...	...	...
					(0.020)			
CC_{igpt}	...	-0.155***	-0.155**	-0.158**	...	-0.118***	-0.118*	-0.121*
		(0.048)	(0.075)	(0.074)		(0.045)	(0.063)	(0.063)
TFP_{igpt}	-0.152**	...	...	...	-0.144**	...	...	...
	(0.066)				(0.066)			
$SIZE_{igpt}$	0.186***	0.088**	0.090**	0.090**	0.179***	0.085*	0.087**	0.088**
	(0.056)	(0.044)	(0.040)	(0.040)	(0.055)	(0.044)	(0.040)	(0.040)
AGE_{igpt}	-0.071***	-0.002	-0.014	-0.009	-0.069***	0.002	-0.011	-0.006
	(0.025)	(0.141)	(0.109)	(0.109)	(0.025)	(0.140)	(0.110)	(0.109)
$WAGE_{igpt}$	...	0.078*	0.081*	0.083*	...	0.078*	0.081*	0.082*
		(0.047)	(0.043)	(0.043)		(0.047)	(0.043)	(0.043)
$VERTICAL_{igpt}$	...	-0.170	-0.158	-0.162	...	-0.154	-0.142	-0.147
		(0.138)	(0.117)	(0.117)		(0.137)	(0.117)	(0.116)
$SALES_{igpt}$	...	0.005	0.005	0.005	...	0.004	0.004	0.004
		(0.003)	(0.004)	(0.004)		(0.003)	(0.004)	(0.004)
VA_{igpt}	...	0.494	-0.169	-0.042	...	0.488	-0.191	-0.063
		(0.576)	(0.903)	(0.900)		(0.575)	(0.906)	(0.903)
ΔVA_{igpt}	...	-0.601	-0.348	-0.416	...	-0.616	-0.356	-0.425
		(0.513)	(0.641)	(0.638)		(0.516)	(0.643)	(0.640)
Number of Observations	70,711	70,711	70,711	70,711	70,711	70,711	70,711	70,711
Number of Firms	1,1953	1,1953	1,1953	1,1953	1,1953	1,1953	1,1953	1,1953
Number of Instruments	191	...	...	...	192	...	...	...

Table D4 - Continued

AR(1) (*p*-value)	0.000	...	...	...	0.000	...	...	...
AR(2) (*p*-value)	0.000	...	...	...	0.000	...	...	...
AR(3) (*p*-value)	0.652	...	...	...	0.656	...	...	...
Hansen *J*-statistic. (*p*-value)	0.210	...	0.162	0.162	0.240	...	0.163	0.163
R^2	...	0.008	...	...	...	0.006	...	...
Kleibergen-Paap rk LM-statistic (*p*-value)	...	...	0.000	0.000	...	...	0.000	0.000
F-statistic on $\mathrm{GC_{gpt}}$ (*p*-value)	...	...	0.000	0.000	...	...	0.000	0.000
F-statistic on $\mathrm{URB_{pt}}$ (*p*-value)	...	...	0.000	0.000	...	...	0.000	0.000
Mean VIF	1.17	1.58	1.58	1.58	1.76	1.58	1.58	1.58

Notes: Bootstrapped standard errors are shown in parentheses and they are clustered at province-industrial sector level (1,291 units). Investment equations are estimated using a two-step System GMM estimator, with WINDMEIJER's (2005) correction; they include a constant term, industrial sector, NUTS-2 and year dummies. The dummy and age variables are used as instruments for themselves only in levels. The $\mathrm{GC_{gpt}}$ and $\mathrm{URB_{pt}}$ variables are treated as endogenous and instrumented using their 1971 values, plus a population density measure (population in the province per square kilometres) dated 1921. The other variables are treated as endogenous and instrumented using their values lagged 3 to 6 both in levels and first differences (the sales growth variable uses instruments only in levels). TFP equations include year dummies; first-stage F statistics of excluded instruments for $\mathrm{GC_{gpt}}$ and $\mathrm{URB_{pt}}$ equal, respectively, to 18.9 and 33.3 in all instrumental-variable specifications. The $\mathrm{GC_{gpt}}$ and $\mathrm{URB_{pt}}$ variables are instrumented using the one-year lag of their growth between 1971 and current periods of observation, plus the one-year lag of the growth of population density between 1921 and current periods of observation. $\mathrm{CC_{igpt}}$ is the measure of credit constraints from the investment equations. The Kleibergen-Paap rk LM-statistic refers to the KLEIBERGEN-PAAP's (2006) under-identification test of the instruments.

$*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

Chapter 2

Industrial Clusters, Organised Crime and Productivity Growth in Italian SMEs*

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Abstract: This paper examines whether the presence of organised crime (*mafia*-type criminality) affects a firm's performance (defined in terms of 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 empirical analysis uses the economic performance of a large sample of Italian manufacturing small and medium sized firms over the period 2008-2011. The results suggest a negative direct relationship between organised crime and firms' productivity growth. Any positive effect derived from industrial clustering is thoroughly debilitated by a strong presence of local organised crime, and the negative moderation effect of organised crime on productivity growth is greater for smaller than for larger firms. In particular, extortions have a very strong incidence in weakening a firm's performance.

Keywords: Total Factor Productivity; Organised crime; Industrial clustering

JEL classification: C3; D24; K4; R12

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1. INTRODUCTION

How the local environment where Italian firms operate affects their economic performance and behaviour has been the object of great scrutiny. Research has focused on issues such as local institutional quality (LASAGNI *et al.*, 2015), financial development (MORETTI, 2014), the presence of innovative milieu (BELUSSI *et al.*, 2010), or industrial agglomeration (CAINELLI *et al.*, 2015), among others. Most of this literature tends to point towards the idea that, as firms interact with local actors (e.g. neighbouring firms, banks, local institutions, research centres), their capacity to get and assimilate knowledge, their competitiveness, and their economic performance is positively or negatively affected by the socio-economic context of where they are located. Firms operating in different environments are likely to gain (or suffer) from both tangible (e.g. the local availability of inputs and intermediate goods, the reduction of transportation costs) and intangible (e.g. the reduction of transaction costs favoured by repeated interactions and increasing trust among local actors) agglomeration externalities which reduce the costs of the economic activity, thus fostering their efficiency and growth (MARTIN *et al.*, 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, henceforth) growth -, it particularly focuses on what is widely regarded as an important negative externality: organised crime in Italy.

Organised crime (namely, *mafia*-type criminality) represents an Italian symbol. Italy is often identified as a country with pervasive organised crime. From its locations of origin - Western Sicily, Campania, Calabria, and Apulia - *mafia*-type activities have spread to many other parts of the country. The presence of criminality is likely to affect the economic activity and therefore the performance of individual firms. Criminal organisations reduce the level of legality and security of the places they operate (LA SPINA and LO FORTE, 2006), undermining both the socio-economic environment where a firm operates and its performance. Organised crime makes the business environment less secure and dynamic and increases uncertainty, reducing trust and reciprocity among agents. Criminal organisations operate in the market through controlled "illicit" firms, altering competition and market rules. It can be said that organised crime acts as a tax on the local economic system (DETOTTO and OTRANTO, 2010): it increases the costs and reduces the returns of the economic activity, thus downsizing firms' efficiency (ALBANESE and MARINELLI, 2013). Yet, despite its expansion beyond its place of origin, the presence of organised crime across Italy remains extremely uneven. Areas of the country completely ravaged by crime coexist, often in close proximity, with regions where organised 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 organised crime in the firm's region. The hypothesis driving the research is that organised crime will undermine a firm's growth potential by reducing trust and reciprocity in the local system and weakening the traditional market-based linkages among firms, thus increasing transaction costs and diluting any positive externalities arising from the location in a highly agglomerated area.

The empirical analysis covers a large sample of Italian manufacturing small and medium sized firms over the period 2008-2011. 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 organised crime and industrial clustering, as well as by estimating the firm's TFP through two different approaches. Overall, empirical results support the theoretical hypotheses: while agglomeration and clustering foster firms' productivity growth, organised crime has a direct negative effect on it, as well as a harmful indirect impact offsetting the benefits of agglomeration. The indirect effect is mainly driven by the presence of extortion.

The rest of the paper is structured as follows. Section 2 presents the literature on organised 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, ORGANISED 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, favouring the economic performance of both the local system and of individual agents within it (GLAESER *et al*., 1992; ROSENTHAL and STRANGE, 2004; PUGA, 2010).

Benefits of agglomeration are realised through two fundamental types of externalities: localisation and diversification economies. Localisation 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 specialised 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 favour the cross-fertilisation of existing ideas and technologies in a diversified local economic environment, as well as tangible positive externalities related to the availability of specialised business services providers, and the presence of intermediate goods' suppliers operating at different stages of the production chain (CAINELLI *et al.*, 2015).

There is no shortage of cross-country literature on the agglomeration-productivity relationship at the firm-level (e.g. HENDERSON, 2003; CINGANO and SCHIVARDI, 2004; CAINELLI and LUPI, 2010; LEE *et al.*, 2010; MARTIN *et al.*, 2011; CAINELLI *et al.*, 2015; GANAU, 2015). This literature distinguishes between static (short-run) and dynamic (long-run) effects of localisation and diversification economies. The static component of the agglomeration phenomenon concerns tangible and intangible externalities arising from market-based relationships (e.g. availability of specialised inputs' suppliers, reduced transport and transaction costs). The dynamic component involves intangible externalities derived from knowledge and information flows and technological spillovers (MARTIN *et al.*, 2011; GANAU, 2015).

In this paper we explicitly consider tangible and intangible market-based externalities, by building on the distinction between localisation and diversification economies. We synthesise 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 localisation- 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.*, 2015) - 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 (MISTRI and SOLARI, 2003; CAINELLI, 2008). 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. Organised crime and productivity

The effect of organised crime on productivity has featured in economic literature since, at least, the work of SCHELLING (1971). Organised crime is widely regarded to have both direct and indirect negative effects on the economic activity. First, the presence of criminal organisations weakens legality and security (LA SPINA and LO FORTE, 2006; DANIELE and MARANI, 2011). Such a situation makes the business environment less secure and dynamic, increases uncertainty, increases the risk of new investment opportunities, and reduces trust and reciprocity among economic agents. In these circumstances the formation and development of economic networks is jeopardised, as firms are less willing to establish solid and long-lasting production linkages. Second, organised crime increases the costs and reduces the returns of the economic activity (BUONANNO *et al.*,2009; POWELL *et al.*, 2010), thus acting like a tax on the economic system (DETOTTO and OTRANTO, 2010). Organised 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 (NETTI, 1999; FELLI and TRIA, 2000). Finally, firms may be also coerced by criminal organisations, for instance, into acquiring inputs from suppliers controlled by the criminal organisation (ALBANESE and MARINELLI, 2013) or into directly paying the organisation 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 analysed the economic effects of organised crime. Some works have focused on its macroeconomic implications in terms of labour productivity (e.g. FELLI and TRIA 2000; CENTORRINO and OFRIA, 2008), GDP growth (e.g. TULLIO and QUARELLA, 1999; PINOTTI, 2012), employment rates (e.g. PERI, 2004), inward foreign direct investments (e.g. DANIELE and MARANI, 2011), and public transfers (BARONE and NARCISO, 2013). The microeconomic effects of organised crime and, specifically, the effects on an average firm economic activity have, by contrast, drawn much less attention. Among these limited contributions, NETTI (1999), OFRIA (2000) and ALBANESE and MARINELLI (2013) can be highlighted. ALBANESE and MARINELLI (2013) explicitly focus on the effect of organised crime on the productivity of Italian firms. They find that organised crime reduces firm-level productivity regardless of firm size and sector. This negative effect is robust to the potential endogeneity of the organised 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) organisations.

Based on the theoretical relationship between organised 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. Organised 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, organised crime is further likely to cancel out any potential positive relationships between industrial clustering and firm-level productivity growth. Criminal organisations 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 organisations also reduces trust and reciprocity in the local system, increasing transaction costs among local actors. Therefore, organised 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 small and medium sized firms (SME, henceforth), 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 2007-2011. In addition, firms included in the analysis have to report a value added-to-turnover ratio ≥ 0 and ≤ 1.[2] Firms with missing or inconsistent data in terms of value added, total labour cost, tangible assets, and intermediate inputs have been removed from the dataset. This leaves an unbalanced panel including 41,484 firms (for a total of 179,233 observations over the period 2007-2011) which is used to estimate firms' TFP. This sample is further cleaned removing firms with missing information on location at province level (NUTS-3 level of the European Union territorial classification - Nomenclature des Unités Territoriales Statistiques) and the year of set up. The final panel thus covers 36,737 firms for the period 2008-2011. The 36,737 firms are used to analyse the effects of industrial clustering and organised crime on productivity growth. Tables A1 and A2 in the Appendix display the sample distribution taking into account, respectively, industry and geographic location.[3]

3.2. Econometric modelling

In order to investigate whether and how (i) industrial clustering fosters TFP growth at the level of the firm and whether and how (ii) organised 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:

$$\Delta TFP_{ipg} = \beta_0 + \beta_1 TFP_{ipg}^{2008} + \beta_2 AGE_{ipg}^{2008} + \beta_3 SIZE_{ipg}^{2008} + \beta_4 WAGE_{ipg}^{2008}$$
$$+\beta_5 IC_{pg}^{2008} + \beta_6 OC_p^{2008} + \beta_7 \left(IC_{pg}^{2008}\right) \times \left(OC_p^{2008}\right) + \beta_8 MD_p^{2008}$$
$$+\beta_9 S\&I + \boldsymbol{\gamma}_g + \varepsilon_{ipg} \tag{1}$$

where $\Delta TFP_{ipg} = TFP_{ipg}^{2011} - TFP_{ipg}^{2008}$ denotes the productivity growth of firm i, in the two-digit industry g, located in province $p = 1, \dots, 103$, over the three-year period 2008-2011; and TFP_{ipg}^{2008} and TFP_{ipg}^{2011} denote the natural logarithms of a firm's TFP in 2008 and 2011, respectively. The TFP of a firm is estimated as the residual of a Cobb-Douglas production function specified as follows in logarithmic form:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + u_{it} + \eta_{it} \tag{2}$$

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 labour inputs; and η_{it} is an independent and identically distributed (i.i.d.) component which represents productivity shocks not affecting a firm's decision process. The firm-level productivity can be specified as $\omega_{it} = \beta_0 + u_{it}$, where ω_{it} is a state variable-transmitted component indicating that part of productivity (i.e. technology) known by the firm and influencing its decision process (OLLEY and PAKES, 1996). Consequently, the estimated productivity can be computed solving for ω_{it} as follows (VAN BEVEREN, 2012):

$$\widehat{\omega}_{it} = \hat{u}_{it} + \hat{\beta}_0 = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} \tag{3}$$

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", which concerns 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 $m_{it} = m_t(k_{it}, \omega_{it})$ in the second-stage estimation, and under the assumptions of monotonicity and intermediate inputs strictly increasing in productivity, equation (2) can be re-specified as follows:

$$
\begin{aligned}
y_{it} &= \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \eta_{it} \\
\omega_{it} &= s_t(k_{it}, m_{it})
\end{aligned}
\tag{4}
$$

where ω_{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 labour coefficient is likely to emerge in the first-stage estimation (VAN BEVEREN, 2012). This collinearity may be the consequence of choosing labour 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.* (2006), the labour coefficient results not identified in the first-stage estimation because it is not possible to estimate the non-parametric function of productivity and capital input with the labour variable's coefficient simultaneously, as the labour 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 Generalised Method of Moments (GMM) approach where β_k and β_l are estimated in one step, hence addressing the possible collinearity between the labour 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 η_{it} with current and past values of capital, labour 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:

$$\begin{cases} y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + f(k_{it}, m_{it}) + \eta_{it} \\ y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + h[f(k_{it-1}, m_{it-1})] + \eta_{it} + a_{it} \end{cases} \tag{5}$$

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):

$$y_{it} = (\beta_0 + \tau) + \beta_k k_{it} + \beta_l l_{it} + f(k_{it-1}, m_{it-1}) + \eta_{it} + a_{it} \tag{6}$$

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). Twenty-one production functions are estimated at the two-digit industry level using both estimators.[4] 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 labour inputs.

The key explanatory variables entering the productivity growth equation are those capturing organised crime and industrial clustering. The variable capturing organised crime (OC_p^{2008}) is defined considering three main types of crime: (i) *mafia*-type association ($association_p^{2008}$); (ii) *mafia*-murders ($murder_p^{2008}$); and (iii) extortions ($extortion_p^{2008}$). The variable is operationalised as follows:

$$OC_p^{2008} = \ln\left[\left(\frac{association_p^{2008} + murder_p^{2008} + extortion_p^{2008}}{POP_p^{2008}}\right) * 100{,}000\right] \tag{7}$$

where POP_p^{2008} denotes the population living in province p. Data on criminality are drawn from the Istat (Italian National Institute of Statistics) online databank *Territorial Information System on Justice*, and the province is used as the geographic unit of analysis. No finer geographical scale can be used, as crime geographic data are only provided at the level of the 103 Italian provinces for the period of analysis. Data on population are provided by the Istat online database on demographics. Fig. A1 in the Appendix displays the quartile map of the organised crime variable. As expected there is a concentration of reported organised crime in the South of Italy (the *Mezzogiorno*) and, particularly, in the regions of Apulia, Calabria, Campania, and Sicily. However, part of the *Mezzogiorno*, such as Sardinia, has a low incidence of organised crime, while *mafia*-type activities are strong in some Northern and Central Italian provinces, such as Novara, Bologna, Forlì-Cesena, Rimini, Pistoia, or Viterbo (see Fig. A1).

The variable capturing industrial clustering 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:

$$IC_{pg}^{2008} = \ln\left[\frac{\left(N_{pg}^{2008} \cdot w_{gg}^{2008}\right) + \sum_{\substack{j=1 \\ j \neq g}}^{J}\left(N_{pj}^{2008} \cdot w_{gj}^{2008}\right)}{A_p}\right] \quad (8)$$

where N_{pg}^{2008} denotes the number of active firms operating in the two-digit industry g in province p; N_{pj}^{2008} represents the number of active firms in the two-digit industry j, with $j \neq g$; w_{gg}^{2008} and w_{gj}^{2008} are the weights capturing the share of inputs that firms in industry *g* may acquire from, respectively, the same industry and other industries; A_p denotes the area of the corresponding province p. 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 2008 *use* table of the Italian input-output matrix provided by Istat.[5]

A cluster can be defined as a geographic concentration of related firms (as well as organisations and institutions) in a given territory (PORTER, 1990; DELGADO *et al.*, 2015). The industrial clustering variable defined in equation (8) 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, the greater the density of market-interconnected firms. From an agglomeration literature perspective, this variable captures the effects of both localisation and (vertically-)related diversification economies (FRENKEN *et al.*, 2007; CAINELLI *et al.*, 2015).

Equation (1) also includes the interaction term between the industrial clustering and organised crime variables. The introduction of the interaction is aimed at evaluating whether organised 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. All variables are included in the equation (1) in logarithmic form: the beginning-of-the period TFP (TFP_{ipg}^{2008}); a measure of firm age (AGE_{ipg}^{2008}) defined as the difference between the year 2008 and the year the firm was set up; a measure of size ($SIZE_{ipg}^{2008}$) defined by the number of employees; the average wage ($WAGE_{ipg}^{2008}$) defined as the ratio between deflated wages and number of employees. Equation (1) includes also a metropolitan dummy variable (MD_{p}^{2008}), which equals one if a province has a population equal to or greater than one million inhabitants (20.64% of the sample's firms belong to a metropolitan area). The metropolitan dummy aims to control for the effect of urbanisation economies arising from the location in highly urbanised areas. Metropolitan areas generate additional externalities, such as the presence of public facilities, infrastructure, transportation systems, and knowledge produced by both private and public actors (JACOBS, 1969; MELO *et al.*, 2009; PUGA, 2010). An additional dummy variable is included to capture the location of a firm in the South of Italy and the two main islands ($S\&I$). The introduction of this variable is intended to take into account structural differences between the Italian *Mezzogiorno* and the rest of Italy (Northern and Central areas) in terms of socio-economic conditions, industrial development, and infrastructure endowment. Finally, equation (1) includes a set of industry dummy variables ($\boldsymbol{\gamma}_g$) to capture industry fixed effects.

3.2.1. 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 *et al.*, 2012) -, we therefore resort to a two-step sample-selection model *à la* HECKMAN (1979). This model is estimated to account for firm exit over the period 2008-2011. Specifically, a first-stage reduced-form selection equation is estimated by Maximum Likelihood specifying a dummy ($SURVIVAL_{ipg}$) as dependent variable. The dummy equals one if the firm observed in 2008 is still accounted for in 2011, 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 ($EXIT_p$), capturing the average exit rate in province p over the period 1998-2007. The idea behind the exclusion restriction is that a high (past) level of firms' mortality in the local system captures high turbulence of the local business environment, which is likely to be associated with a low firm survival rate, without being necessarily associated with the economic performance of surviving firms.[6]

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 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 2008-2011 (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 (ROSENTHAL and STRANGE, 2004; GRAHAM *et al.*, 2010; MARTIN *et al.*, 2011) and organised crime (ALBANESE and MARINELLI, 2013). Endogeneity can occur in the context of equation (1) for several reasons: (i) shocks occurring at province level may affect the productivity growth of firms, as well as the local industrial structure and the level of criminality; (ii) variables misspecification may occur because measuring industrial relationships among firms and the criminal activity are not easy; (iii) reverse causality is likely to occur if the most productive firms self-select into the most agglomerated areas, or they move towards more secure business environments.

Therefore, equation (1) is estimated applying an IV estimator to check the robustness of the results. Specifically, a two-stage least squares (TSLS) approach is adopted specifying a set of three instruments: a variable capturing industrial clustering in 1996 (IC_{pg}^{1996}); a measure of population density in 1971 (PD_{p}^{1971}), defined as the population living in province p in 1971 per square kilometre; and a proxy for the efficiency of the legal system in 2001 (CR_{p}^{2001}), defined as the ratio between the number of condemned individuals and the number of individuals reported for crime. These instruments are considered valid, as they are likely to be correlated with both the potentially endogenous variables without affecting a firm's productivity growth (GREENE, 2003). There are several reasons for this. First, the literature on agglomeration economies proposes lagged values of agglomeration and population density as valid instruments for current agglomeration measures (e.g. CICCONE and HALL 1996; MELO and GRAHAM, 2009; CAINELLI *et al.*, 2015). Second, a more efficient legal system may facilitate the clustering of firms and more efficient market relations. Third, previous contributions also suggest that current levels of (organised) crime are positively associated with high levels of industrialisation (DEL MONTE and PENNACCHIO, 2012) and urbanisation, while negatively associated with the efficiency of the legal system (BUONANNO *et al.*, 2009).[7]

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 set of 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.

The endogeneity of the variables for industrial clustering and organised crime is tested through the Durbin-Wu-Hausman test in its regression-based form (WOOLDRIDGE, 2010, pp. 129-134). The null hypothesis of exogeneity is rejected in all specifications. The relevance of the instruments is tested through the Lagrange Multiplier (LM) version of KLEIBERGEN and PAAP's (2006) rank statistic. The results of the test reject the null hypothesis that the matrix of reduced-form coefficients is under-identified, suggesting that the chosen instruments are relevant. The exogeneity of the whole set of instruments is tested through HANSEN's (1982) *J*-statistic, which fails to reject the null hypothesis of instruments' exogeneity in all cases. The mean variance inflation factor (VIF) is used to detect multicollinearity problems. It is lower than the conservative cut-off value of 10 for multiple regression models in all the estimated specifications, underlining the absence of potential multicollinearity problems (NETER *et al.*, 1985).

4. EMPIRICAL RESULTS

Table 1 reports results of the OLS estimation of equation (1), corrected for sample selection. The coefficients of the exclusion restriction included in the selection equation and the parameter λ (i.e. the inverse Mills ratio computed from the selection equation) are statistically significant. This indicates the need to correct for sample selection and the validity of the adopted strategy. Specifically, the negative coefficients of the exclusion restriction identifying the first-stage selection equations suggest that a firm's probability of surviving is negatively affected by its location in local systems characterised by a high level of firm mortality in the previous period.

The results of Specification (1) - estimated without including the interaction term between the variables for industrial clustering and organised crime - point to, as hypothesised, a negative effect of organised 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 organised crime and firm productivity (e.g. ALBANESE and MARINELLI, 2013) and on the relationship between industrial clustering and productivity (CAINELLI *et al.*, 2015).

Specification (2) complements Specification (1) by identifying a negative indirect effect of organised 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 effects arising from the geographic concentration of (intra- and inter-industry) market-related firms decrease as the incidence of local organised crime increases. Following WOOLDRIDGE's (2009) approach to TFP estimation, the results reveal that a 1% increase in the level of industrial clustering is associated with a 2.36% increase of productivity growth, when the value of organised crime is in the 25th percentile of its distribution; with a 1.95% increase of productivity growth, when the value of organised crime is in the 50th percentile of its distribution; and with a 1.72% increase of productivity growth, when the value of organised crime is in the 75th percentile of its distribution. Fig. 1 allows to discern the moderation effect of organised crime on the industrial clustering-productivity growth relationship: the marginal effect of industrial clustering on productivity growth clearly decreases as the level of organised crime increases.

The results of the analysis thus confirm the theoretical predictions. On the one hand, firms located in local systems characterised 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, organised crime reduces trust among individuals, alters competition in the market, and undermines the established local industrial structure, causing a weakening of existing market relationships among local firms. Organised 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, leading to a clear decrease in firm-level efficiency.

Regarding the controls, the beginning-of-the period TFP variable has negative coefficients, as does the age variable. The variables for firm-size and average wage have positive and significant coefficients. The dummies capturing the metropolitan and *Mezzogiorno* effects both have negative and significant coefficients. This hints, in contrast to expectations, to a negative effect of urbanisation economies. They also indicate that firm-level productivity growth suffers in the least industrialised and developed area of Italy.

The robustness of the results is tested by controlling for the potential endogeneity of the variables capturing industrial clustering and organised crime. Re-location processes of the most productive firms towards the most agglomerated areas, or towards areas characterised by lower levels of criminality, may cause biases in the estimated coefficients due to reverse causality. Table 2 reports the second-stage results of the TSLS estimation of equation (1) aimed at controlling for the potential endogeneity. Similarly to the exogenous analysis, the coefficients of the exclusion restriction and the parameter λ are statistically significant. Diagnostic tests for the IV approach are reported at the bottom of Table 2. The null hypothesis of exogeneity is never rejected and the under- and over-identification tests support the chosen instrumentation strategy.

Overall, the findings reported above are confirmed when controlling for endogeneity. There is a negative direct effect of organised crime on productivity growth and a positive one of industrial clustering. The results also confirm an indirect negative effect of organised crime on the positive relationship between industrial clustering and productivity growth. The dimensions of this effect are quite high: a 1% increase in the level of industrial clustering is associated with a 5.38% increase of productivity growth, when the value of organised crime is in the 25th

percentile of its distribution; with a 2.75% increase of productivity growth, when the value of organised crime is in the 50th percentile of its distribution; and with a 1.29% increase of productivity growth, when the value of organised crime is in the 75th percentile of its distribution. Once endogeneity is controlled for, the negative indirect effect of organised crime increases, making the positive marginal effect of industrial clustering on productivity growth negative for high levels of organised crime. This pattern is reproduced in Fig. 2. The presence of criminal organisations 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 characterised with a high incidence of organised crime. Negative agglomeration externalities may arise due to 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.

The coefficients of the control variables display the same signs and significance levels than in the previous exercise. The coefficients of the variable capturing urbanisation effects are positive and statistically different from zero when the interaction term between industrial clustering and organised crime is accounted for. This last result is in line with previous contributions reporting a positive urbanisation effect on firm-level productivity (e.g. DI GIACINTO *et al.*, 2014). The *Mezzogiorno* variable shows positive but non-significant coefficients.

A second robustness exercise is conducted accounting only for extortion crime. The rationale for this exercise is twofold. First, it is the only type of crime accounted for in the organised crime variable which is present in all 103 Italian provinces, while the *mafia*-association and *mafia*-murder crimes are recorded only in a limited number of provinces (Fig. A2 in the Appendix maps the spatial distribution of the three types of crime considered in the analysis). Second, extortion is the archetypical crime associated to criminal organisations and has a strict economic nature: it allows criminal organisations to obtain huge amounts of money (e.g. through protection racketeering) as well as to control the local area where they operate and its economic activities. By contrast, *mafia*-association crime is more general since it may concern various illegal activities, such as the rigging of public tenders, the corruption of public officers, and the infiltration of public institutions by members of the criminal organisation. Therefore, it is more likely to influence the overall institutional conditions rather than directly affect firms' daily activity in an immediate way. Similarly, *mafia*-murders do not necessarily have a short-term direct economic effect, as very often the victims of these crimes are members of the crime syndicate fighting over the control of territory.

Equation (1) is thus modified substituting the organised crime variable with a variable capturing the density of extortions:

$$EC_p^{2008} = \ln\left[\left(\frac{extortion_p^{2008}}{POP_p^{2008}}\right) * 100{,}000\right] \tag{9}$$

where the term $extortion_p^{2008}$ denotes the number of extortion crimes recorded in province p in 2008; the term POP_p^{2008} captures the population living in the corresponding province.

Table 3 reports the second-stage results of the TSLS estimation of equation (1), modified to account for the extortion crime only. Diagnostic tests support the estimation and instrumentation strategies adopted. Once again, the results confirm the previous findings: industrial clustering has a positive effect on firm-level productivity growth, while the effect of extortions is negative and significant. Extortions also reduce the benefits of industrial clustering on productivity growth. The effect is again considerable: a 1% increase in the level of industrial clustering is associated with a 3.32% increase of productivity growth, when the extortion variable is in the 25th percentile of its distribution; with a 3% increase of productivity growth, when the extortion variable is in the 50th percentile of its distribution; and with a 2.84% increase of productivity growth, when the extortion variable is in the 75th percentile of its distribution. These results imply that the presence of criminal organisations in the local system and a high incidence of extortions have a strong negative influence on the way local firms interact and set up inter-firm transactions.

Fig. 3 compares the marginal effects of industrial clustering on firms' TFP growth at different percentiles of the organised crime and extortion variables. The negative moderation effect of the criminal activity is only marginally lower when only the extortion crime is accounted for, relative to the previous analysis when *mafia*-murders and *mafia*-associations were considered. However, this pattern changes for high levels of criminality. The results indicate that the negative moderation effect played by criminal organisations is driven by extortions from about the 50th percentile: the short-dash dotted line, which captures the difference in the marginal effects of industrial clustering on firms' TFP growth between organised crime and extortion crime, is positively sloped.

Finally, equation (1) is modified to test whether the negative moderation effect of organised crime on the industrial clustering-productivity growth relationship differs for firms of different sizes. Firms have been split into two categories according to their beginning-of-the period size. A dummy variable ($SIZE\_CLASS_{ipg}^{2008}$) has been constructed accordingly. The first category includes firms reporting a level of employment lower than the average size of a firm in the sample in 2008 (i.e. 25 employees), while the second category includes firms reporting a level of employment greater than or equal to the average firms' size:

$$SIZE\_CLASS_{ipg}^{2008} = \begin{cases} 0, & if\ size_{ipg}^{2008} < 25 \\ 1, & if\ size_{ipg}^{2008} \geq 25 \end{cases} \tag{10}$$

The right-hand side of equation (1) now includes the dummy variable capturing the two size classes (instead of the size variable previously considered) and its three-way interaction with the variables for industrial clustering and organised crime. The idea is that the effects of organised 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 difficulties in competing in the market dominated by criminal organisations, 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 4 reports the second-stage results of the TSLS estimation of the augmented version of equation (1). The diagnostic tests - presented at the bottom of Table 4 - support the estimation and instrumentation strategies adopted. The coefficients of the firm-level controls display the same signs and significance levels than in the previous analysis. The dummy variables capturing urbanisation externalities and the *Mezzogiorno* effect show positive but non-significant coefficients. The coefficients of the three-way interaction term are negative and statistically significant. A clearer interpretation of this last result emerges from Fig. 4. First, the slope of the industrial clustering variable referring to smaller firms (i.e. those with a below average size relative to the sample in 2008) is steeper than the slope referring to larger firms (i.e. those above the average size). This evidence suggests, as expected, that the indirect negative effect of organised crime is higher for smaller than for larger firms. Second, the marginal effect of industrial clustering on productivity growth becomes negative at a lower level of organised crime for smaller firms.

5. CONCLUSIONS

This paper has contributed to 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 organised crime (*mafia*-type criminality) affects a firm's performance (defined in terms of Total Factor Productivity 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 observed over the period 2008-2011, 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 organised crime and industrial clustering. Two different approaches have been also employed to estimate firm-level TFP.

The empirical results demonstrate the presence of a negative (direct) effect of organised crime on firm-level productivity growth. The negative influence of organised crime is also indirect, as *mafia*-type associations, murders, and extortions 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 medium-size and larger firms. The positive impact of industrial clustering decreases as the level of organised crime at the local level increases, to the extent that it becomes negative in those areas with particularly high levels of criminality.

These results can be interpreted considering two interrelated consequences of the criminal activity. On the one hand, criminal organisations gain from the economic control of specific productions and, therefore, may influence their dynamics. On the other hand, the presence of criminal organisations also reduces trust and reciprocity among individuals, increasing transaction costs, thus contributing to make the local business environment less competitive. This produces negative effects on local market-based relationships among firms: market transactions become more expensive, in particular if the criminal organisation imposes, as is normally the case, protection rackets and other illegal payments to the local firms. Hence, high levels of organised crime destabilise traditional competition/cooperation relationships existing among firms within a locality and smaller firms and businesses are the biggest victims. These aspects contribute to determine the negative (indirect) effect which can be ascribed to the presence of criminal organisations: 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. In particular, they highlight the importance of accounting for several dimensions charactering the local environment where firms operate, as well as how these local-level factors interact with one another in order to determine the economic behaviour 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. Organised 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.

NOTES

1. The literature has focused on different dimensions of the cluster phenomenon. For instance, FESER and BERGMAN (2000) and FESER (2005) analyse the input-output component of industrial clusters, while FELDMAN and AUDRETSCH (1999) and KOO (2005) focus on knowledge-based clusters. DELGADO *et al.* (2015) 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.
2. 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.
3. Firms are ascribed to different sectors and subsectors following the Ateco 1991 classification of economic activities. All two-digit manufacturing industries are considered, except for the industries "16 - Tobacco" and "37 - Recycling", due to the absence of firms after the cleaning procedure.
4. Deflated balance sheet data on value added, total labour cost, intermediate inputs and tangible assets are used to estimate the industry-specific production functions. Value added (VA_{it}) is deflated with the corresponding two-digit production price index and is used as output in the production functions; total labour cost (L_{it}) is deflated with the corresponding two-digit wage index and is used as labour input; total tangible assets (K_{it}) are deflated with the corresponding two-digit 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 data and the reference year for depreciation is 2006.

5. The weighting scheme has been defined excluding public services (e.g. defence, public administration, public infrastructures, etc.), domestic services, education, restaurants and leisure activities, construction, real estate, and commercial activities. These two-digit 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.*, 2015). In any case, the industrial clustering variable has been constructed also using an alternative weighting scheme, which excludes only public services, education, and domestic services industries. The results are robust to this alternative approach and can be supplied upon request.
6. First-step selection equations have been identified using an alternative exclusion restriction, i.e. a dummy variable for mid-high and high technology firms. The rationale of this exclusion restriction is that firms operating in mid-high and high technology sectors are less likely to be influenced by general economic downturns or involved in the international outsourcing processes of the production phases with respect to firms operating in traditional manufacturing sectors. Hence, mid-high and high technology firms are expected to face a lower probability of exiting the market. Results using this alternative exclusion restriction are in line with the main findings.
7. Two alternative sets of instruments have been tested for the industrial clustering and organised crime variables. Historical variables capturing past dominations in Italian provinces (from DI LIBERTO and SIDERI, 2015) have been tested to capture the effect of historical institutional settings. This is because past institutions may have influenced current levels of industrialisation and criminality. A set of dummy variables capturing the agricultural structure (*mezzadria*, *latifondo*, small and large property) characterising current provinces in the pre-unitary period (before 1871) have been tested to capture the effect of different agricultural and

property structures which could have been likely to influence the development of criminal organisations and the process of industrialisation. However, both sets of instruments are uncorrelated with the (potentially) endogenous variables.

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TABLES AND FIGURES

Table 1. TFP growth equation: OLS results

Dependent variable	$\Delta\mathrm{TFP}_{\mathrm{ipg}}$ (LP)		$\Delta\mathrm{TFP}_{\mathrm{ipg}}$ (W)	
Specification	(1)	(2)	(1)	(2)
$\mathrm{TFP}_{\mathrm{ipg}}^{2008}$	-0.290***	-0.293***	-0.291***	-0.294***
	(0.014)	(0.014)	(0.014)	(0.014)
$\mathrm{AGE}_{\mathrm{ipg}}^{2008}$	-0.043***	-0.043***	-0.042***	-0.042***
	(0.003)	(0.003)	(0.003)	(0.003)
$\mathrm{SIZE}_{\mathrm{ipg}}^{2008}$	0.200***	0.197***	0.196***	0.193***
	(0.013)	(0.013)	(0.013)	(0.013)
$\mathrm{WAGE}_{\mathrm{ipg}}^{2008}$	0.163***	0.161***	0.161***	0.159***
	(0.011)	(0.011)	(0.011)	(0.011)
$\mathrm{IC}_{\mathrm{pg}}^{2008}$	0.020***	0.020***	0.020***	0.020***
	(0.005)	(0.005)	(0.005)	(0.005)
$\mathrm{OC}_{\mathrm{p}}^{2008}$	-0.033***	-0.036***	-0.032***	-0.036***
	(0.009)	(0.010)	(0.009)	(0.010)
$\mathrm{IC}_{\mathrm{pg}}^{2008} \times \mathrm{OC}_{\mathrm{p}}^{2008}$	...	-0.015**	...	-0.015**
		(0.007)		(0.007)
$\mathrm{MD}_{\mathrm{p}}^{2008}$	-0.058***	-0.051***	-0.057***	-0.050***
	(0.012)	(0.012)	(0.012)	(0.013)
S&I	-0.107***	-0.103***	-0.106***	-0.102***
	(0.012)	(0.012)	(0.012)	(0.012)
λ	1.378***	1.349***	1.358***	1.329***
	(0.151)	(0.147)	(0.151)	(0.148)
Industry fixed effects	Yes	Yes	Yes	Yes
Number of Observations	29,170	29,170	29,170	29,170
Censored Observations	7,567	7,567	7,567	7,567
Adj. R^2	0.19	0.19	0.19	0.19
F-statistic	83.90***	81.63***	83.19***	80.93***
Mean VIF	4.29	4.04	4.30	4.06
Selection Equation				
Number of Observations	36,737	36,737	36,737	36,737
Exclusion restriction (std. error)	-0.039* (0.021)	-0.049** (0.022)	-0.039* (0.021)	-0.048** (0.022)

Notes: 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. The main variables forming the interaction term are mean-centred in Specification (2). LP denotes LEVINSOHN and PETRIN's (2003) approach, while W denotes WOOLDRIDGE's (2009) approach to firms' TFP estimation. λ denotes the inverse Mills ratio from the first-stage selection equations (see Table A7 in the Appendix). The exclusion restriction in the selection equation captures the average exit rate of firms over the period 1998-2007 at the province level.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 2. TFP growth equation: TSLS results

Dependent variable	$\Delta\text{TFP}_{\text{ipg}}$ (LP)		$\Delta\text{TFP}_{\text{ipg}}$ (W)	
Specification	(1)	(2)	(1)	(2)
$\text{TFP}_{\text{ipg}}^{2008}$	-0.286***	-0.291***	-0.288***	-0.293***
	(0.015)	(0.016)	(0.015)	(0.016)
$\text{AGE}_{\text{ipg}}^{2008}$	-0.044***	-0.044***	-0.043***	-0.043***
	(0.003)	(0.003)	(0.003)	(0.003)
$\text{SIZE}_{\text{ipg}}^{2008}$	0.199***	0.193***	0.195***	0.189***
	(0.014)	(0.014)	(0.014)	(0.014)
$\text{WAGE}_{\text{ipg}}^{2008}$	0.156***	0.150***	0.154***	0.148***
	(0.013)	(0.012)	(0.013)	(0.012)
$\text{IC}_{\text{pg}}^{2008}$	0.028***	0.030***	0.027***	0.029***
	(0.009)	(0.009)	(0.010)	(0.009)
$\text{OC}_{\text{p}}^{2008}$	-0.283**	-0.321***	-0.268**	-0.312***
	(0.115)	(0.092)	(0.115)	(0.093)
$\text{IC}_{\text{pg}}^{2008} \times \text{OC}_{\text{p}}^{2008}$	...	-0.098***	...	-0.096***
		(0.032)		(0.032)
$\text{MD}_{\text{p}}^{2008}$	0.011	0.056*	0.009	0.054*
	(0.033)	(0.032)	(0.032)	(0.032)
S&I	0.051	0.076	0.043	0.072
	(0.075)	(0.056)	(0.076)	(0.057)
λ	1.401***	1.334***	1.377***	1.309***
	(0.162)	(0.159)	(0.161)	(0.158)
Industry fixed effects	Yes	Yes	Yes	Yes
Number of Observations	29,170	29,170	29,170	29,170
Censored Observations	7,567	7,567	7,567	7,567
F-statistic	78.48***	73.78***	77.74***	72.89***
Mean VIF	4.16	3.43	4.17	3.44
Exogeneity test (*p*-value)	0.000	0.000	0.000	0.000
Kleibergen-Paap rk LM-statistic (*p*-value)	0.000	0.000	0.000	0.000
Hansen *J*-statistic (*p*-value)	0.288	0.601	0.356	0.644
Selection Equation				
Number of Observations	36,737	36,737	36,737	36,737
Exclusion restriction (std. error)	-0.036* (0.021)	-0.038* (0.023)	-0.036* (0.021)	-0.037* (0.023)

Notes: 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. The main variables forming the interaction term are mean-centred in Specification (2). LP denotes LEVINSOHN and PETRIN's (2003) approach, while W denotes WOOLDRIDGE's (2009) approach to firms' TFP estimation. λ denotes the inverse Mills ratio from the first-stage selection equations (see Table A8 in the Appendix). The exclusion restriction in the selection equation captures the average exit rate of firms over the period 1998-2007 at the province level. The Kleibergen-Papp rk LM-statistic refers to KLEIBERGEN and PAAP's (2006) under-identification test. The variables for industrial clustering and organised crime are instrumented using the measure of industrial clustering in 1996 ($\text{IC}_{\text{pg}}^{1996}$), a measure of population density in 1971 ($\text{PD}_{\text{p}}^{1971}$), and the ratio of condemned individuals over people reported for crimes dated 2001 ($\text{CR}_{\text{p}}^{2001}$), while their interaction term is instrumented using the interactions among the instruments.

$*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table 3. TFP growth equation: TSLS results accounting for extortions only

Dependent variable	$\Delta\mathrm{TFP_{ipg}}$ (LP)		$\Delta\mathrm{TFP_{ipg}}$ (W)	
Specification	(1)	(2)	(1)	(2)
$\mathrm{TFP_{ipg}^{2008}}$	-0.288****	-0.294****	-0.289****	-0.295****
	(0.016)	(0.016)	(0.016)	(0.016)
$\mathrm{AGE_{ipg}^{2008}}$	-0.044****	-0.043****	-0.043****	-0.043****
	(0.003)	(0.004)	(0.003)	(0.003)
$\mathrm{SIZE_{ipg}^{2008}}$	0.198****	0.191****	0.194****	0.187****
	(0.015)	(0.014)	(0.015)	(0.014)
$\mathrm{WAGE_{ipg}^{2008}}$	0.154****	0.147****	0.152****	0.145****
	(0.014)	(0.012)	(0.014)	(0.012)
$\mathrm{IC_{pg}^{2008}}$	0.029***	0.032****	0.028***	0.030***
	(0.010)	(0.009)	(0.010)	(0.010)
$\mathrm{EXT_{p}^{2008}}$	-0.322**	-0.370****	-0.305**	-0.359****
	(0.142)	(0.105)	(0.142)	(0.106)
$\mathrm{IC_{pg}^{2008}} \times \mathrm{EXT_{p}^{2008}}$	...	-0.116***	...	-0.113***
		(0.035)		(0.035)
$\mathrm{MD_{p}^{2008}}$	0.019	0.069**	0.016	0.067*
	(0.039)	(0.035)	(0.038)	(0.034)
S&I	0.064	0.093	0.056	0.088
	(0.089)	(0.061)	(0.089)	(0.062)
λ	1.388****	1.305****	1.365****	1.281****
	(0.166)	(0.161)	(0.165)	(0.160)
Industry fixed effects	Yes	Yes	Yes	Yes
Number of Observations	29,170	29,170	29,170	29,170
Censored Observations	7,567	7,567	7,567	7,567
F-statistic	77.44***	73.23***	76.72***	72.38***
Mean VIF	4.16	3.42	4.17	3.43
Exogeneity test (*p*-value)	0.000	0.000	0.000	0.000
Kleibergen-Paap rk LM-statistic (*p*-value)	0.001	0.000	0.001	0.000
Hansen *J*-statistic (*p*-value)	0.331	0.554	0.396	0.593
Selection Equation				
Number of Observations	36,737	36,737	36,737	36,737
Exclusion restriction (std. error)	-0.036* (0.021)	-0.038* (0.023)	-0.036* (0.021)	-0.037* (0.023)

Notes: 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. The main variables forming the interaction term are mean-centred in Specification (2). LP denotes LEVINSOHN and PETRIN's (2003) approach, while W denotes WOOLDRIDGE's (2009) approach to firms' TFP estimation. λ denotes the inverse Mills ratio from the first-stage selection equations (see Table A8 in the Appendix). The exclusion restriction in the selection equation captures the average exit rate of firms over the period 1998-2007 at the province level. The Kleibergen-Papp rk LM-statistic refers to KLEIBERGEN and PAAP's (2006) under-identification test. The variables for industrial clustering and extortion crime are instrumented using the measure of industrial clustering in 1996 ($\mathrm{IC_{pg}^{1996}}$), a measure of population density in 1971 ($\mathrm{PD_{p}^{1971}}$), and the ratio of condemned individuals over people reported for crimes dated 2001 ($\mathrm{CR_{p}^{2001}}$), while their interaction term is instrumented using the interactions among the instruments.

$*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

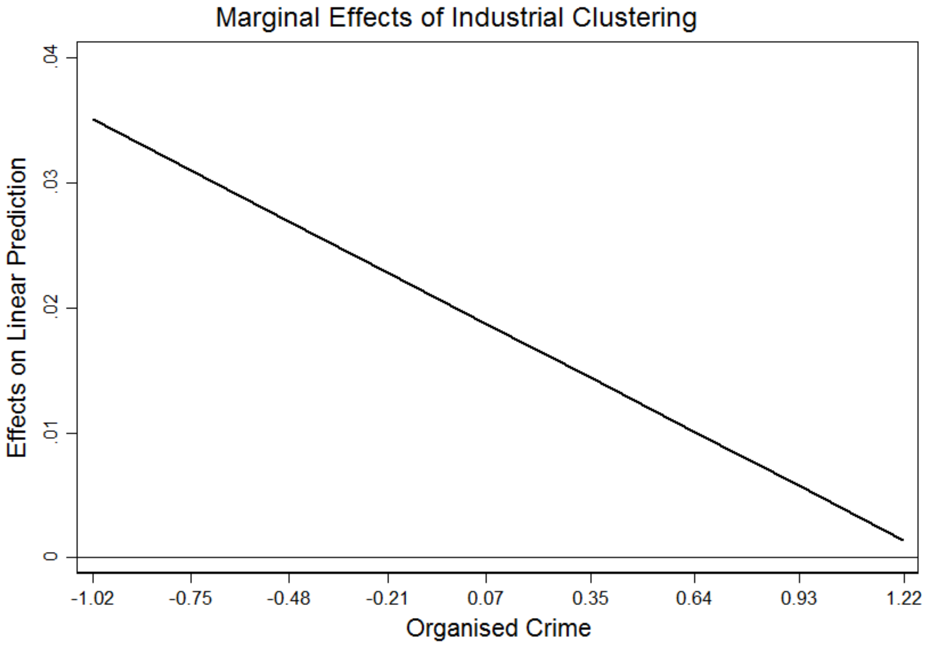
Table 4. TFP growth equation: TSLS results accounting for size effects

Dependent variable	$\Delta\mathrm{TFP}_{\mathrm{ipg}}$ (LP)	$\Delta\mathrm{TFP}_{\mathrm{ipg}}$ (W)
$\mathrm{TFP}_{\mathrm{ipg}}^{2008}$	-0.132***	-0.137***
	(0.030)	(0.030)
$\mathrm{AGE}_{\mathrm{ipg}}^{2008}$	-0.027***	-0.027***
	(0.003)	(0.003)
$\mathrm{SIZE\_CLASS}_{\mathrm{ipg}}^{2008}$	0.649***	0.645***
	(0.062)	(0.063)
$\mathrm{WAGE}_{\mathrm{ipg}}^{2008}$	0.143***	0.144***
	(0.014)	(0.014)
$\mathrm{IC}_{\mathrm{pg}}^{2008}$	0.043***	0.042***
	(0.012)	(0.013)
$\mathrm{OC}_{\mathrm{p}}^{2008}$	-0.465***	-0.458***
	(0.123)	(0.126)
$\mathrm{IC}_{\mathrm{pg}}^{2008} \times \mathrm{OC}_{\mathrm{p}}^{2008} \times \mathrm{SIZE\_CLASS}_{\mathrm{ipg}}^{2008}$	-0.121***	-0.121***
	(0.043)	(0.043)
$\mathrm{MD}_{\mathrm{p}}^{2008}$	0.031	0.030
	(0.034)	(0.034)
S&I	0.093	0.090
	(0.078)	(0.080)
λ	2.298***	2.281***
	(0.279)	(0.281)
Industry fixed effects	Yes	Yes
Number of Observations	29,170	29,170
Censored Observations	7,567	7,567
F-statistic	68.60***	67.78***
Mean VIF	5.07	5.10
Exogeneity test (*p*-value)	0.000	0.000
Kleibergen-Paap rk LM-statistic (*p*-value)	0.000	0.000
Hansen *J*-statistic (*p*-value)	0.689	0.715
Selection Equation		
Number of Observations	36,737	36,737
Exclusion restriction (std. error)	-0.047** (0.022)	-0.046** (0.022)

Notes: 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. The main (continuous) variables forming the interaction term are mean-centred. LP denotes LEVINSOHN and PETRIN's (2003) approach, while W denotes WOOLDRIDGE's (2009) approach to firms' TFP estimation. λ denotes the inverse Mills ratio from the first-stage selection equations (see Table A9 in the Appendix). The exclusion restriction in the selection equation captures the average exit rate of firms over the period 1998-2007 at the province level. The Kleibergen-Paap rk LM-statistic refers to KLEIBERGEN and PAAP's (2006) under-identification test. The variables for industrial clustering and organised crime are instrumented using the measure of industrial clustering in 1996 ($\mathrm{IC}_{\mathrm{pg}}^{1996}$), a measure of population density in 1971 ($\mathrm{PD}_{\mathrm{p}}^{1971}$), and the ratio of condemned individuals over people reported for crimes dated 2001 ($\mathrm{CR}_{\mathrm{p}}^{2001}$), while the interaction term among the size classes, industrial clustering and organised crime variables is instrumented using the interactions among the instruments and the size classes variable.

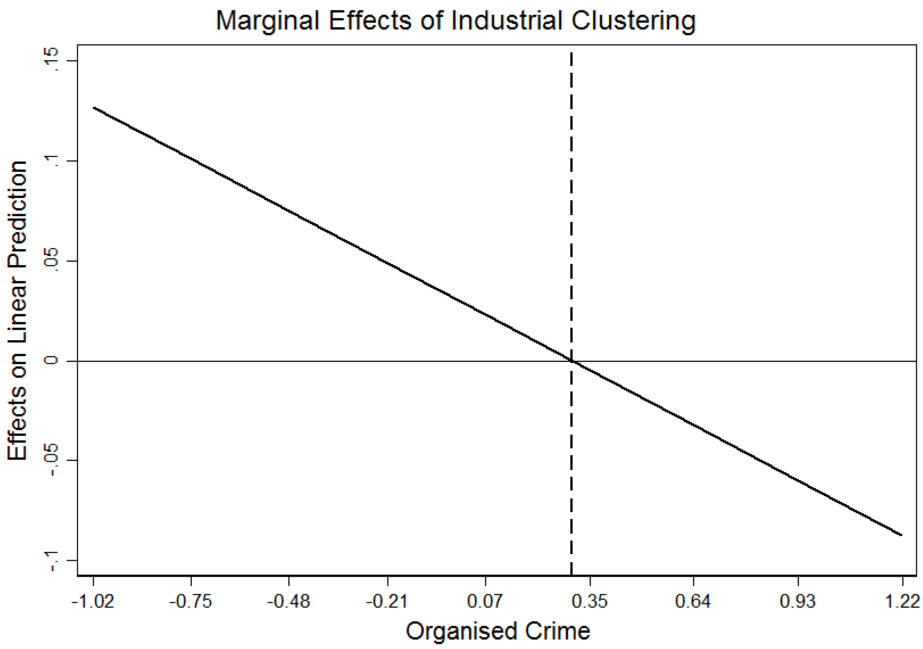
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Fig. 1. Marginal effects of industrial clustering: exogenous model



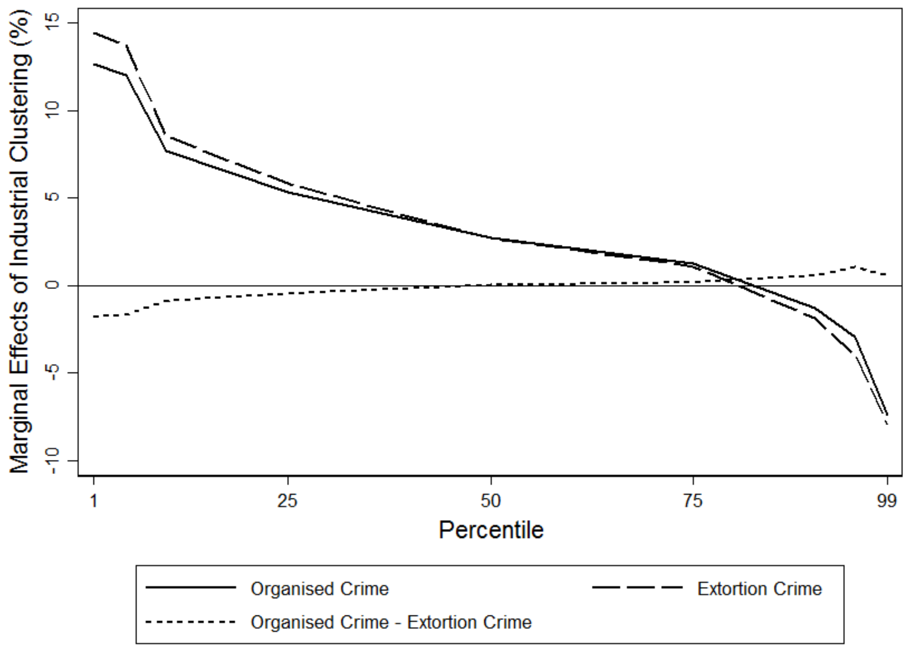
Notes: TFP is estimated using WOOLDRIDGE's (2009) approach.

Fig. 2. Marginal effect of industrial clustering: endogenous model



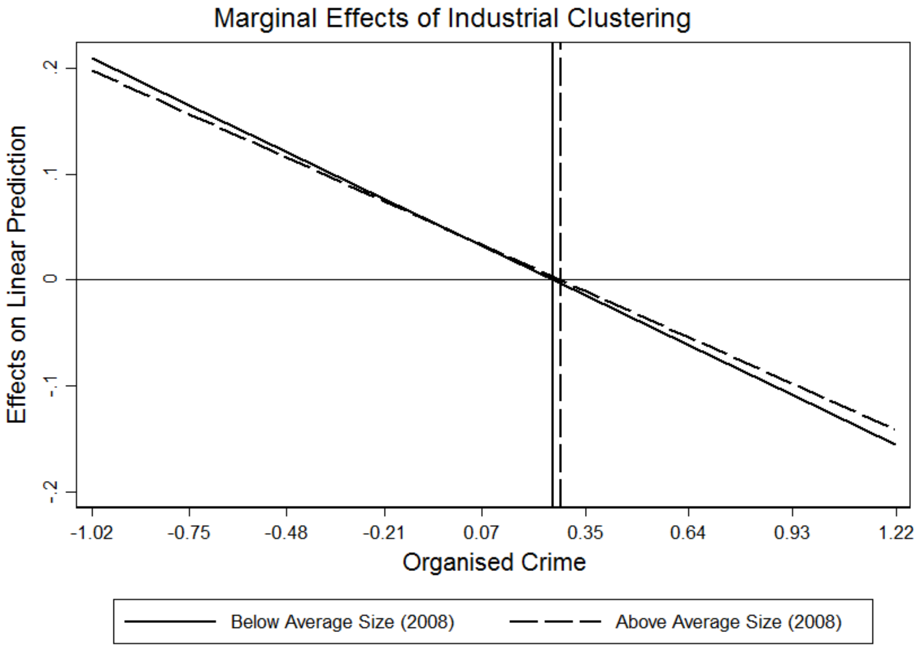
Notes: TFP is estimated using WOOLDRIDGE's (2009) approach.

Fig. 3. Comparison between marginal effects: organised crime vs. extortions



Notes: TFP is estimated using WOOLDRIDGE's (2009) approach.

Fig. 4. Marginal effect of industrial clustering by size classes



Notes: TFP is estimated using WOOLDRIDGE's (2009) approach.

APPENDIX

Table A1. Sample distribution by industry

Category	Two-digit Industry	Number of Firms	
		a. v.	%
DA	15 - Food and beverages	3,417	9.30
	16 - Tobacco	0	0.00
DB	17 - Textiles	1,951	5.31
	18 - Clothing	1,208	3.29
DC	19 - Leather	1,246	3.39
DD	20 - Wood	1,185	3.23
DE	21 - Paper products	804	2.19
	22 - Printing and publishing	1,344	3.66
DF	23 - Coke, oil refinery, nuclear fuel	110	0.30
DG	24 - Chemicals	1,522	4.14
DH	25 - Rubber and plastics	1,980	5.39
DI	26 - Non-metals minerals	2,312	6.29
DJ	27 - Metals	816	2.22
	28 - Metal products	8,053	21.92
DK	29 - Non-electric machinery	4,147	11.29
DL	30 - Office equipments and computers	275	0.75
	31 - Electric machinery	1,424	3.88
	32 - Electronic material	458	1.25
	33 - Medical apparels and instruments	841	2.29
DM	34 - Vehicles	524	1.43
	35 - Other transportation	457	1.24
DN	36 - Furniture	2,663	7.25
	37 - Recycling	0	0.00
	Total sample	36,737	100.00

Notes: Firms are classified according to the Ateco 1991 classification of economic activities adopted by Istat, which corresponds to the NACE Rev. 1 classification.

Table A2. Sample distribution by geographic area

Geographic Area	Number of Firms	
	a. v.	%
North West	13,825	37.63
North East	11,180	30.43
Centre	6,428	17.50
South and Islands	5,304	14.44
Total Sample	36,737	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. Statistics and correlation matrix of the variables entering the production function

		Mean	Std. Dev.	Min.	Max.	va_{igpt}	k_{igpt}	l_{igpt}	m_{igpt}
va_{igpt}	overall	6.388	1.467	-0.166	14.165				
	between		1.428	0.593	13.795	1			
	within		0.306	1.035	9.933				
k_{igpt}	overall	6.009	2.110	-6.705	14.895				
	between		2.064	-3.646	14.676	0.721	1		
	within		0.445	-1.475	11.761				
l_{igpt}	overall	5.892	1.438	-0.249	13.593				
	between		1.417	0.770	13.532	0.952	0.695	1	
	within		0.218	0.116	9.252				
m_{igpt}	overall	7.211	1.711	-0.176	16.549				
	between		1.683	0.804	16.493	0.856	0.671	0.819	1
	within		0.261	1.780	11.486				

Notes: All variables are log-transformed. va_{igpt} denotes value added; k_{igpt} denotes the capital input; l_{igpt} denotes the labour input; m_{igpt} denotes intermediate inputs. Descriptive statistics and the correlation matrix refer to a sample of 41,484 firms, i.e. 179,233 observations over the period 2007-2011.

Table A4. Estimated inputs' elasticities of the production functions

LEVINSOHN and PETRIN (2003)							
Industry	k_{igpt}			l_{igpt}			No. Obs.
15	0.077	(0.010)	[0.000]	0.663	(0.011)	[0.000]	16,876
17	0.039	(0.011)	[0.000]	0.728	(0.012)	[0.000]	9,470
18	0.069	(0.013)	[0.000]	0.715	(0.016)	[0.000]	5,853
19	0.058	(0.013)	[0.000]	0.735	(0.014)	[0.000]	6,120
20	0.031	(0.013)	[0.019]	0.702	(0.014)	[0.000]	5,720
21	0.050	(0.021)	[0.015]	0.717	(0.024)	[0.000]	3,945
22	0.036	(0.013)	[0.004]	0.723	(0.017)	[0.000]	6,289
23	0.056	(0.084)	[0.444]	0.703	(0.048)	[0.000]	567
24	0.051	(0.013)	[0.000]	0.734	(0.014)	[0.000]	7,700
25	0.079	(0.014)	[0.000]	0.705	(0.013)	[0.000]	9,541
26	0.068	(0.011)	[0.000]	0.681	(0.014)	[0.000]	11,159
27	0.063	(0.023)	[0.005]	0.725	(0.018)	[0.000]	4,197
28	0.059	(0.005)	[0.000]	0.747	(0.005)	[0.000]	38,821
29	0.066	(0.008)	[0.000]	0.708	(0.010)	[0.000]	20,486
30	0.063	(0.018)	[0.000]	0.793	(0.026)	[0.000]	1,301
31	0.058	(0.011)	[0.000]	0.703	(0.016)	[0.000]	6,909
32	0.037	(0.021)	[0.079]	0.745	(0.026)	[0.000]	2,319
33	0.077	(0.016)	[0.000]	0.715	(0.016)	[0.000]	4,122
34	0.027	(0.021)	[0.205]	0.746	(0.020)	[0.000]	2,809
35	0.066	(0.024)	[0.006]	0.725	(0.021)	[0.000]	2,300
36	0.059	(0.008)	[0.000]	0.703	(0.011)	[0.000]	12,729
WOOLDRIDGE (2009)							
Industry	k_{igpt}			l_{igpt}			No. Obs.
15	0.075	(0.010)	[0.000]	0.666	(0.012)	[0.000]	12,965
17	0.041	(0.011)	[0.000]	0.723	(0.013)	[0.000]	7,302
18	0.069	(0.013)	[0.000]	0.724	(0.017)	[0.000]	4,461
19	0.056	(0.013)	[0.000]	0.735	(0.015)	[0.000]	4,686
20	0.030	(0.012)	[0.014]	0.720	(0.015)	[0.000]	4,362
21	0.053	(0.021)	[0.010]	0.710	(0.024)	[0.000]	3,054
22	0.038	(0.011)	[0.000]	0.735	(0.019)	[0.000]	4,793
23	0.036	(0.065)	[0.580]	0.704	(0.057)	[0.000]	441
24	0.053	(0.013)	[0.000]	0.752	(0.015)	[0.000]	5,973
25	0.083	(0.013)	[0.000]	0.695	(0.013)	[0.000]	7,364
26	0.068	(0.011)	[0.000]	0.690	(0.014)	[0.000]	8,563
27	0.062	(0.020)	[0.002]	0.730	(0.020)	[0.000]	3,263
28	0.058	(0.005)	[0.000]	0.752	(0.006)	[0.000]	29,765
29	0.066	(0.008)	[0.000]	0.730	(0.010)	[0.000]	15,828
30	0.057	(0.018)	[0.001]	0.804	(0.027)	[0.000]	993
31	0.057	(0.011)	[0.000]	0.716	(0.017)	[0.000]	5,313
32	0.040	(0.020)	[0.062]	0.753	(0.027)	[0.000]	1,783
33	0.075	(0.017)	[0.000]	0.732	(0.019)	[0.000]	3,162
34	0.026	(0.021)	[0.209]	0.762	(0.021)	[0.000]	2,179
35	0.064	(0.025)	[0.010]	0.741	(0.026)	[0.000]	1,750
36	0.059	(0.009)	[0.000]	0.707	(0.012)	[0.000]	9,749

Notes: k_{igpt} denotes the capital input, while l_{igpt} denotes the labour input. TFP is estimated on a sample of 41,484 firms, i.e. 179,233 observations over the period 2007-2011. Standard errors are shown in parentheses: they are bootstrapped in LEVINSOHN and PETRIN's (2003) approach, while they are clustered at the firm level in WOOLDRIDGE's (2009) approach. *P*-values are shown in brackets.

Table A5. Descriptive statistics of the dependent and main explanatory variables

	No. Obs.	Mean	Std. Dev.	Min.	Max.
$\Delta\mathrm{TFP}_{\mathrm{ipg}}$ (LP)	29,170	-0.034	0.407	-6.125	5.555
$\Delta\mathrm{TFP}_{\mathrm{ipg}}$ (W)	29,170	-0.035	0.407	-6.119	5.559
$\mathrm{TFP}_{\mathrm{ipg}}^{2008}$ (LP)	36,737	1.809	0.495	-4.252	5.404
$\mathrm{TFP}_{\mathrm{ipg}}^{2008}$ (W)	36,737	1.768	0.489	-4.356	5.342
$\mathrm{AGE}_{\mathrm{ipg}}^{2008}$	36,737	2.610	0.915	0	4.875
$\mathrm{SIZE}_{\mathrm{ipg}}^{2008}$	36,737	2.504	1.196	0	5.517
$\mathrm{WAGE}_{\mathrm{ipg}}^{2008}$	36,737	3.211	0.443	-1.749	7.994
$\mathrm{IC}_{\mathrm{pg}}^{2008}$	36,737	-0.883	1.139	-6.153	1.861
$\mathrm{OC}_{\mathrm{p}}^{2008}$	36,737	2.888	0.414	1.870	4.104
$\mathrm{MD}_{\mathrm{p}}^{2008}$	36,737	0.206	0.405	0	1

Notes: LP denotes LEVINSOHN and PETRIN's (2003) approach, while W denotes WOOLDRIDGE's (2009) approach to firms' TFP estimation. Δ denotes the log difference between time T and $(\mathrm{T}-\mathrm{t})$.

Table A6. Correlation matrix of the main explanatory variables

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$\mathrm{TFP}_{\mathrm{ipg}}^{2008}$ (LP)	[1]	1							
$\mathrm{TFP}_{\mathrm{ipg}}^{2008}$ (W)	[2]	0.995	1						
$\mathrm{AGE}_{\mathrm{ipg}}^{2008}$	[3]	0.205	0.201	1					
$\mathrm{SIZE}_{\mathrm{ipg}}^{2008}$	[4]	0.458	0.444	0.305	1				
$\mathrm{WAGE}_{\mathrm{ipg}}^{2008}$	[5]	0.228	0.210	0.276	0.090	1			
$\mathrm{IC}_{\mathrm{pg}}^{2008}$	[6]	0.071	0.075	0.078	-0.016	0.125	1		
$\mathrm{OC}_{\mathrm{p}}^{2008}$	[7]	-0.061	-0.058	-0.066	-0.077	-0.108	0.150	1	
$\mathrm{MD}_{\mathrm{p}}^{2008}$	[8]	-0.003	-0.010	0.038	-0.021	0.106	0.546	0.287	1

Notes: LP denotes LEVINSOHN and PETRIN's (2003) approach, while W denotes WOOLDRIDGE's (2009) approach to firms' TFP estimation.

Table A7. Selection equation: exogenous model

Dependent variable	$\mathrm{SURVIVAL}_{\mathrm{ipg}}$			
TFP estimation approach	LEVINSOHN and PETRIN (2003)		WOOLDRIDGE (2009)	
Specification	(1)	(2)	(1)	(2)
$\mathrm{TFP}_{\mathrm{ipg}}^{2008}$	0.238***	0.239***	0.239***	0.240***
	(0.018)	(0.018)	(0.018)	(0.018)
$\mathrm{AGE}_{\mathrm{ipg}}^{2008}$	-0.030***	-0.030***	-0.030***	-0.030***
	(0.008)	(0.008)	(0.008)	(0.008)
$\mathrm{SIZE}_{\mathrm{ipg}}^{2008}$	0.212***	0.212***	0.214***	0.214***
	(0.007)	(0.007)	(0.007)	(0.007)
$\mathrm{WAGE}_{\mathrm{ipg}}^{2008}$	0.124***	0.122***	0.125***	0.124***
	(0.019)	(0.019)	(0.019)	(0.019)
$\mathrm{IC}_{\mathrm{pg}}^{2008}$	0.028**	0.029**	0.028**	0.029**
	(0.013)	(0.013)	(0.013)	(0.013)
$\mathrm{OC}_{\mathrm{p}}^{2008}$	-0.066***	-0.082***	-0.066***	-0.082***
	(0.025)	(0.026)	(0.025)	(0.026)
$\mathrm{IC}_{\mathrm{pg}}^{2008} \times \mathrm{OC}_{\mathrm{p}}^{2008}$	...	-0.053***	...	-0.053***
		(0.018)		(0.019)
$\mathrm{MD}_{\mathrm{p}}^{2008}$	-0.075**	-0.052	-0.074**	-0.052
	(0.036)	(0.036)	(0.036)	(0.036)
S&I	-0.078**	-0.063*	-0.077**	-0.063*
	(0.034)	(0.034)	(0.034)	(0.034)
Exclusion restriction	-0.039*	-0.049**	-0.039*	-0.048**
	(0.021)	(0.022)	(0.021)	(0.022)
Industry fixed effects	Yes	Yes	Yes	Yes
Number of Observations	36,737	36,737	36,737	36,737
Wald χ^2	1,939.03***	1,949.71***	1,941.29***	1,950.52***
Log Likelihood	-17,714.48	-17,709.63	-17,713.78	-17,708.00
Mean VIF	1.72	1.71	1.72	1.71

Notes: 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. The main variables forming the interaction term are mean-centred in Specification (2). The exclusion restriction in the selection equation captures the average exit rate of firms over the period 1998-2007 at the province level.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table A8. Selection equation: endogenous model

Dependent variable	$\text{SURVIVAL}_{\text{ipg}}$			
TFP estimation approach	LEVINSOHN and PETRIN (2003)		WOOLDRIDGE (2009)	
Specification	(1)	(2)	(1)	(2)
$\text{TFP}_{\text{ipg}}^{2008}$	0.238***	0.240***	0.239***	0.240***
	(0.018)	(0.018)	(0.018)	(0.018)
$\text{AGE}_{\text{ipg}}^{2008}$	-0.029***	-0.030***	-0.030***	-0.030***
	(0.008)	(0.009)	(0.008)	(0.009)
$\text{SIZE}_{\text{ipg}}^{2008}$	0.213***	0.212***	0.214***	0.214***
	(0.007)	(0.007)	(0.007)	(0.007)
$\text{WAGE}_{\text{ipg}}^{2008}$	0.126***	0.125***	0.127***	0.126***
	(0.019)	(0.019)	(0.019)	(0.019)
$\text{IC}_{\text{pg}}^{1996}$	0.027	0.018	0.029	0.020
	(0.034)	(0.031)	(0.034)	(0.031)
$\text{PD}_{\text{p}}^{1971}$	-0.015	-0.006	-0.018	-0.008
	(0.038)	(0.035)	(0.038)	(0.035)
$\text{CR}_{\text{p}}^{2001}$	0.044	0.059*	0.044	0.060*
	(0.029)	(0.034)	(0.029)	(0.034)
$\text{IC}_{\text{pg}}^{1996} \times \text{PD}_{\text{p}}^{1971}$	...	-0.019**	...	-0.019**
		(0.009)		(0.009)
$\text{IC}_{\text{pg}}^{1996} \times \text{CR}_{\text{p}}^{2001}$	...	-0.128*	...	-0.126*
		(0.072)		(0.072)
$\text{PD}_{\text{p}}^{1971} \times \text{CR}_{\text{p}}^{2001}$	...	0.242***	...	0.240***
		(0.077)		(0.077)
$\text{MD}_{\text{p}}^{2008}$	-0.077**	-0.054	-0.076**	-0.053
	(0.037)	(0.040)	(0.037)	(0.040)
S&I	-0.112***	-0.081***	-0.111***	-0.080**
	(0.031)	(0.031)	(0.031)	(0.031)
Exclusion restriction	-0.036*	-0.038*	-0.036*	-0.037*
	(0.021)	(0.023)	(0.021)	(0.023)
Industry fixed effects	Yes	Yes	Yes	Yes
Number of Observations	36,737	36,737	36,737	36,737
Wald χ^2	1,931.69***	1,910.32***	1,934.42***	1,912.45***
Log Likelihood	-17,718.18	-17,706.91	-17,717.41	-17,706.23
Mean VIF	2.40	2.86	2.40	2.85

Notes: 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. The main variables forming the interaction terms are mean-centred in Specification (2). The exclusion restriction in the selection equation captures the average exit rate of firms over the period 1998-2007 at the province level.

$*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table A9. Selection equation: endogenous model accounting for size effects

Dependent variable	$\mathrm{SURVIVAL_{ipg}}$	
TFP estimation approach	LEVINSOHN and PETRIN (2003)	WOOLDRIDGE (2009)
$\mathrm{TFP_{ipg}^{2008}}$	0.268***	0.267***
	(0.018)	(0.018)
$\mathrm{AGE_{ipg}^{2008}}$	-0.013	-0.012
	(0.008)	(0.008)
$\mathrm{SIZE\_CLASS_{ipg}^{2008}}$	0.641***	0.645***
	(0.025)	(0.025)
$\mathrm{WAGE_{ipg}^{2008}}$	0.085***	0.087***
	(0.020)	(0.020)
$\mathrm{IC_{pg}^{1996}}$	0.029	0.031
	(0.033)	(0.034)
$\mathrm{PD_{p}^{1971}}$	-0.021	-0.024
	(0.038)	(0.038)
$\mathrm{CR_{p}^{2001}}$	0.054*	0.055*
	(0.030)	(0.030)
$\mathrm{IC_{pg}^{1996}} \times \mathrm{PD_{p}^{1971}} \times \mathrm{SIZE\_CLASS_{ipg}^{2008}}$	-0.037**	-0.037**
	(0.016)	(0.016)
$\mathrm{IC_{pg}^{1996}} \times \mathrm{CR_{p}^{2001}} \times \mathrm{SIZE\_CLASS_{ipg}^{2008}}$	-0.276*	-0.273*
	(0.142)	(0.142)
$\mathrm{PD_{p}^{1971}} \times \mathrm{CR_{p}^{2001}} \times \mathrm{SIZE\_CLASS_{ipg}^{2008}}$	0.413***	0.410***
	(0.157)	(0.157)
$\mathrm{MD_{p}^{2008}}$	-0.071*	-0.069*
	(0.038)	(0.038)
S&I	-0.106***	-0.105***
	(0.031)	(0.032)
Exclusion restriction	-0.047**	-0.046**
	(0.022)	(0.022)
Industry fixed effects	Yes	Yes
Number of Observations	36,737	36,737
Wald χ^2	1,857.22	1,859.78
Log Likelihood	-17,679.73	-17,680.99
Mean VIF	2.71	2.71

Notes: 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. The main (continuous) variables forming the interaction terms are mean-centred. The exclusion restriction in the selection equation captures the average exit rate of firms over the period 1998-2007 at the province level.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Fig. A1: Spatial distribution of the organised crime variable (quartile map)

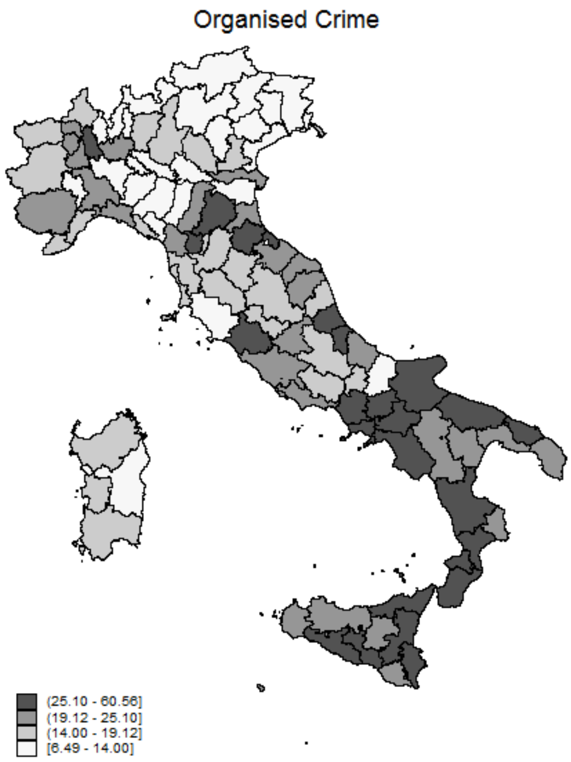
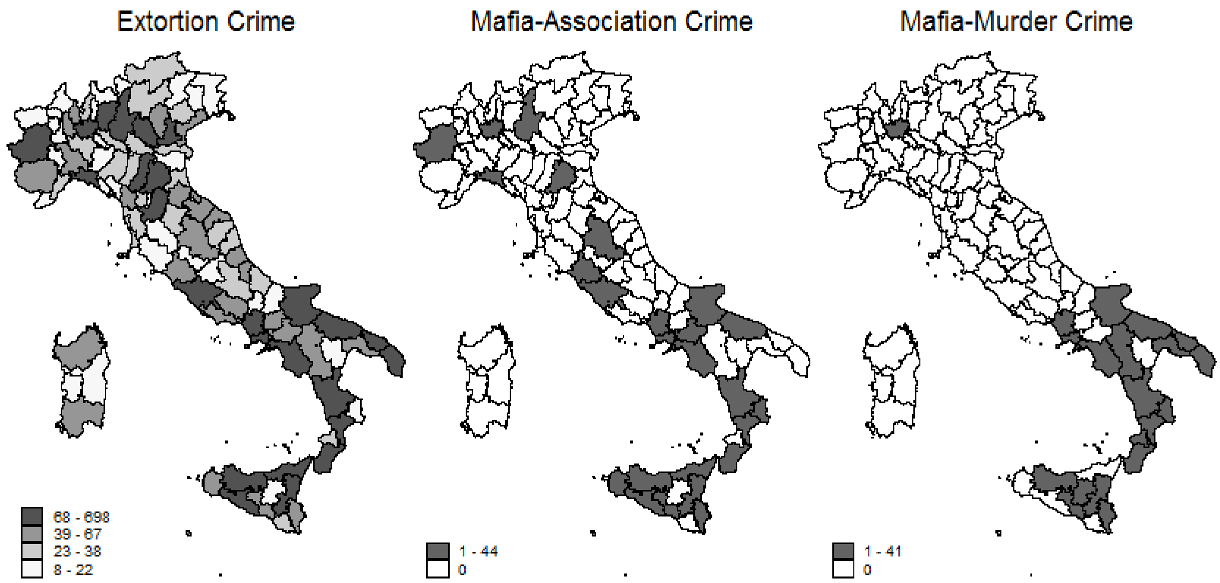


Fig. A2: Spatial distribution of the types of crime



Chapter 3

Agglomeration, Heterogeneity and Firm Productivity[*]

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Abstract: This paper investigates two issues related to the link between agglomeration economies and firms' short-run productivity growth. First, the Modifiable Areal Unit Problem is examined using distance-based agglomeration measures constructed over a continuous space. Second, the hypothesis of firm heterogeneity among spatially agglomerated firms acting as the source of local externalities is tested. Results underline spatial nonlinearities of the agglomeration forces, which would have been difficult to identify using pre-defined geographic units. We find that intra-industry externalities have positive effects over short distances, while inter-industry externalities have positive effects at a longer distance on productivity growth. Intra-industry externalities seem to decrease with increasing distance, although this decreasing-with-distance pattern changes if firm heterogeneity (in terms of size and productivity) is taken into account. Firm heterogeneity seems to matter for generating intra-industry externalities: bigger and more productive firms belonging to the same industry produce more externalities resulting in an increasing-with-distance pattern of intra-industry forces.

Keywords: Agglomeration; Heterogeneity; Total Factor Productivity; Italy

JEL classification: C3; D24; R12

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1. INTRODUCTION

The spatial agglomeration of economic activities is a remarkable feature of the economic geography of many countries, regions and local systems (PORTER, 1990). Silicon Valley (SAXENIAN, 1994), carpet manufacturing industry in Dalton, Georgia, (KRUGMAN, 1991) and the industrial districts in Italy (BECATTINI, 1990; CAINELLI, 2008) are well-known examples of a general and complex phenomenon.

Since MARSHALL's (1920) seminal contribution, investigations of the determinants and main features of geographically agglomerated areas have proliferated in the fields of economics and business studies, and have identified three different mechanisms which may induce firms to co-localise: the availability of skilled labour (labour market pooling), access to specialised suppliers (shared inputs) and the spread of inter-firm knowledge spillovers (GLAESER *et al.*, 1992; HENDERSON *et al.*, 1995). The theoretical and empirical contributions suggest that firms located in an agglomerated area benefit from these local externalities, which contribute to reductions in production costs. Several studies have attempted to understand whether agglomeration forces (in particular localisation and diversification economies) play a role in explaining firms' economic performance, in particular measured as Total Factor Productivity (TFP, henceforth). However, starting from the contributions of DE LUCIO *et al.* (2002) and CINGANO and SCHIVARDI (2004), the empirical results tend to be mixed and not conclusive.

This literature is characterised by two main issues. The first is the use of exogenously pre-defined geographic units of analysis to capture agglomeration phenomena. However, Standard Metropolitan Areas (SMAs), Local Labour Systems (LLSs) and administrative units (e.g. NUTS-2 or NUTS-3 regions) do not necessarily coincide with real economic areas, and the discretionary choice of the space may introduce statistical biases related to the level of aggregation and the geographic scale (ARBIA, 1989). This is generally known as the Modifiable

Areal Unit Problem (MAUP) and refers to the arbitrary choice of the spatial partition used to analyse geographic-based phenomena (ARBIA, 2001).[1]

The second issue is firm heterogeneity. Theoretical and empirical studies neglect this issue and assume that firms operating in an agglomerated space are homogeneous (ALCACER and CHUNG, 2007), i.e. they assume that all the firms located in a given geographic area contribute in the same way, and with the same intensity, to the production of the agglomeration externalities in the local system. SHAVER and FLYER (2000) underline that the theoretical models proposed by ROMER (1986), DAVID and ROSENBLOOM (1990) and RAUCH (1993) make this assumption (or assume that firms are "small" relative to the industry output), thus assuming also that firms do not have differential effects on externalities. However, firms differ not only in terms of the technological endowments and human capital stock but also in terms of their capability to produce tangible and intangible externalities. It follows that a firm cannot be seen only as a "receiver" of local externalities, it is also a potential "source" of these local effects. For instance, ALCACER and CHUNG (2007, p. 761) note that "firms are neither equally equipped to receive knowledge nor homogeneously willing to serve as sources of spillovers".

The aim of this paper is to contribute to this debate. It analyses a large sample of Italian manufacturing firms to empirically investigate the relationship between agglomeration (localisation- and diversification-type) externalities and firms' short-run productivity growth, taking account of these two issues. First, the MAUP issue is tackled using distance-based agglomeration measures computed for each firm in the sample over a continuous space. We next perform a hierarchical cluster analysis in order to avoid (or at least to limit) an arbitrary *ad hoc* identification of the distance bands (as done, on the contrary, in previous studies, e.g. CAINELLI and LUPI, 2010). Second, the hypothesis of firm heterogeneity is explicitly tested considering the firms located in the agglomerative space as sources of local externalities. Specifically, the role of firm heterogeneity is tested using weighted agglomeration measures constructed to account for the size and (estimated) TFP of neighbour firms within each distance band. This allows us to capture the phenomenon of "agglomerative heterogeneity" in terms of firm-specific characteristics (such as size and TFP) which proxy for firms' differential effects in the production of agglomeration externalities. The idea is that spatial agglomeration forces may depend not only on the number of co-localised firms (i.e. critical mass effect) but also on firm-specific characteristics since firms may contribute differently to the production of local externalities depending on their characteristics.

The paper is structured as follows. Section 2 presents and discusses the literature related to these two issues. Section 3 presents the data and the methodology adopted. Section 4 reports and discusses the empirical results. Section 5 presents our conclusions.

2. RELATED LITERATURE

2.1. Agglomeration and firm productivity

The literature on agglomeration economies identifies two main forms of local externalities arising from the geographic concentration of economic activities, i.e. localisation externalities and diversification externalities. Localisation externalities arise from the spatial concentration of firms operating in the same industry, and their relevance dates back to MARSHALL's (1920) contribution on the industrial district concept. The key idea is that firms located close to other firms operating in the same industry benefit from reduced transportation costs, emergence of external-scale economies, availability of specialised workers and suppliers, and diffusion of intra-industry knowledge and technological spillovers which reduce economic costs, thus fostering efficiency and growth (GLAESER *et al.*, 1992; DURANTON and PUGA, 2004; MARTIN *et al.*, 2011). Conversely, diversification externalities arise from the geographic concentration of firms operating in different industries. The main advantages derived from location in a highly diversified environment are related to availability of inputs from suppliers operating at different stages in the production chain, and cross-fertilisation among existing ideas and technologies favoured by the variety in the local economic structure (JACOBS, 1969).

Empirical analysis of the role played by these types of agglomeration economies on productivity and firms' TFP growth has become especially relevant in the last decade (e.g. DE LUCIO *et al*., 2002; HENDERSON, 2003; CINGANO and SCHIVARDI, 2004; CAINELLI and LUPI, 2010; MARTIN *et al.*, 2011, CAINELLI *et al.*, 2015a; CAINELLI *et al.*, 2015b). However, similar to investigations of the impact of these agglomeration forces on employment growth (e.g. GLAESER *et al.*, 1992; HENDERSON *et al.*, 1995; CAINELLI and LEONCINI, 1999; USAI and PACI, 2003), the empirical results from this research strand are rather puzzling. For example, DE LUCIO *et al.* (2002) find a positive effect of industrial variety and a U-shaped effect of localisation externalities on labour productivity at province level in Spain. Their results show that low levels of localisation reduce productivity growth while high levels foster it. HENDERSON (2003) finds strong positive effects of localisation economies on productivity at plant level on US high-tech industries, but not in machinery industries, and he finds little evidence of diversification economies. CINGANO and SCHIVARDI (2004) find a positive effect of localisation, but a negligible effect of diversification externalities on TFP growth at the LLS level in Italy. The same study finds a negative effect of localisation and a positive effect of diversification externalities on employment growth, thus confirming the results of GLAESER *et al.* (1992). MARTIN *et al.* (2011) find that French firms' productivity benefits from localisation, but not from diversification economies. However, the benefits from industrial clustering (although highly significant from a statistical point of view) are quite modest in magnitude. CAINELLI *et al.* (2015a) adopt a panel smooth transition regression model to analyse the nonlinear effects of agglomeration forces on Italian firms and find that localisation and diversification externalities materialise for values of, respectively, intra-industry agglomeration and extra-sector diversity above a certain threshold. FAZIO and MALTESE (2015) find that the effect of agglomeration forces on Italian small and medium sized firms' performance varies depending on whether the level of or growth of TFP is taken into account: TFP levels are influenced mostly by localisation externalities, while TFP growth is higher in the presence of diversification (and Porterian/competition) externalities. Finally, CAINELLI *et al.* (2015b) find that the effect of localisation externalities is stronger than the effect of diversification externalities (i.e. industry related variety) on Italian manufacturing firms' TFP.

2.2. The MAUP

Previous contributions capture agglomeration forces using pre-defined geographic units of analysis such as SMAs, LLSs and NUTS-2 or NUTS-3 administrative units. These geographic units can vary in size and shape, and their boundaries are arbitrary pre-defined independently of the criteria adopted for their definition. In other words, standard spatial units of analysis do not necessarily coincide with real economic areas, and the discretionary choice of the space may introduce statistical biases related to the level of aggregation and geographic scale (ARBIA, 1989). This issue is known as the MAUP and is related to the arbitrary choice of the spatial partition used to analyse geographic-based phenomena (ARBIA, 2001).

The MAUP helps to explain the varying results in empirical works analysing the relationship between agglomeration forces and firms' TFP. These differences may be due to the different geographic units considered as well as the different measures of agglomeration employed (ROSENTHAL and STRANGE, 2003; BEAUDRY and SCHIFFAUEROVA, 2009; BURGER *et al.*, 2010). The geographic scale at which agglomeration phenomena are analysed is a critical issue since agglomeration forces may produce different effects at different spatial scales (SCOTT, 1982; OLSEN, 2002; VAN OORT, 2004; BURGER *et al.*, 2010). Moreover, their effects are likely to attenuate over space (ROSENTHAL and STRANGE, 2008; CAINELLI and LUPI, 2010). This is probable when distinguishing between localisation and diversification externalities, as well as between market- and knowledge-based externalities within each type of agglomeration force (MARTIN, 1999).

The literature proposes alternative solutions to mitigate the MAUP in the case of geographic-based phenomena. Some contributions suggest controlling for extra-region spillovers through the inclusion of spatially-lagged agglomeration variables computed within administrative areas or labour market regions (e.g. VAN OORT, 2004, 2007; BURGER *et al.*, 2010). Others propose a multilevel approach to enable simultaneous modelling at the micro and macro levels of analysis (e.g. VAN OORT *et al.*, 2012; SANFILIPPO and SERIC, 2014).

ARBIA (2001) suggested a new solution using micro-geographic data, thus moving the analysis from the meso- to the micro-geographic level. The idea is to consider the firm as the spatial unit of analysis and to treat the space as continuous in order to avoid the use of pre-defined spatial partitions. Along similar lines, some authors propose the use of distance-based measures to identify the geographic concentration of economic activities (ARBIA and ESPA, 1996; DURANTON and OVERMAN, 2005; MARCON and PUECH, 2010). These contributions exploit spatial statistics (e.g. probability or cumulative density functions), which use pair distances between observations (i.e. individual firms) in order to evaluate at which geographic scale a particular industry shows a clustering pattern. This allows industrial clustering to be identified in the space regardless of pre-defined geographic partitions.

CAINELLI and LUPI (2010) and GABRIELE *et al.* (2013) extended this approach by constructing agglomeration measures over a continuous space. The main intuition in these two works is to use a continuous approach to the space, rather than arbitrary pre-defined spatial units of analysis, so that the sample of firms is treated as a spatial points pattern with each firm representing an individual point identified by its geographic coordinates. Distance-based agglomeration measures are computed within continuous distance bands identified around each firm in the sample to evaluate the space component of the agglomeration phenomenon.

CAINELLI and LUPI (2010) analyse a sample of about 23,000 Italian manufacturing firms observed over the period 1998-2001, and find that localisation effects are positive within 2 km, but decreasing over distance. On the contrary, diversification effects are negative for distances up to 10 km, but positive between 10 km and 30 km. GABRIELE *et al.* (2013) analyse a sample of about 8,300 Italian manufacturing firms observed over the period 1996-2004, and find that small sized firms' growth is fostered by localisation externalities, while medium and large sized firms benefit more from diversification externalities. However, they do not find evidence of spatial nonlinearities of agglomeration forces.

2.3. Heterogeneous agglomeration

Theoretical and empirical economics contributions tend to overlook the possibility of firm heterogeneity, i.e. they assume firm homogeneity in the agglomerative space. However, as SHAVER and FLYER (2000, p. 1175) underline, "firms not only capture benefits from agglomeration economies, but they also contribute to agglomeration economies". In other words, the hypothesis of firm homogeneity assumes that all the firms located in a given geographic area contribute in the same way, and with the same intensity, to the production of agglomeration externalities in the local system. It is not surprising that "firms operating in industrial districts have been traditionally modelled as undifferentiated and characterized by low variance in their strategies and business models" (MUNARI *et al.*, 2012, p. 430). However, firms differ not only across countries and industries but also across regions and local systems within the same country (SAXENIAN, 1994; ALMEIDA and KOGUT, 1999). Firms can differ in their ability to identify, absorb and utilise new knowledge and information (ALCACER and CHUNG, 2014). According to absorptive capacity theory (COHEN and LEVINTHAL, 1990), this is true both when firms act as "receivers" of local externalities and when they act as potential "sources" of local externalities: firms co-localised in a given geographic area have specific characteristics which may influence the way they contribute to the production of tangible and intangible externalities (ALCACER and CHUNG, 2007). For example, firms with more technological endowments may generate more externalities (e.g. local knowledge spillovers) than firms with smaller technological endowments. Similarly, firms employing workers with higher levels of education may generate more local externalities than firms employing less highly educated workers. It follows that this form of "firm heterogeneity in technological capabilities" (WANG, 2015) may contribute differently to the production of agglomeration externalities. This strand of the business studies suggest that the agglomeration phenomenon cannot be seen only as a mechanism of "appropriation" of local externalities; it is also a mechanism for their generation.

The following example helps our understanding of what firm heterogeneity means in this context. Consider two geographic areas, A and B, with the same surface (i.e. $area_A = area_B$), and suppose that the same number of firms is located in both these two geographic areas (i.e. $N_A = N_B$). Then, suppose that the two populations of firms differ in some specific characteristics, e.g. size and TFP, such that, on average, $\overline{size}_A > \overline{size}_B$ and $\overline{TFP}_A > \overline{TFP}_B$. Under the assumption of firm homogeneity, computation of a simple agglomeration index capturing the density of firms in a geographic area would lead to $N_A/area_A = N_B/area_B$, even though the firms located in area A are, on average, bigger and more productive than those located in area B. Therefore, accounting for firm heterogeneity in computing agglomeration indexes may better capture the agglomeration phenomenon as a mechanism generating local externalities if it is true that firm-specific characteristics influence the way firms contribute to this externality generation process.

3. DATA AND METHODOLOGY

3.1. The dataset

Our empirical analysis employs an Italian firm-level balance sheet dataset covering the period 2003-2012, which is drawn from the *AIDA* databank (Bureau Van Dijk). The analysis consists of three main steps. First, we estimate TFP at firm-level using the approach proposed by WOOLDRIDGE (2009); second, we conduct a hierarchical cluster analysis to identify the geographic scale at which agglomeration forces emerge and produce their effects, and then compute agglomeration measures; third, we estimate a productivity growth equation to test whether and how agglomeration forces influence firm productivity growth in the short-run, and to test the hypothesis of firm heterogeneity in the context of agglomeration externalities.

The analysis is conducted using three different (nested) samples in order to maximise the sample size in each step of the empirical exercise. The original sample was cleaned to remove firms with missing or inconsistent data on value added, tangible assets, total labour costs and intermediate inputs. We excluded firms reporting a value added-to-turnover ratio ≥ 0 and ≤ 1, and firms observed for less than seven consecutive years during the period 2003-2012, obtaining an unbalanced panel of 69,933 firms observed over the period 2003-2012, which we use to estimate firms' TFP.

Following MARTIN *et al.* (2011), agglomeration measures are constructed using sample rather than census data. We conducted a further cleaning of the sample, removing firms with no information on longitude and latitude coordinates (or an exact address). It is necessary to know the exact geographic location of each firm in order to compute the agglomeration measures. We also excluded firms with missing data for number of employees in order to construct weighted agglomeration variables in terms of size (DURANTON and OVERMAN, 2005; GABRIELE *et al.*, 2013) and estimated TFP, to test the hypothesis of firm heterogeneity. The year 2009 was selected to construct the agglomeration variables since this year has the largest number of valid observations, i.e. firms reporting data on geographic coordinates, number of employees and estimated TFP. This second cleaning procedure led to a sample of 41,574 firms observed in the year 2009, which we use to construct the agglomeration measures.

Starting from this last sample, we performed a third cleaning procedure to construct the final dataset to be employed in the empirical analysis to examine the relationship between agglomeration forces and firms' productivity growth. We excluded firms with missing or inconsistent data on net income and annual depreciation for year 2009, and firms with missing data for year of establishment, resulting in a final sample of 28,597 firms observed over the period 2009-2012.

3.2. The econometric analysis

3.2.1. TFP estimation

The first step in the empirical analysis employs an unbalanced panel of 69,933 firms observed over the period 2003-2012 to estimate firms' TFP. This is estimated as the residual of a Cobb-Douglas production function which can be specified as follows in logarithmic form:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + u_{it} + \eta_{it} \tag{1}$$

where β_0 represents the mean efficiency level across firms and over time; y_{it}, k_{it} and l_{it} denote value added, capital input and labour input of firm i at time t, respectively; η_{it} is an independent and identically distributed (i.i.d.) component which represents productivity shocks not affecting the firm's decision process. Firm-level productivity can be specified as $\omega_{it} = \beta_0 + u_{it}$, where ω_{it} is a state variable-transmitted component indicating that part of the firm's productivity which is known by the firm and which affects its decision process (OLLEY and PAKES, 1996). The estimated productivity is then computed solving for ω_{it} as follows (VAN BEVEREN, 2012):

$$\hat{\omega}_{it} = \hat{u}_{it} + \hat{\beta}_0 = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} \tag{2}$$

The simple fixed effects (FE) estimation of firms' TFP is likely to produce biased estimates of the inputs' elasticities, due mainly to endogeneity of inputs caused by 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). Based on OLLEY and PAKES's (1996) contribution, LEVINSOHN and PETRIN (2003) proposed a two-step semi-parametric approach which uses intermediate inputs (m_{it}) as a proxy for unobserved productivity in order to solve the simultaneity problem between input choices and productivity shocks. However, a major limitation of this approach is the collinearity between labour and intermediate inputs: identification of the labour input in the first-step estimation requires some variation in the data independent of the intermediate input (VAN BEVEREN, 2012). Perfect collinearity of the labour input arises in the absence of this variation, such that the labour coefficient results not identified in the first-step estimation (ACKERBERG *et al.*, 2006).

WOOLDRIDGE (2009) proposes to estimate β_k and β_l within a Generalised Method of Moments (GMM) framework to correct for possible collinearity between the labour and intermediate inputs. This approach consists of the simultaneous estimation of two equations with the same dependent variable and input variables, but different sets of instruments so that the coefficients of the input variables in the first equation are identified exploiting information from the second equation. Given a production function (1) and assuming that η_{it} is not correlated with current and past values of capital, labour and intermediate inputs, and restriction of the dynamics of the unobserved productivity component ω_{it}, WOOLDRIDGE (2009) proposes the following two equations:

$$\begin{cases} y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + f(k_{it}, m_{it}) + \eta_{it} \\ y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + q[g(k_{it-1}, m_{it-1})] + \eta_{it} + a_{it} \end{cases} \tag{3}$$

where a_{it} denotes productivity innovations and is correlated with l_{it} and m_{it}, but is uncorrelated with k_{it} and past values of k_{it}, l_{it} and m_{it}. The function $f(\cdot)$ can be specified as a low-degree polynomial of the order of up to three, while the productivity process $q(\cdot)$ can be defined as a random walk with drift such that $\omega_{it} = \tau + \omega_{it-1} + a_{it}$. Then, equation (1) can be re-specified as follows (GALUŠČÁK and LÍZAL, 2011):

$$y_{it} = (\beta_0 + \tau) + \beta_k k_{it} + \beta_l l_{it} + f(k_{it-1}, m_{it-1}) + \eta_{it} + a_{it} \tag{4}$$

and can be estimated using an instrumental-variable (IV) approach using polynomials in k_{it-1} and m_{it-1} of the order of 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 the order of up to three as instruments for l_{it} (PETRIN and LEVINSOHN, 2012).

This approach is employed to estimate twenty-three production functions at the two-digit industry level. Value added (VA_{it}) is used as output in the production function and is deflated with the corresponding two-digit production price index; total tangible assets (K_{it}) are used as capital input and are deflated with the corresponding two-digit capital deflator; total labour cost (L_{it}) is used as labour input and is deflated with the corresponding two-digit wage index; intermediate inputs (M_{it}) are defined (at current prices) as the sum of services, raw materials and consumptions, and are deflated with an intermediate consumption index. The deflators are calculated using Istat (Italian National Institute of Statistics) data, and the reference year for depreciation is 2002. Appendix Table A1 reports some descriptive statistics and the correlation matrix of the variables entering the production functions; Appendix Table A2 reports the estimated elasticities of the capital and labour inputs.

3.2.2. Identifying the geographic scale of the agglomeration forces

One of the contributions of this paper concerns the identification of the geographic scale at which agglomeration forces are likely to emerge and produce their effects. Following CAINELLI and LUPI (2010) and GABRIELE *et al.* (2013), agglomeration measures are constructed over a continuous space. The main idea is to use a continuous approach to the space, rather than arbitrary pre-defined spatial units of analysis, such that the sample of firms is treated as a spatial points pattern in which each firm represents an individual point identified by its geographic coordinates (latitude and longitude). Distance-based agglomeration measures are computed within continuous and non-overlapping distance bands, identified around each firm in the sample, to evaluate the space component of the agglomeration phenomena, i.e. the presence of potential geographic nonlinearities of the agglomeration externalities. Then, specific characteristics (i.e. size and TFP) of the neighbour firms located within each distance band are used to construct weighted agglomeration measures in order to test whether the heterogeneity of neighbour firms matters for the generation of agglomeration externalities.

Fig. 1 depicts the adopted approach. Consider a representative firm i located in a given area, and suppose to draw a series of circles around it. Then, the agglomeration variables are constructed considering the neighbour firms j located within each non-overlapping distance band defined by an increasing radius r.

Identification of the geographic scale of the agglomeration forces and construction of the agglomeration variables, are based on a sample of 41,574 firms observed in year 2009. Their distribution by industry and NUTS-1 geographic area is reported in Appendix Table A3.

The first step to identify the distance bands within which the agglomeration phenomena are captured is to specify a maximum threshold distance. Following CAINELLI and LUPI (2010), this threshold value is set equal to 30 km, i.e. a radius of 30 km represents the maximum distance (defined around each firm in the sample) within which agglomeration forces are hypothesised to emerge. There are three main reasons supporting the chosen maximum distance value: first, by definition, agglomeration economies are local and spatially bounded forces; second, 30 km is not an excessive distance for cross-firm spillover effects to materialise; third, a radius of 30 km gives a surface which is close to the average area of the Italian provinces (NUTS-3 regions), which are usually adopted as geographic units of analysis in agglomeration studies.[2]

Setting this maximum distance value allows seven continuous and non-overlapping distance bands of increasing radius r (d_r) to be specified for the following intervals: $0 \leq d_2 \leq 2$, $2 < d_3 \leq 5$, $5 < d_5 \leq 10$, $10 < d_5 \leq 15$, $15 < d_5 \leq 20$, $20 < d_5 \leq 25$ and $25 < d_5 \leq 30$. With the exception of the first two bands, which are split around a radius of 2 km following CAINELLI and LUPI (2010) who find significant agglomeration externalities within 2 km, these preliminary distance bands are constructed based on equidistant intervals of 5 km.

Then, we compute a density measure counting the number of neighbour firms j located within each distance band defined around the reference firm i (given the Euclidean distance between the reference firm i and each neighbour j), for each firm in the sample (without accounting for the industry to which the firms belong, i.e. without distinguishing between localisation- and diversification-type externalities) as follows:

$$\widehat{D}_{x_i}(d_r) = \frac{e(x_i)\left[\sum_{\substack{j=1 \\ j\neq i}}^{N} 1\left(\left\|x_i - x_j\right\| \in d_r\right)\right]}{A_{x_i}(d_r)} \tag{5}$$

where d_r denotes the distance band (i.e. the circle) with radius r; the denominator is the (net) area of the circle centred in the reference firm i, which is denoted by x_i as a spatial point identified by its geographic coordinates; the numerator is the sum of all the neighbour firms j (denoted by x_j as spatial points) within the distance band d_r according to their Euclidean distance from x_i ($\|x_i - x_j\|$); $1(\cdot)$ is an indicator function; and $e(x_i)$ denotes RIPLEY's (1977) edge correction, which is defined as follows:

$$e(x_i) = \frac{2\pi r}{length[c(x_i, r) \cap W]} \tag{6}$$

where the numerator defines the circumference of the circle with radius r; the denominator is the length of the overlap between the circle c centred in x_i with radius r and the window W defining the study region (i.e. Italy). This correction term allows one to account for edge effects which may influence the agglomeration phenomenon around firms located close to the boundaries of the study region. In fact, those firms may be surrounded by fewer neighbour firms with respect to other firms located at longer distances from the study region's boundaries.

The subsequent step consists of a hierarchical cluster analysis to identify the distance bands which are closer in terms of density. The idea is to reduce redundancy among the seven distance bands previously constructed, thus identifying a reduced number of distance bands which may be meaningful to capture spatial agglomeration forces. Although the maximum distance value of 30 km and the seven distance bands identified within it were specified randomly, the use of a statistical approach to identify the distances at which agglomeration phenomena may matter and show geographic nonlinearities, represents a step forward with respect to previous contributions with analyses based exclusively on arbitrary distances (although avoiding the use of pre-defined geographic partitions).

Fig. 2 plots the result of the cluster analysis performed using the un-weighted pair-group method of average and suggests the presence of three distance clusters : 0 to 5 km ($0 \leq d_5 \leq 5$), 5 to 15 km ($5 < d_{10} \leq 15$) and 15 to 30 km ($15 < d_{15} \leq 30$).

Comparison of the surfaces of the three distance bands identified (see Table 1) with the average surfaces of the usually employed spatial units of analysis for the Italian case (see Table

2) suggests that the three distance bands identified provide a relatively good partition of the continuous space in order to capture potential geographic nonlinearities of the agglomeration forces, which could not be captured using standard (pre-defined) spatial partitions. In fact, the (cumulative) areas of the three distance bands encompass the average areas of municipalities, local labour markets and provinces.

3.2.3. Agglomeration and firm heterogeneity

Intra-industry (i.e. localisation-type) and inter-industry (i.e. diversification-type) externalities are captured through absolute density measures which are computed within the three distance bands previously identified. Specifically, two main types of agglomeration variables are constructed: un-weighted and weighted. Un-weighted agglomeration measures represent the baseline variables since they are built on the hypothesis of firm homogeneity (explicitly or implicitly) assumed in previous contributions. In fact, they are defined considering the number of neighbour firms located within a certain distance, without accounting for their specific characteristics. In contrast, weighted agglomeration measures are constructed accounting for neighbour firms' characteristics, i.e. accounting for their heterogeneity. It follows that weighted intra- and inter-industry agglomeration variables allow us to test the hypothesis of firm heterogeneity, i.e. whether firm-specific characteristics influence the way firms located within the agglomerated area contribute to the production of the agglomeration externalities. Therefore, comparison of the estimated coefficients of un-weighted and weighted agglomeration variables should allow us to evaluate whether agglomeration externalities are driven by a "critical-mass effect" or by specific characteristics of the co-localised firms, i.e. whether externalities depend on the number of firms or on their specific characteristics.

Two firm-specific characteristics are considered as weights: size, defined in terms of employment, and (estimated) TFP. Employment-based indexes have been proposed in the literature to proxy for localisation (e.g. specialisation indexes) and diversification (e.g. Herfindahl-Hirschman indexes) externalities (e.g. GLAESER *et al.*, 1992; HENDERSON, 2003; CINGANO and SCHIVARDI, 2004). These measures are generally constructed considering employment of an industry-area pair with respect to the national dimension or total employment in an industry or area. Contributions using employment-based agglomeration variables implicitly consider the role of firm heterogeneity in the agglomeration context, although they make no assumptions about the role of firm-specific characteristics in the generation of agglomeration externalities, nor do they compare agglomeration variables constructed with and without considering the employment dimension. Also, employment-based variables computed within spatial units of different sizes do not allow us to capture the role of firm employment in the process of generating agglomeration externalities because this is likely to be influenced by the size of the local system: a larger area is likely to host a higher number of firms so the overall number of employees in a given area may depend on its surface. However, the use of areas characterised by the same surface may facilitate comparison between standard and employment-based agglomeration variables, under the assumption that firms are homogeneously distributed over the space, and also identification of the role ascribable to co-localised firms' employment size in the production of agglomeration externalities. Employment-based measures are proposed by GABRIELE *et al.* (2013) in the context of distance-based agglomeration variables. However, their analysis neither assumes firm heterogeneity, nor compares the results of un-weighted and weighted variables.

The second weighting component is firm TFP; this paper is the first attempt to account for this dimension when constructing agglomeration variables. TFP-weighted agglomeration variables are a better proxy to capture the role of firm heterogeneity in the generation of agglomeration externalities than size-weighted variables. The firm's TFP is correlated with its technological endowment and, consequently, its (potential) ability to produce externalities. On the contrary, size-weighted variables can be only a rough proxy for the human capital endowment of co-localised firms if the skill dimension of employment cannot be identified.

Agglomeration variables are constructed for each firm in the sample and within each distance band as follows:

$$\widehat{D}_{x_i^s}(d_r) = \frac{e(x_i^s)\left[\sum_{\substack{j=1 \\ j\neq i}}^{N} 1\left(\left\|x_i^s - x_j^g\right\| \in d_r\right) w\left(x_j^g\right)\right]}{A_{x_i^s}(d_r)} \tag{7}$$

where d_r denotes the distance band with radius r defined in km, such that $0 \leq d_5 \leq 5$, $5 < d_{10} \leq 15$ and $15 < d_{15} \leq 30$; the denominator is the (net) area of the distance band (i.e. the circle) centred in the reference firm i belonging to the two-digit industry s (x_i^s); the numerator is the sum of all the neighbour firms j belonging to the two-digit industry g (x_j^g) and located within a certain distance band, with $s = g$ in the intra-industry (i.e. localisation-type) case and $s \neq g$ in the inter-industry (i.e. diversification-type) case; the term $\left\|x_i^s - x_j^g\right\|$ denotes the Euclidean distance between the reference firm i and each neighbour firm j; $1(\cdot)$ is an indicator function; the term $w\left(x_j^g\right)$ denotes the weighting scheme capturing the heterogeneity of the neighbour firms within each distance band, such that $w(\cdot) = 1$ in the un-weighted case, $w(\cdot) = size_j^g$ in the size-weighted case and $w(\cdot) = tfp_j^g$ in the TFP-weighted case (where tfp_j^g denotes the TFP of a firm in level); and the term $e(x_i^s)$ denotes RIPLEY's (1977) edge correction, which is defined as in equation (6).[3]

Therefore, two forms of agglomeration externalities are captured through un-weighted and size- and TFP-weighted agglomeration variables: intra-industry externalities arising from the spatial concentration of firms operating in the same industry as the reference firm (i.e. localisation-type forces), and inter-industry externalities arising from the spatial concentration of firms operating in industries different from the industry of the reference firm (i.e. diversification-type forces).

3.2.4. The growth equation

The empirical exercise is based on the estimation of a simple productivity growth equation specified as follows:

$$\Delta TFP_{is} = \alpha + \sum_{k=1}^{K} \beta_k X_{is}^k + \sum_{d=1}^{D} \delta_{1d}\, INTRA_{is}^d + \sum_{d=1}^{D} \delta_{2d}\, INTER_{is}^d + \boldsymbol{\gamma}_c + \boldsymbol{v}_m + \varepsilon_{is} \qquad (8)$$

where $\Delta TFP_{is} = TFP_{is}^{2012} - TFP_{is}^{2009}$ denotes the productivity growth of firm i operating in the two-digit industry s over the period 2009-2012, where TFP_{is}^{2009} and TFP_{is}^{2012} denote the estimated TFP (in logarithmic form) from equation (4); the vector X_{is}^k of log-transformed firm-specific control variables includes the beginning-of-the period TFP (TFP_{is}), the number of employees at the beginning of the growth period ($SIZE_{is}$), the difference between the year 2009 and the year of a firm's set up (AGE_{is}), the ratio between acquired services and total acquired inputs in 2009 to proxy for services outsourcing ($OUTSOURCING_{is}$) and the cash flow defined as net income plus annual depreciation over tangible assets at the beginning of the growth period ($CASH_{is}$); the terms $INTRA_{is}^d$ and $INTER_{is}^d$ capture the log-transformed variables for, respectively, intra- and inter-industry agglomeration externalities computed within the three distance bands; the term $\boldsymbol{\gamma}_c$ refers to a set of industrial category dummy variables; the term $\boldsymbol{v}_m$ refers to a set of macro-geographic dummy variables defined at the NUTS-1 level; the term ε_{is} denotes the error term. Some descriptive statistics and the correlation matrices among the firm-level and agglomeration variables are reported in Appendix Tables A4 to A9. Appendix Table A10 compares the sample used for the empirical exercise with the population of Italian manufacturing firms. Appendix Table A11 reports the sample distribution by industry, and defines the industrial categories included in the productivity growth equation.

3.2.5. The identification strategy

The Ordinary Least Squares (OLS) estimation of equation (8) is likely to be affected by sample selection since productivity growth is observed only for the sub-sample of firms that survived during the growth period (e.g. SLEUTJES *et al.*, 2012). Therefore, we estimate a two-step sample-selection model *à la* HECKMAN (1979) to account for firm exit over the period 2009-2012. A first-stage reduced-form selection equation is estimated by Maximum Likelihood specifying the dependent variable as a dummy ($SURVIVAL_{is}$) which equals one if the firm observed at the beginning of the growth period (i.e. year 2009) is observed also at the end of the growth period (i.e. year 2012), and zero otherwise. The selection equation is identified including on its right-hand side the explanatory variables in equation (8) plus an exclusion restriction ($TURBULENCE_s$) capturing the average entry/exit rate over the period 2006-2008, and defined at the two-digit industry level. The idea is that a high value of this variable is likely to be associated with a low (current) probability of firm survival, without necessarily being associated with the surviving firms' economic performance.[4]

Having estimated the selection equation on the whole sample of firms based on a Probit model, the computed inverse Mills ratio (λ) is added to the right-hand side of the productivity growth equation to correct for the sample selection bias. Thus, the augmented version of equation (8) is estimated via OLS for the sub-sample of firms which survived during the period 2009-2012 (WOOLDRIDGE, 2010).

4. EMPIRICAL RESULTS

Table 3 reports the results of the estimated productivity growth equation using un-weighted and size- and TFP-weighted agglomeration variables (the results of the first-stage selection equations are reported in Appendix Table A12). The exclusion restriction identifying the selection equations shows negative and statistically significant coefficients, suggesting that a firm's survival probability is negatively affected by the level of industry-specific turbulence, while the estimated inverse Mills ratio (λ) shows positive and significant coefficients. Therefore, the results suggest the need to correct for sample selection.

The results of the un-weighted agglomeration variables (see Table 3, Column 1) support the findings in CAINELLI and LUPI (2010). We find a positive effect of intra-industry externalities within 15 km which is decreasing in the distance, while the short-distance negative effect of inter-industry externalities turns positive at a greater distance. This result highlights a sort of substitution effect between localisation- and diversification-type forces: firms' TFP growth benefits from industry similarity at short distances, while it seems to benefit from industry diversification at a greater distance.

However, the decreasing-with-distance positive effect of intra-industry externalities changes significantly if firm-specific characteristics are taken into account when capturing the agglomeration phenomenon (see Table 3, Columns 2 and 3). In fact, the positive effect of intra-industry externalities turns increasing with distance when firm-specific characteristics are accounted for, and this pattern is particularly strong when the size of the neighbour firms is considered. This means that positive externalities related to localisation forces tend to be higher the bigger and more productive the neighbour firms operating in the same industry. This result suggests also that intra-industry externalities do not attenuate over distance.

It seems that the pattern characterising inter-industry externalities is unrelated to the specific characteristics of the neighbour firms: un-weighted and weighted diversification-type forces have a negative effect on the firm's TFP growth at short distances (up to 15 km), but a positive effect at larger distances regardless of the weighting scheme considered.

In addition, the substitution effect characterising intra- and inter-industry externalities seems to attenuate at larger distances if neighbour firms' size and TFP are taken into account when capturing agglomeration forces. These results suggest that, effectively, co-localised firms participate in the process of generating local externalities and, also, that their contribution depends on their characteristics: bigger and more productive firms seem to contribute more to the production of agglomeration externalities, especially in the context of localisation-type externalities.

These results are depicted in Fig. 3, which plots the estimated coefficients of the un-weighted and weighted agglomeration variables from Table 3. The plot shows the presence of geographic nonlinearities characterising both intra- and inter-industry agglomeration externalities. The key message is that firm heterogeneity seems to matter in the context of localisation-type agglomeration forces: in fact, the positive but decreasing-with-distance effect of intra-industry externalities becomes increasing with distance if neighbour firms' characteristics are taken in to account.

The estimated coefficients of the firm-level control variables have the same signs and significance levels in all the specifications reported in Table 3. The coefficients of the beginning-of-the-period TFP variable are negative, suggesting a β-convergence effect; a firm's TFP growth seems to be positively affected by its initial size, and also by its age and level of services outsourced. We find a positive productivity-to-cash flow sensitivity, meaning that the firm's productivity growth tends to be affected by credit rationing (i.e. firm growth is pushed by internally generated resources).

4.1. Robustness checks

This section presents two econometric exercises performed to test the robustness of the main results for the un-weighted agglomeration variables. The first exercise is aimed at verifying the validity of the proposed density measures and their comparability with standard specialisation and diversification indexes. Specifically, the first exercise replicates the un-weighted case using specialisation and diversification agglomeration measures as proposed in CINGANO and SCHIVARDI (2004). The variable capturing specialisation externalities is defined as follows:

$$\widehat{SPEC}_{x_i^s}(d_r) = e(x_i^s)\left[\frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} 1\left(\left\|x_i^s - x_j^s\right\| \in d_r\right)}{\sum_{\substack{j=1 \\ j\neq i}}^{N} 1\left(\left\|x_i^s - x_j\right\| \in d_r\right)}\right] \tag{9}$$

where all the terms entering the formula are defined as before. The specialisation variable captures, for each distance band, the share of neighbour firms j operating in the same two-digit industry s of the reference firm i with respect to the total number of neighbour firms j. The variable capturing diversification externalities is defined as follows:

$$\widehat{DIV}_{x_i^s}(d_r) = e(x_i^s)\sum_{\substack{g=1 \\ g\neq s}}^{G}\left\{\frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} 1\left(\left\|x_i^s - x_j^g\right\| \in d_r\right)}{\left[\sum_{\substack{j=1 \\ j\neq i}}^{N} 1\left(\left\|x_i^s - x_j\right\| \in d_r\right)\right] - \left[\sum_{\substack{j=1 \\ j\neq i}}^{N} 1\left(\left\|x_i^s - x_j^s\right\| \in d_r\right)\right]}\right\}^2 \tag{10}$$

where all the terms entering the formula are defined as before. The diversification variable is computed for each distance band as a Hirschman-Herfindahl index and captures industry variety around the reference firm i. Appendix Table A13 reports the correlation matrix among the specialisation and diversification variables.

The second robustness exercise replicates the baseline specification for the un-weighted case considering only those firms in the estimation sample aged at least ten years, i.e. firms located in a specific point in the space at least ten years before the agglomeration phenomena are captured. This exercise provides a (rough) test to control for potential endogeneity of the agglomeration variables, which is likely to emerge if there is reverse causality between agglomeration forces and firms' productivity, i.e. whether firms tend to relocate towards more productive areas, thereby reinforcing the agglomeration.

Table 4 reports the results of the estimated productivity growth equation; Appendix Table A14 presents the results of the first-step selection equation. Overall, the results for the agglomeration variables computed following CINGANO and SCHIVARDI (2004) support the previous findings (see Table 4, Column 1). They confirm a positive, but decreasing-with-distance effect of localisation-type externalities at short distances, which becomes negative at longer distances, and a negative effect of diversification-type externalities at short distances, which becomes positive at longer distances.

Overall, the results for the sub-sample of firms aged at least ten years (see Table 4, Column 2) confirm those for the whole sample of firms (see Table 3, Column 1). We find that intra-industry externalities have a positive and significant decreasing effect moving from the first to the second distance band, while the effect of inter-industry externalities seems to be negative within 5 km, but positive at longer distances.

Therefore, the robustness of the proposed density measures is confirmed using more "standard" specialisation and diversification indexes, and controlling for the potential endogeneity of the agglomeration variables.

5. CONCLUSIONS

The relationship between agglomeration forces and TFP (growth) at firm level has been investigated extensively in the last decade, but the results of this empirical literature are mixed and rather than conclusive. The contribution of this paper is twofold: first, it tackles the MAUP; second, it tests the hypothesis of firm heterogeneity in the agglomerative space, accounting for the role played by firm-specific characteristics (in terms of size and TFP) in the generation of local externalities (so-called agglomerative heterogeneity).

The empirical findings confirm that intra-industry (i.e. localisation-type) externalities have a positive effect at short distances, while inter-industry (i.e. diversification-type) externalities have a positive effect only at longer distances (CAINELLI and LUPI, 2010). Our results suggest also that firm heterogeneity matters for the generation of agglomeration externalities, at least in the context of intra-industry forces. In fact, the positive, but decreasing-with-distance effect of localisation-type externalities becomes increasing with distance when specific characteristics of the neighbour firms (operating in the same industry as the reference firm) are accounted for. This effect turns out to be particularly relevant when considering the size of neighbour firms, rather than their TFP. However, TFP-weighted agglomeration variables are considered a better proxy for agglomerative heterogeneity with respect to size-weighted agglomeration variables. In fact, a firm's TFP level is strictly related to its technological endowments and, therefore, to its ability to produce local externalities. Thus, these results support the theoretical intuitions of some business studies (ALCACER, 2006; ALCACER and CHUNG, 2007, 2014; WANG, 2015) that firms with different characteristics contribute differently to the production of local externalities.

The results proposed in this paper underline several limitations characterising the empirical analysis of spatial agglomeration forces (e.g. the use of pre-defined spatial partitions and the assumption of homogeneous firms). However, our study has two main weaknesses which should be addressed in further research. First, agglomeration variables are computed using sample rather than census data, with the consequence that only a (selected) sub-sample of the population of Italian manufacturing firms is included in the analysis. Second, size and TFP of neighbour firms are rough proxies for the firm's capabilities to produce agglomeration externalities. Alternative firm-specific characteristics (e.g. R&D and innovativeness, level of education of employees, etc.) should be considered to capture the role of firm heterogeneity in generating local externalities.

As MARTIN *et al.* (2011) suggest, the analysis of agglomeration economies is relevant to understand both the mechanisms and effects of these phenomena on firms' economic performance, and the potential effects of clustering and industry policies. The results from the present study would suggest that the geographic scale might differ depending on whether localisation- or diversification-type externalities are considered. Also, the optimal policy should combine cluster policies with interventions aimed at promoting diversification processes within an area. In this context, many of the core ideas in the Smart Specialisation Strategy (S3) could be useful to incentivise and promote firms' economic performance.

NOTES

1. The MAUP has been widely investigated by statisticians and quantitative geographers. See GEHLKE and BIEHL (1934), OPENSHAW (1981), ARBIA (1989), AMRHEIN (1995) and WONG and AMRHEIN (1996) among others.
2. GABRIELE *et al.* (2013) consider a maximum distance of 100 km, which, however, seems too large to characterise spatial agglomeration phenomena.
3. The agglomeration variables in equations (5) and (7) are computed using the R Project for Statistical Computing (R DEVELOPMENT CORE TEAM, 2013). Original coding is based on the "dbmss" R package developed by MARCON *et al.* (2012).
4. A dummy variable for medium-high and high technology firms was tested as an alternative exclusion restriction in the first-step selection equation. The idea is that medium-high and high technology sectors are less likely to be influenced by general economic downturns and also less involved in international outsourcing of the production phases (the most value-added), compared to traditional low-tech manufacturing sectors. Therefore, firms operating in these sectors are expected to have a lower probability of exiting the market, at least as a result of a non-industry specific external shock. The results using this alternative exclusion restriction are in line with the main findings.

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TABLES AND FIGURES

Table 1: Geographic features of spatial bands considered in the empirical analysis

Distance Band	Radius in km	Area in Square km
$0 \leq d_5 \leq 5$	5	79
$5 < d_{10} \leq 15$	10 [15]	628 [707]
$15 < d_{15} \leq 30$	15 [30]	2,121 [2,827]

Notes: Cumulative values are shown in brackets.

Table 2: Average area of standard geographic units of investigation

Geographic Unit	Average Area in Square km
8,177 Municipalities (LAU-2)	37
611 Local Labour Markets	494
110 Provinces (NUTS-3)	2,739

Table 3. TFP growth equation: un-weighted and weighted agglomeration variables

Dependent Variable	ΔTFP_{is}		
	Un-weighted	Size-weighted	TFP-weighted
TFP_{is}	-0.355***	-0.346***	-0.342***
	(0.020)	(0.021)	(0.021)
$SIZE_{is}$	0.143***	0.143***	0.145***
	(0.006)	(0.006)	(0.006)
AGE_{is}	0.025***	0.030***	0.030***
	(0.010)	(0.010)	(0.010)
$OUTSOURCING_{is}$	0.073***	0.079***	0.078***
	(0.011)	(0.011)	(0.011)
$CASH_{is}$	0.027***	0.028***	0.028***
	(0.002)	(0.002)	(0.002)
$INTRA_{is}^{0-5}$	0.021***	0.009***	0.021***
	(0.005)	(0.003)	(0.004)
$INTRA_{is}^{5-15}$	0.018***	0.014***	0.022***
	(0.006)	(0.004)	(0.006)
$INTRA_{is}^{15-30}$	0.005	0.019***	0.023***
	(0.006)	(0.005)	(0.006)
$INTER_{is}^{0-5}$	-0.052***	-0.037***	-0.052***
	(0.007)	(0.005)	(0.006)
$INTER_{is}^{5-15}$	-0.008	-0.017***	-0.016**
	(0.008)	(0.005)	(0.007)
$INTER_{is}^{15-30}$	0.054***	0.040***	0.033***
	(0.009)	(0.007)	(0.008)
λ	1.630***	1.717***	1.753***
	(0.204)	(0.206)	(0.207)
Number of Observations	22,239	22,239	22,239
Censored Observations	6,358	6,358	6,358
Adj. R^2	0.254	0.255	0.255
F-Statistic	79.45***	78.17***	79.85***
Mean VIF	7.98	7.62	8.04
Selection Equation			
Number of Observations	28,597	28,597	28,597
Pseudo R^2	0.056	0.056	0.056
Log Likelihood	-14,307.72	-14,303.20	-14,303.18
Wald χ^2	1,623.96***	1,617.72***	1,629.92***
Mean VIF	2.80	2.37	2.59
$TURBULENCE_s$ (p-value)	-1.321** (0.606)	-1.185* (0.610)	-1.153* (0.610)

Notes: All specifications include a constant term, as well as industrial category and NUTS-1 dummy variables. Bootstrapped standard errors are shown in parentheses and they are corrected for heteroscedasticity. λ denotes the Inverse Mills Ratio parameter from first-step selection equations (see Appendix Table A12).

$*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table 4. TFP growth equation: robustness exercises

Dependent Variable	$\Delta\mathrm{TFP}_{\mathrm{is}}$	
	CINGANO and SCHIVARDI (2004)	Firms aged at least 10 years
$\mathrm{TFP}_{\mathrm{is}}$	-0.355***	-0.340***
	(0.021)	(0.023)
$\mathrm{SIZE}_{\mathrm{is}}$	0.144***	0.146***
	(0.006)	(0.007)
$\mathrm{AGE}_{\mathrm{is}}$	0.025***	-0.013
	(0.010)	(0.009)
$\mathrm{OUTSOURCING}_{\mathrm{is}}$	0.073***	0.070***
	(0.011)	(0.011)
$\mathrm{CASH}_{\mathrm{is}}$	0.027***	0.032***
	(0.002)	(0.003)
$\mathrm{SPEC}_{\mathrm{is}}^{0-5}$	0.035***	...
	(0.006)	
$\mathrm{SPEC}_{\mathrm{is}}^{5-15}$	0.023***	...
	(0.007)	
$\mathrm{SPEC}_{\mathrm{is}}^{15-30}$	-0.018***	...
	(0.007)	
$\mathrm{DIV}_{\mathrm{is}}^{0-5}$	-0.036***	...
	(0.006)	
$\mathrm{DIV}_{\mathrm{is}}^{5-15}$	-0.046***	...
	(0.012)	
$\mathrm{DIV}_{\mathrm{is}}^{15-30}$	0.127***	...
	(0.016)	
$\mathrm{INTRA}_{\mathrm{is}}^{0-5}$	...	0.027***
		(0.005)
$\mathrm{INTRA}_{\mathrm{is}}^{5-15}$	...	0.013*
		(0.007)
$\mathrm{INTRA}_{\mathrm{is}}^{15-30}$	...	0.002
		(0.007)
$\mathrm{INTER}_{\mathrm{is}}^{0-5}$	...	-0.053***
		(0.007)
$\mathrm{INTER}_{\mathrm{is}}^{5-15}$	...	-0.007
		(0.009)
$\mathrm{INTER}_{\mathrm{is}}^{15-30}$	...	0.060***
		(0.010)
λ	1.641***	1.802***
	(0.211)	(0.231)
Number of Observations	22,239	18,380
Censored Observations	6,358	4,814
Adj. R^2	0.254	0.255
F-Statistic	79.63***	72.47***
Mean VIF	7.74	8.08
Selection Equation		
Number of Observations	28,597	23,194
Pseudo R^2	0.054	0.051
Log Likelihood	-14,329.40	-11,237.75
Wald χ^2	1,578.72***	1,188.79***
Mean VIF	2.25	2.82
$\mathrm{TURBULENCE}_{\mathrm{s}}$ (p-value)	-1.426** (0.605)	-1.290* (0.718)

Notes: Specifications include a constant term, as well as industrial category and NUTS-1 dummy variables. Bootstrapped standard errors are shown in parentheses and they are corrected for heteroscedasticity. λ denotes the Inverse Mills Ratio parameter from first-step equations (see Appendix Table A14).

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Fig. 1. Sketch of the continuous approach to the analysis of agglomeration forces

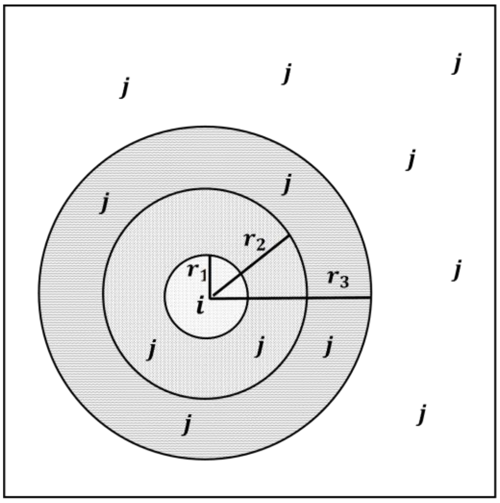
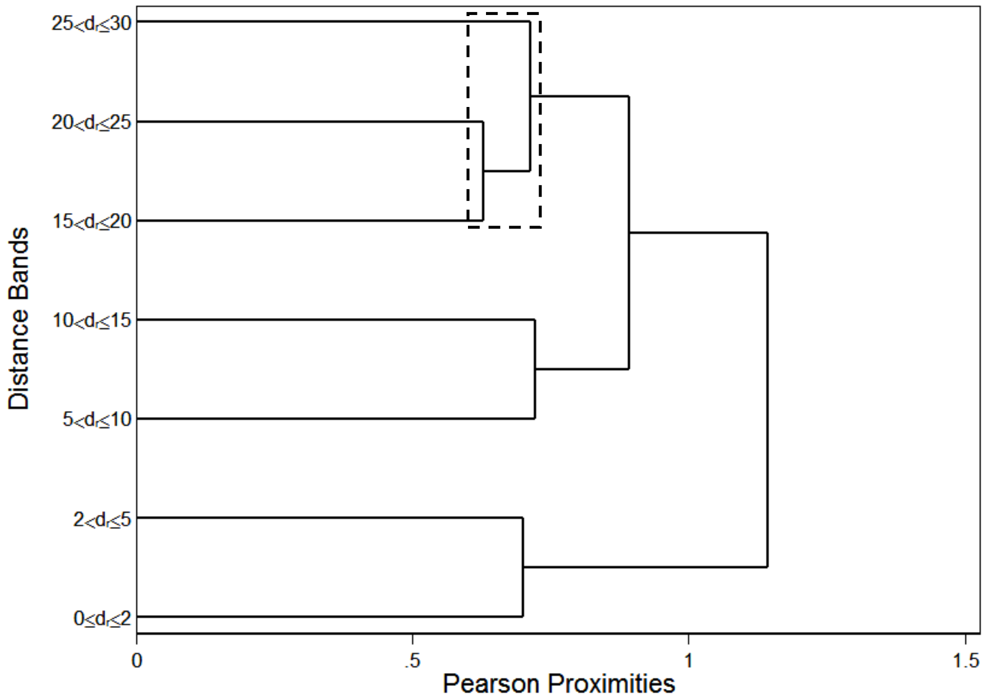
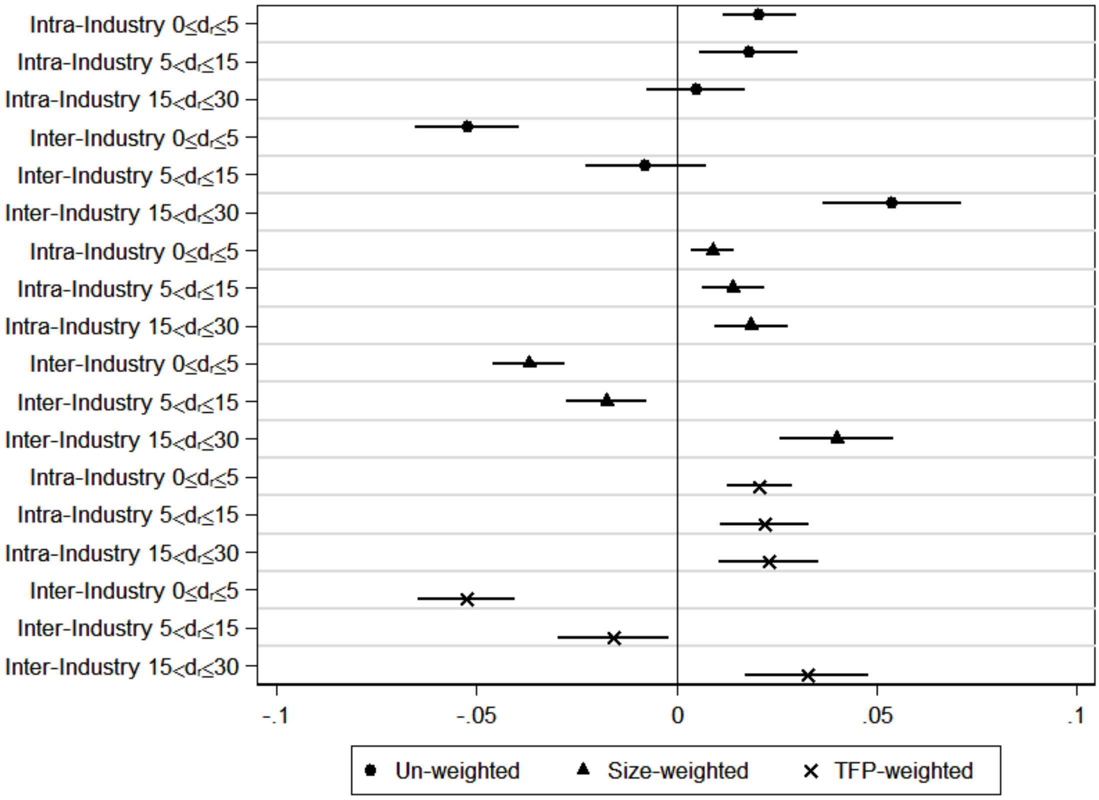


Fig. 2. Hierarchical cluster analysis on the seven distance bands



Notes: The analysis uses the un-weighted pair-group method of average. The density measures are constructed considering all firms falling within the threshold distances, independently of the industrial sector to which they belong.

Fig. 3: Coefficients of un-weighted, size- and TFP-weighted agglomeration variables



APPENDIX

Table A1: Descriptive statistics and correlation matrix of the variables used in estimating TFP

		Mean	Std. Dev.	Min.	Max.	va_{it}	k_{it}	l_{it}	m_{it}
va_{it}	overall	6.149	1.402	-0.166	14.165	1			
	between		1.383	0.188	13.584				
	within		0.419	-1.275	12.494				
k_{it}	overall	5.666	2.019	-6.913	14.895	0.688	1		
	between		1.974	-4.298	14.614				
	within		0.645	-5.062	12.383				
l_{it}	overall	5.666	1.426	-0.249	13.661	0.935	0.648	1	
	between		1.443	-0.233	13.544				
	within		0.372	-1.776	12.616				
m_{it}	overall	6.962	1.579	-0.434	16.569	0.813	0.623	0.759	1
	between		1.576	-0.376	16.494				
	within		0.372	-0.611	13.675				

Notes: Descriptive statistics refer to a sample of 69,933 firms, i.e. 584,547 observations over the period 2003-2012. va_{it}, k_{it}, l_{it} and m_{it} denote the natural logarithms of, respectively, value added, capital input, labour input, and intermediate input.

Table A2: TFP estimation: elasticities of capital and labour inputs

Two-digit Industry	k_{it}			l_{it}			No. Firms	No. Obs.
10	0.085	(0.008)	[0.000]	0.657	(0.010)	[0.000]	5,113	37,011
11	0.099	(0.031)	[0.001]	0.540	(0.024)	[0.000]	849	6,139
12	0.043	(0.066)	[0.509]	0.266	(0.150)	[0.077]	19	102
13	0.072	(0.007)	[0.000]	0.696	(0.009)	[0.000]	3,338	23,748
14	0.086	(0.007)	[0.000]	0.709	(0.010)	[0.000]	3,919	25,292
15	0.068	(0.008)	[0.000]	0.707	(0.010)	[0.000]	2,804	19,668
16	0.037	(0.008)	[0.000]	0.666	(0.013)	[0.000]	2,273	16,409
17	0.058	(0.012)	[0.000]	0.680	(0.023)	[0.000]	1,397	10,783
18	0.068	(0.007)	[0.000]	0.691	(0.012)	[0.000]	2,714	19,199
19	0.110	(0.035)	[0.002]	0.637	(0.032)	[0.000]	198	1,500
20	0.085	(0.009)	[0.000]	0.650	(0.016)	[0.000]	2,156	16,494
21	0.082	(0.017)	[0.000]	0.657	(0.029)	[0.000]	346	2,637
22	0.085	(0.008)	[0.000]	0.660	(0.012)	[0.000]	3,523	26,831
23	0.055	(0.007)	[0.000]	0.661	(0.010)	[0.000]	4,443	32,003
24	0.062	(0.012)	[0.000]	0.697	(0.014)	[0.000]	1,382	10,538
25	0.059	(0.003)	[0.000]	0.705	(0.006)	[0.000]	14,348	107,229
26	0.078	(0.008)	[0.000]	0.713	(0.012)	[0.000]	2,719	19,219
27	0.061	(0.008)	[0.000]	0.707	(0.011)	[0.000]	3,042	22,558
28	0.074	(0.004)	[0.000]	0.679	(0.008)	[0.000]	7,198	54,322
29	0.060	(0.012)	[0.000]	0.720	(0.016)	[0.000]	984	7,265
30	0.068	(0.015)	[0.000]	0.744	(0.016)	[0.000]	969	6,297
31	0.060	(0.007)	[0.000]	0.658	(0.016)	[0.000]	3,471	24,684
32	0.070	(0.008)	[0.000]	0.685	(0.012)	[0.000]	2,728	19,362

Notes: TFP is estimated on a sample of 69,933 firms observed over the period 2003-2012. TFP is estimated separately for twenty-three two-digit industries defined according to the Ateco 2007 classification of the economic activities adopted by Istat. Standard errors are shown in parentheses and they are clustered at the firm level. P-values are shown in brackets. k_{it} and l_{it} denote the natural logarithms of, respectively, the capital input and the labour input.

Table A3: Distribution of the sample used to estimate agglomeration measures

Industry	North West		North East		Centre		South		Islands		Total	
	a. v.	%	a. v.	%	a. v.	%	a. v.	%	a. v.	%	a. v.	%
10	811	25.22	872	27.11	508	15.80	739	22.98	286	8.89	3,216	100.00
11	140	24.87	176	31.26	63	11.19	118	20.96	66	11.72	563	100.00
12	0	0.00	0	0.00	6	100.00	0	0.00	0	0.00	6	100.00
13	973	51.54	275	14.57	515	27.28	113	5.99	12	0.64	1,888	100.00
14	467	24.58	548	28.84	492	25.89	371	19.53	22	1.16	1,900	100.00
15	184	12.36	348	23.37	733	49.23	218	14.64	6	0.40	1,489	100.00
16	319	24.24	474	36.02	271	20.59	189	14.36	63	4.79	1,316	100.00
17	330	35.60	236	25.46	234	25.24	95	10.25	32	3.45	927	100.00
18	611	39.57	386	25.00	355	22.99	151	9.78	41	2.66	1,544	100.00
19	44	30.99	18	12.68	31	21.83	38	26.76	11	7.75	142	100.00
20	713	48.21	356	24.07	220	14.87	127	8.59	63	4.26	1,479	100.00
21	137	51.70	29	10.94	72	27.17	19	7.17	8	3.02	265	100.00
22	999	45.70	606	27.72	286	13.08	218	9.97	77	3.52	2,186	100.00
23	626	23.68	767	29.01	568	21.48	447	16.91	236	8.93	2,644	100.00
24	515	54.90	205	21.86	119	12.69	75	8.00	24	2.56	938	100.00
25	3,697	43.56	2,625	30.93	1,133	13.35	814	9.59	219	2.58	8,488	100.00
26	744	45.81	371	22.84	335	20.63	125	7.70	49	3.02	1,624	100.00
27	822	44.22	594	31.95	278	14.95	134	7.21	31	1.67	1,859	100.00
28	2,027	45.33	1,978	44.23	172	3.85	196	4.38	99	2.21	4,472	100.00
29	295	48.28	150	24.55	73	11.95	76	12.44	17	2.78	611	100.00
30	169	32.69	117	22.63	126	24.37	69	13.35	36	6.96	517	100.00
31	469	24.29	740	38.32	489	25.32	183	9.48	50	2.59	1,931	100.00
32	534	34.03	450	28.68	425	27.09	117	7.46	43	2.74	1,569	100.00
Total	15,626	37.59	12,321	29.64	7,504	18.05	4,632	11.14	1,491	3.59	41,574	100.00

Notes: Manufacturing industries (10 to 32) are defined at the two-digit level of the Ateco 2007 classification of the economic activities adopted by Istat (Italian National Institute of Statistics). Percentage values are expressed on row totals. North West includes Piedmont, Aosta Valley, Liguria and Lombardy. North East includes Veneto, Emilia-Romagna, Friuli-Venezia Giulia and Trentino-Alto Adige. Centre includes Toscana, Umbria, Marche and Lazio. South includes Abruzzi, Molise, Campania, Apulia, Basilicata and Calabria. Islands are Sicily and Sardinia.

Table A4: Descriptive statistics of firm-level explanatory variables

	No. Obs.	Mean	Std. Dev.	Min.	Max.
$\Delta \mathrm{TFP}_{\mathrm{is}}$	22,239	0.017	0.491	-5.456	6.638
$\mathrm{TFP}_{\mathrm{is}}$	28,597	1.857	0.613	-4.402	6.715
$\mathrm{SIZE}_{\mathrm{is}}$	28,597	0.004	1.278	-2.499	7.560
$\mathrm{AGE}_{\mathrm{is}}$	28,597	0.001	0.622	-1.283	1.991
$\mathrm{OUTSOURCING}_{\mathrm{is}}$	28,597	-1.529	0.563	-5.504	-0.012
$\mathrm{CASH}_{\mathrm{is}}$	28,597	3.655	2.723	-6.908	12.377

Notes: Δ denotes log difference. Statistics are based on a sample of 28,597 firms.

Table A5: Correlation matrix: firm-level explanatory variables

		[1]	[2]	[3]	[4]	[5]
$\mathrm{TFP}_{\mathrm{is}}$	[1]	1				
$\mathrm{SIZE}_{\mathrm{is}}$	[2]	0.490	1			
$\mathrm{AGE}_{\mathrm{is}}$	[3]	0.138	0.320	1		
$\mathrm{OUTSOURCING}_{\mathrm{is}}$	[4]	-0.024	-0.048	0.014	1	
$\mathrm{CASH}_{\mathrm{is}}$	[5]	0.392	0.398	0.194	0.017	1

Notes: Statistics are based on a sample of 28,597 firms.

Table A6: Descriptive statistics of the agglomeration variables

	Mean	Std. Dev.	Min.	Max.
$\mathrm{INTRA}_{\mathrm{is}}^{0-5}$ (UW)	-15.659	1.219	-17.486	-12.555
$\mathrm{INTRA}_{\mathrm{is}}^{5-15}$ (UW)	-16.518	1.199	-19.565	-13.857
$\mathrm{INTRA}_{\mathrm{is}}^{15-30}$ (UW)	-17.180	1.203	-20.782	-14.490
$\mathrm{INTER}_{\mathrm{is}}^{0-5}$ (UW)	-13.867	1.288	-17.486	-10.709
$\mathrm{INTER}_{\mathrm{is}}^{5-15}$ (UW)	-14.398	1.109	-19.000	-12.158
$\mathrm{INTER}_{\mathrm{is}}^{15-30}$ (UW)	-14.823	0.974	-19.172	-12.924
$\mathrm{INTRA}_{\mathrm{is}}^{0-5}$ (SW)	-12.531	1.562	-17.081	-7.598
$\mathrm{INTRA}_{\mathrm{is}}^{5-15}$ (SW)	-13.266	1.413	-19.160	-9.446
$\mathrm{INTRA}_{\mathrm{is}}^{15-30}$ (SW)	-13.938	1.370	-19.882	-10.782
$\mathrm{INTER}_{\mathrm{is}}^{0-5}$ (SW)	-10.482	1.530	-16.233	-6.754
$\mathrm{INTER}_{\mathrm{is}}^{5-15}$ (SW)	-10.930	1.262	-18.423	-8.425
$\mathrm{INTER}_{\mathrm{is}}^{15-30}$ (SW)	-11.386	1.062	-16.872	-9.233
$\mathrm{INTRA}_{\mathrm{is}}^{0-5}$ (PW)	-13.677	1.251	-18.305	-10.479
$\mathrm{INTRA}_{\mathrm{is}}^{5-15}$ (PW)	-14.529	1.199	-18.622	-11.961
$\mathrm{INTRA}_{\mathrm{is}}^{15-30}$ (PW)	-15.196	1.203	-20.108	-12.646
$\mathrm{INTER}_{\mathrm{is}}^{0-5}$ (PW)	-11.797	1.360	-16.732	-8.444
$\mathrm{INTER}_{\mathrm{is}}^{5-15}$ (PW)	-12.312	1.144	-17.034	-9.996
$\mathrm{INTER}_{\mathrm{is}}^{15-30}$ (PW)	-12.758	0.980	-17.269	-10.718
$\mathrm{SPEC}_{\mathrm{is}}^{0-5}$	-2.022	0.970	-5.432	0.701
$\mathrm{SPEC}_{\mathrm{is}}^{5-15}$	-2.233	0.953	-6.707	1.393
$\mathrm{SPEC}_{\mathrm{is}}^{15-30}$	-2.388	0.928	-6.149	0.911
$\mathrm{DIV}_{\mathrm{is}}^{0-5}$	2.215	0.562	-1.030	5.411
$\mathrm{DIV}_{\mathrm{is}}^{5-15}$	2.066	0.341	-1.263	2.680
$\mathrm{DIV}_{\mathrm{is}}^{15-30}$	2.089	0.324	-0.521	2.652

Notes: Statistics are based on a sample of 28,597 firms. UW denotes un-weighted, SW denotes size-weighted, PW denotes TFP-weighted agglomeration variables.

Table A7: Correlation matrix: un-weighted agglomeration variables

		[1]	[2]	[3]	[4]	[5]	[6]
$\mathrm{INTRA}_{\mathrm{is}}^{0-5}$	[1]	1					
$\mathrm{INTRA}_{\mathrm{is}}^{5-15}$	[2]	0.640	1				
$\mathrm{INTRA}_{\mathrm{is}}^{15-30}$	[3]	0.343	0.706	1			
$\mathrm{INTER}_{\mathrm{is}}^{0-5}$	[4]	0.523	0.343	0.145	1		
$\mathrm{INTER}_{\mathrm{is}}^{5-15}$	[5]	0.348	0.571	0.380	0.741	1	
$\mathrm{INTER}_{\mathrm{is}}^{15-30}$	[6]	0.215	0.444	0.599	0.472	0.754	1

Notes: Statistics are based on a sample of 28,597 firms.

Table A8: Correlation matrix: size-weighted agglomeration variables

		[1]	[2]	[3]	[4]	[5]	[6]
$\mathrm{INTRA}_{\mathrm{is}}^{0-5}$	[1]	1					
$\mathrm{INTRA}_{\mathrm{is}}^{5-15}$	[2]	0.539	1				
$\mathrm{INTRA}_{\mathrm{is}}^{15-30}$	[3]	0.275	0.618	1			
$\mathrm{INTER}_{\mathrm{is}}^{0-5}$	[4]	0.479	0.337	0.147	1		
$\mathrm{INTER}_{\mathrm{is}}^{5-15}$	[5]	0.337	0.573	0.363	0.694	1	
$\mathrm{INTER}_{\mathrm{is}}^{15-30}$	[6]	0.197	0.442	0.624	0.399	0.679	1

Notes: Statistics are based on a sample of 28,597 firms.

Table A9: Correlation matrix: TFP-weighted agglomeration variables.

		[1]	[2]	[3]	[4]	[5]	[6]
$\mathrm{INTRA}_{\mathrm{is}}^{0-5}$	[1]	1					
$\mathrm{INTRA}_{\mathrm{is}}^{5-15}$	[2]	0.591	1				
$\mathrm{INTRA}_{\mathrm{is}}^{15-30}$	[3]	0.291	0.677	1			
$\mathrm{INTER}_{\mathrm{is}}^{0-5}$	[4]	0.528	0.341	0.133	1		
$\mathrm{INTER}_{\mathrm{is}}^{5-15}$	[5]	0.346	0.575	0.360	0.731	1	
$\mathrm{INTER}_{\mathrm{is}}^{15-30}$	[6]	0.197	0.446	0.612	0.420	0.705	1

Notes: Statistics are based on a sample of 28,597 firms.

Table A10: Comparison between the sample and the population of manufacturing firms

		Small Firms (≤ 49)		Medium Firms (50 - 249)		Large Firms (≥ 250)		All Sizes	
		a. v.	%	a. v.	%	a. v.	%	a. v.	%
2011 Italian Industry Census	North West	109,879	96.42	3,524	3.09	557	0.49	113,960	100.00
	North East	88,611	96.35	2,946	3.20	407	0.44	91,964	100.00
	Centre	79,137	98.29	1,216	1.51	164	0.20	80,517	100.00
	South	68,275	98.86	721	1.04	67	0.10	69,063	100.00
	Islands	27,742	99.44	143	0.51	12	0.04	27,897	100.00
	Italy	373,644	97.46	8,550	2.23	1,207	0.31	383,401	100.00
		a. v.	%	a. v.	%	a. v.	%	a. v.	%
Sample	North West	10,557	84.37	1,734	13.86	222	1.77	12,513	100.00
	North East	7,276	83.24	1,334	15.26	131	1.50	8,741	100.00
	Centre	4,289	88.87	481	9.97	56	1.16	4,826	100.00
	South	1,978	90.61	182	8.34	23	1.05	2,183	100.00
	Islands	311	93.11	23	6.89	0	0.00	334	100.00
	Italy	24,411	85.36	3,754	13.13	432	1.51	28,597	100.00

Notes: The number of employees defining the size classes is shown in parentheses. Only manufacturing industries between 10 and 32 of the Ateco 2007 Classification of Economic Activities are considered. Percentage values are expressed on row totals. North West includes Piedmont, Aosta Valley, Liguria and Lombardy. North East includes Veneto, Emilia-Romagna, Friuli-Venezia Giulia and Trentino-Alto Adige. Centre includes Toscana, Umbria, Marche and Lazio. South includes Abruzzi, Molise, Campania, Apulia, Basilicata and Calabria. Islands are Sicily and Sardinia.

Table A11: Sample distribution by industrial sector

Category	Industry	No. of Firms	
		a. v.	%
1	10 - Manufacture of food products	1,836	6.42
	11 - Manufacture of beverages	141	0.49
	12 - Manufacture of tobacco products	0	0
2	13 - Manufacture of textiles	1,453	5.08
	14 - Manufacture of wearing apparel	1,306	4.57
3	15 - Manufacture of leather and related products	1,183	4.14
4	16 - Manufacture of wood and its products, cork (except furniture), articles of straw, plaiting materials	547	1.91
5	17 - Manufacture of paper and paper products	463	1.62
	18 - Printing and reproduction of recorded media	1,023	3.58
6	19 - Manufacture of coke and refined petroleum products	21	0.07
7	20 - Manufacture of chemicals and chemical products	865	3.02
	21 - Manufacture of basic pharmaceutical products and pharmaceutical preparations	126	0.44
8	22 - Manufacture of rubber and plastic products	1,420	4.97
9	23 - Manufacture of other non-metallic mineral products	1,517	5.30
10	24 - Manufacture of basic metals	504	1.76
	25 - Manufacture of fabricated metal products, except machinery and equipment	7,398	25.87
11	26 - Manufacture of computer, electronic and optical products	1,071	3.75
	27 - Manufacture of electrical equipment	1,247	4.36
12	28 - Manufacture of machinery and equipment n.e.c.	3,740	13.08
13	29 - Manufacture of motor vehicles, trailers and semi-trailers	212	0.74
	30 - Manufacture of other transport equipment	142	0.50
14	31 - Manufacture of furniture	1,310	4.58
	32 - Other manufacturing	1,072	3.75
	33 - Repair and installation of machinery and equipment	0	0
	Total sample	28,597	100

Notes: Percentage values are expressed on the cleaned total sample. Industries are defined at the two-digit level according to the Ateco 2007 classification of the economic activities. Industrial categories are defined according to Istat (Italian National Institute of Statistics) classification.

Table A12. Selection equation: un-weighted and weighted agglomeration variables

Dependent Variable	$\mathrm{SURVIVAL_{is}}$		
	Un-weighted	Size-weighted	TFP-weighted
$\mathrm{TFP_{is}}$	0.249***	0.249***	0.249***
	(0.017)	(0.017)	(0.017)
$\mathrm{SIZE_{is}}$	0.057***	0.056***	0.056***
	(0.009)	(0.009)	(0.009)
$\mathrm{AGE_{is}}$	0.098***	0.098***	0.098***
	(0.015)	(0.015)	(0.015)
$\mathrm{OUTSOURCING_{is}}$	0.098***	0.099***	0.098***
	(0.015)	(0.015)	(0.015)
$\mathrm{CASH_{is}}$	0.018***	0.018***	0.018***
	(0.004)	(0.004)	(0.004)
$\mathrm{INTRA_{is}^{0-5}}$	0.005	-0.004	0.002
	(0.012)	(0.007)	(0.011)
$\mathrm{INTRA_{is}^{5-15}}$	0.010	0.009	0.014
	(0.016)	(0.010)	(0.014)
$\mathrm{INTRA_{is}^{15-30}}$	0.026*	0.021*	0.033**
	(0.015)	(0.012)	(0.015)
$\mathrm{INTER_{is}^{0-5}}$	-0.056***	-0.041***	-0.054***
	(0.014)	(0.009)	(0.012)
$\mathrm{INTER_{is}^{5-15}}$	-0.002	-0.015	-0.010
	(0.021)	(0.014)	(0.018)
$\mathrm{INTER_{is}^{15-30}}$	0.049**	0.051***	0.034*
	(0.020)	(0.016)	(0.019)
$\mathrm{TURBULENCE_{s}}$	-1.321**	-1.185*	-1.153*
	(0.606)	(0.610)	(0.610)
Number of Observations	28,597	28,597	28,597
Pseudo R^2	0.056	0.056	0.056
Log Likelihood	-14,307.72	-14,303.20	-14,303.18
Wald χ^2	1,623.96***	1,617.72***	1,629.92***
Mean VIF	2.80	2.37	2.59

Notes: Specifications include a constant term, as well as industrial category and NUTS-1 dummy variables. Bootstrapped standard errors are shown in parentheses and they are corrected for heteroscedasticity.

$*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table A13: Correlation matrix: variables *à la* CINGANO and SCHIVARDI (2004)

		[1]	[2]	[3]	[4]	[5]	[6]
$\mathrm{SPEC}_{\mathrm{is}}^{0-5}$	[1]	1					
$\mathrm{SPEC}_{\mathrm{is}}^{5-15}$	[2]	0.780	1				
$\mathrm{SPEC}_{\mathrm{i,s}}^{15-30}$	[3]	0.570	0.782	1			
$\mathrm{DIV}_{\mathrm{is}}^{0-5}$	[4]	0.109	0.113	0.091	1		
$\mathrm{DIV}_{\mathrm{is}}^{5-15}$	[5]	-0.051	-0.053	-0.052	0.407	1	
$\mathrm{DIV}_{\mathrm{is}}^{15-30}$	[6]	-0.019	-0.029	0.013	0.250	0.542	1

Notes: Statistics are based on a sample of 28,597 firms.

Table A14. Selection equation: robustness exercises

Dependent Variable	$SURVIVAL_{is}$	
	CINGANO and SCHIVARDI (2004)	Firms aged 10 years or more
TFP_{is}	0.247***	0.245***
	(0.017)	(0.020)
$SIZE_{,s}$	0.058***	0.053***
	(0.009)	(0.011)
AGE_{is}	0.097***	0.061***
	(0.015)	(0.022)
$OUTSOURCING_{is}$	0.096***	0.087***
	(0.015)	(0.019)
$CASH_{is}$	0.018***	0.022***
	(0.004)	(0.004)
$SPEC_{is}^{0-5}$	0.031**	...
	(0.015)	
$SPEC_{is}^{5-15}$	0.010	...
	(0.019)	
$SPEC_{is}^{15-30}$	0.008	...
	(0.017)	
DIV_{is}^{0-5}	-0.035**	...
	(0.017)	
DIV_{is}^{5-15}	-0.067**	...
	(0.031)	
DIV_{is}^{15-30}	0.132***	...
	(0.033)	
$INTRA_{is}^{0-5}$	...	0.011
		(0.014)
$INTRA_{is}^{5-15}$	...	0.004
		(0.018)
$INTRA_{is}^{15-30}$	...	0.024
		(0.018)
$INTER_{is}^{0-5}$	...	-0.055***
		(0.015)
$INTER_{is}^{5-15}$	...	-0.001
		(0.023)
$INTER_{is}^{15-30}$	...	0.053**
		(0.023)
$TURBULENCE_{s}$	-1.426**	-1.290*
	(0.605)	(0.718)
Number of Observations	28,597	23,194
Pseudo R^2	0.054	0.051
Log Likelihood	-14,329.40	-11,237.75
Wald χ^2	1,578.72***	1,188.79***
Mean VIF	2.25	2.82

Notes: Specifications include a constant term, as well as industrial category and NUTS-1 dummy variables. Bootstrapped standard errors are shown in parentheses and they are corrected for heteroscedasticity.

$*p < 0.1$; $**p < 0.05$; $***p < 0.01$.