Papers in Regional Science 105 (2026) 100159

Contents lists available at ScienceDirect

Papers in Regional Science

journal homepage: www.sciencedirect.com/journal/papers-in-regional-science

# The geography of misallocation: Spatial patterns and local distortions in Italian manufacturing

Andrea D'Isidoro *, Matteo Rapagna

*University "G.d'Annunzio" of Chieti-Pescara, Dipartimento di Economia, Pescara, Italy*

ARTICLE INFO

*Keywords:*
Productivity
Resource allocation
Spatial dependence
Spatial filtering
Regional spillovers

ABSTRACT

Productivity and resource allocation could be influenced by the occurrence of spillover effects due to geographical structure. This paper examines the spatial dimension of misallocation and productivity across Italian provinces, using firm-level microdata for manufacturing sector. Methodologically, we build province-level measures of misallocation and total factor productivity, and then we apply a spatial filtering approach to decompose them into two parts: a spatial component, capturing inter-regional spillovers and geographic patterns, and an idiosyncratic component, reflecting province-specific characteristics. By disentangling these two dimensions, the paper provides a clearer view of how geography and local structural conditions jointly shape the distribution of productive resources. This distinction is crucial to identify whether regional productivity disparities are primarily due to local peculiarities or spatially correlated distortions. We find significant spatial autocorrelation in both productivity and misallocation measures, where the geographical component is predominant. Eliminating distortions would raise output by over 20 %, with roughly two-third of these gains associated with the spatial component.

## 1. Introduction

Over the past two decades, the concept of resource misallocation has emerged as a central framework to explain cross-country and within-country differences in productivity. Originating from the seminal contribution of Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), this literature emphasizes how frictions in factor markets—arising from financial constraints, regulations, or institutional rigidities—distort the allocation of inputs across heterogeneous producers, leading to sizable aggregate productivity losses. In an efficient economy, capital and labor should flow toward the most productive firms until the marginal revenue products of inputs are equalized. Persistent dispersion in these returns thus signals allocative inefficiency, whereby productive firms remain inefficiently small and less productive ones survive at inefficiently large scales. Subsequent work has shown that such distortions can account for a substantial fraction of productivity gaps across countries and sectors (Restuccia and Rogerson, 2013; 2017; Bartelsman et al., 2013; Calligaris et al., 2018).

While most of this literature has focused on identifying and quantifying firm-level or sectoral distortions, relatively less attention has been devoted to their spatial dimension. Yet, in economies characterized by strong regional heterogeneity—such as Italy—allocative efficiency and total factor productivity (TFP) are likely to display systematic geographical patterns. Structural differences in infrastructure, financial development, administrative capacity, and institutional quality may generate spatially correlated distortions, leading neighbouring areas to exhibit similar degrees of misallocation and TFP dispersion. The issues arising when observations are not independent over space could be caused by common underlying factors or they are attributable to spatial spillover effects (Capello, 2009). In such cases, the geography of misallocation and TFP cannot be interpreted as a purely idiosyncratic phenomenon: part of it reflects spillovers, common shocks, or diffusion mechanisms that shape local production environments. Some recent works, from Bandt *et al.* (2013) to Fajgelbaum et al. (2019) and Hsieh and Moretti (2019), consider the geographical aspect of misallocation, limiting their definition of spatial misallocation to the analysis of differences between regions. Adamopoulos et al. (2022) explore related issues in the context of agricultural villages, using fixed-effects residuals to capture location-specific distortions. In this way, they account for a sort of spatial heterogeneity effect. The scope of our work is to go beyond these approaches, extending spatial misallocation analysis by considering the mutual influences between territorial units, focusing on

* Correspondence to: University "G.d'Annunzio" of Chieti-Pescara, Dipartimento di Economia, Viale Pindaro, Pescara, PE 42 - 65127, Italy.
*E-mail addresses:* andrea.disidoro@unich.it (A. D'Isidoro), matteo.rapagna@unich.it (M. Rapagna).

https://doi.org/10.1016/j.pirs.2026.100159
Received 9 March 2026; Received in revised form 14 July 2026; Accepted 15 July 2026
Available online 18 July 2026
1056-8190/© 2026 The Author(s). Published by Elsevier B.V. on behalf of The Regional Science Association International. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

the identification of geographical patterns in Italian manufacturing sector.

Empirical evidence from Italy highlights the non-linear impact of spatial agglomeration—encompassing localization, diversity, urbanization, and competition—on firm-level total factor productivity, with positive effects materializing only above certain thresholds (Cainelli et al., 2015). For instance, Calligaris et al., (2018) decompose the variance of misallocation into within- and between-sector components and uncover pronounced geographic patterns in TFP across Italian macro-regions, highlighting the heterogeneity in productivity dynamics. Furthermore, in the Italian context, spatial decompositions of labor productivity inequality reveal how sector-specific differentials and industry-mix variations contribute to regional disparities, particularly considering the neighborhood effects (Mussini, 2019; Emili and Galli, 2025).

This paper is motivated by a simple but largely unexplored question: to what extent is observed misallocation driven by geographically shared factors rather than firm-specific distortions? While the existing literature has extensively documented the magnitude of allocative inefficiency, it remains unclear whether such inefficiencies primarily reflect idiosyncratic wedges at the firm level or instead originate from spatially correlated constraints embedded in local economic environments. Distortions are not randomly distributed across space, but instead arise within a framework in which locations are interconnected through trade, factor mobility, and technological diffusion (Blien et al., 2006; Duguet et al., 2023). Differences in taxation, regulation, and the quality of public goods across regions act as variations in economic fundamentals, inducing inefficient reallocations of firms and workers (Fajgelbaum et al., 2019). As a result, observed distortions reflect not only idiosyncratic heterogeneity, but also systematic spatial structures. Addressing this distinction is crucial, as it speaks directly to the underlying mechanisms of misallocation and to the appropriate design of policy interventions.

To answer this question, we adopt a two-step empirical strategy. First, building on the Hsieh–Klenow framework, we compute firm-level measures of misallocation and productivity using microdata from the AIDA database, which provides a very broad coverage of Italian manufacturing firms over the period 2015–2024. We then aggregate these firm-level distortions at the provincial level and apply spatial tests to assess the extent to which misallocation exhibits spatial autocorrelation. Second, we exploit an eigenvector-based spatial filtering approach (Getis and Griffith, 2002) to decompose both productivity and misallocation into a spatial component, capturing geographically correlated effects, and an idiosyncratic component, reflecting local deviations net of spatial structure. In particular, we employ an eigenvector-based spatial filtering procedure (Griffith, 2003) to decompose the misallocation of each province. The eigenvectors approach allows to identify and map the patterns which cause the spatial autocorrelation of the observations (Patuelli et al., 2012; Griffith et al., 2022). This decomposition allows us to quantify the relative importance of geography in shaping allocative inefficiency and to characterize how spatial and local factors jointly determine productivity outcomes.

Among geographical productivity and resource allocation studies, our work is the first one which apply techniques able to treat spatial dependence, isolating spatial effects from local peculiarities. By clarifying whether misallocation is primarily a spatially correlated or an idiosyncratic phenomenon, we seek to advance the understanding of how regional disparities in productivity arise and persist within advanced economies. Distinguishing between these two dimensions is crucial for the design of effective policies: spatially driven inefficiencies may require place-based interventions targeting networks and spillovers, whereas idiosyncratic distortions call for firm- or sector-level reforms.

The remainder of the paper is organized as follows. Section 2 contextualize the contribution of our work among the existing literature, Section 3 outlines the misallocation analysis and the spatial filtering procedure, Section 4 describes the empirical application, form the data sources and construction of variables to the discussion of results, and Section 5 concludes.

## 2. Literature background and motivation

### 2.1. Misallocation of resources and TFP

The modern literature on misallocation originated with two seminal contributions that formalized and quantified how distortions in resource allocation across heterogeneous firms lead to aggregate productivity losses. Restuccia and Rogerson (2008) developed a theoretical framework showing that idiosyncratic policy distortions—such as size-dependent taxes or regulations—can misallocate capital and labor, compressing firm sizes and reducing TFP by preventing resources from concentrating in high-productivity establishments. This model highlighted the macroeconomic implications of firm-level frictions, laying the groundwork for subsequent research. Complementing this, Hsieh and Klenow (2009) provided the empirical foundation by applying firm-level data from China and India to measure misallocation; they demonstrated that reallocating factors to equalize marginal revenue products could boost manufacturing TFP by 30%–50% in China and 40%–60% in India, establishing a tractable methodology that has become the benchmark for empirical analysis.

Building on these foundations, resource misallocation is defined as the inefficient allocation of factors of production—such as capital and labor—across heterogeneous producers, which prevents the equalization of marginal revenue products and results in substantial aggregate productivity losses, particularly in TFP. This inefficiency arises when frictions in factor markets hinder resources from flowing to their most productive uses, leading to persistent dispersion in returns to inputs and hindering overall economic performance (Banerjee and Duflo, 2005). The study of misallocation remains crucial because it provides a compelling explanation for the large and enduring productivity gaps observed across countries and within economies, complementing traditional accounts focused on technological diffusion or human capital accumulation. Evidence suggests that correcting misallocation can generate substantial productivity gains across a wide range of settings (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008; 2017; Moll, 2014), underscoring its role in development economics and policy design. The literature also shows a broad consistency in the order of magnitude of these effects, and while measurement error may attenuate estimated gains, corrected estimates remain economically meaningful (Bils et al., 2021).

According to Restuccia and Rogerson (2017), misallocation can be categorized into two types. The first one is direct misallocation, which involves distortions that directly affect the allocation of inputs among existing firms, such as taxes, subsidies, or regulations that alter relative factor prices and lead to suboptimal resource use within the current set of producers. The second one is indirect misallocation, which operates through entry, exit, and selection mechanisms, whereby barriers prevent low-productivity firms from exiting the market or deter high-potential entrants, thereby distorting the overall firm distribution and amplifying aggregate inefficiencies.

Subsequent studies have extended these insights, incorporating factors like financial frictions, trade barriers, and institutional quality (Midrigan and Xu, 2014; Gopinath et al., 2017). For instance, Bartelsman et al. (2013) used cross-country microdata to link misallocation to poor allocative efficiency and firm selection, finding it accounts for up to half of TFP differences between developed and developing economies. Surveys such as Hopenhayn (2014) synthesize this body of work, emphasizing how direct distortions (e.g., credit constraints) exacerbate input misallocation among incumbents, while indirect effects (e.g., entry costs) skew the productivity distribution by favoring unproductive survivors.

### 2.2. Spatial structure of misallocation

The misallocation literature, following Restuccia and Rogerson (2017), interprets the dispersion in marginal revenue products as the outcome of distortions that prevent the efficient allocation of inputs across heterogeneous firms. In this framework, taxes, regulations, financial frictions, and informational imperfections generate firm-level wedges that lead firms with different productivities to operate at inefficient scales, thereby reducing aggregate TFP (Fajgelbaum et al., 2019). A key, yet often implicit, assumption in this literature is that such distortions are idiosyncratic and independently distributed across firms.

However, many of the underlying mechanisms emphasized by this literature naturally exhibit a spatial dimension, implying that distortions are unlikely to be independently distributed across economic units (Brandt et al., 2013). Policy distortions are typically defined at a territorial level, so that firms operating within the same jurisdiction face common regulatory and fiscal environments. Financial frictions are often mediated by local banking systems and credit networks, leading to geographically clustered access to capital. Adjustment costs depend on local factor markets, such as labor and housing conditions, while information frictions and learning processes tend to propagate through spatially concentrated networks (López-Rodríguez et al., 2025; Muolo et al., 2026). In addition, sorting mechanisms imply that firms with similar characteristics—such as productivity, technology, or sectoral specialization—tend to co-locate, further reinforcing spatial correlation in observed wedges (Cainelli et al., 2015; Bhattacharjee et al., 2023).

Taken together, these considerations suggest that a non-negligible share of the observed dispersion in marginal revenue products reflects location-specific components that are common across firms within the same area, rather than purely firm-specific shocks. Treating distortions as entirely idiosyncratic therefore implicitly assumes the absence of spatial correlation in wedges—an assumption that is difficult to reconcile with the institutional, financial, and informational channels highlighted by the misallocation literature, as in modern quantitative spatial models, the distribution of economic activity is jointly determined by local fundamentals and interactions across regions, including trade linkages, migration flows, and market access (Redding and Rossi-Hansberg, 2017). In this context, technology and economic activity diffuse across space, generating highly localized and interdependent development dynamics (Desmet and Rossi-Hansberg, 2013).

A first channel of spatial interdependence operates through production and matching externalities. Firm-level productivity may depend on the density and composition of economic activity in nearby areas, as emphasized in urban economic models (Lucas and Rossi-Hansberg, 2002). In addition, matching externalities arise in labor markets: larger and thicker markets increase the likelihood of efficient worker–firm matches, improving match quality and thereby the allocation of factors (Moretti and Yi, 2024). Since these externalities are not internalized by individual firms, they generate a spatial distribution of economic activity that may deviate from the socially efficient allocation, resulting in dispersion in marginal products.

A second channel arises from interdependencies across regions through trade and input–output linkages. Local productivity shocks or policy interventions can propagate to other areas through intermediate goods flows and trade relationships, systematically affecting prices, costs, and demand. In a setting where locations are connected by trade costs and market interactions, these propagation mechanisms imply that initially localized distortions translate into a spatially correlated structure of misallocation.

A third key mechanism is given by frictions in factor mobility, particularly labor. Mobility costs, institutional constraints, or housing market restrictions may prevent workers from relocating to more productive areas, generating persistent mismatches between firms and factors. In particular, housing supply constraints in high-productivity cities limit workers' access to such locations, preventing efficient labor reallocation and amplifying dispersion in marginal products (Hsieh and Moretti, 2019). Empirical evidence further shows that transaction costs in housing markets significantly reduce mobility, with distortionary effects on labor allocation (Hilber and Lyytikäinen, 2017). In the presence of such frictions, highly productive firms may remain inefficiently small, while less productive firms operate at excessive scale.

Additionally, spatial heterogeneity in policies and institutions constitutes another source of misallocation. Recent evidence show that place-based policies and public interventions can directly affect the spatial allocation of factors. For instance, the establishment of special economic zones can lead to an over-allocation of land and a reduction in allocative efficiency (Cui, 2025), while government land supply policies significantly influence the location and evolution of industrial activities (Huang et al., 2025). Moreover, agglomeration forces may shape the sectoral composition of cities, contributing to systematic differences in factor allocation across locations (Bai, 2026).

Because of these mechanisms, dispersion in marginal revenue products—and thus allocative inefficiencies—tends to be spatially correlated. Therefore, this paper aims to provide new evidence on the structure of misallocation by showing that a substantial share of the dispersion in both productivity and allocative inefficiency is spatially structured rather than purely idiosyncratic.

### 2.3. Spatial effects and misallocation in Italian manufacturing sector

In the Italian context, where TFP has stagnated or declined since the mid-1990s, misallocation has emerged as a key explanatory factor. Italy's economy, characterized by regional disparities, small firm dominance, and institutional rigidities, provides a fertile ground for studying these inefficiencies. Cainelli et al. (2015) applied the Hsieh-Klenow framework to Italian manufacturing firms over 1993–2011, estimating that eliminating distortions would boost TFP by 58% in 1993, rising to 80% by 2011, with misallocation disproportionately higher in southern regions, low-tech sectors, and among small or young firms—attributing this to direct factors like financial constraints and indirect barriers to entry and growth. Building on this, Calligaris et al. (2018) extended the analysis economy-wide (1995–2013), decomposing misallocation variance into within- and between-sector components and revealing that inefficiencies increased primarily within sectors, especially those with faster-expanding technological frontiers; holding misallocation at 1995 levels would have raised 2013 aggregate productivity by 18%, implying an annual drag of about 1.3 %age points on GDP growth. This work emphasizes how relative specialization in high-misallocation sectors exacerbates regional divides, with direct capital distortions (e.g., from financial integration issues) playing a growing role over time. Related Eurozone studies, such as Dias et al. (2016) on Portugal, document similar patterns, where misallocation doubled from 1996 to 2011 due to capital wedges amid financial inflows, boosting potential value-added by 79% in 2011 and highlighting indirect effects from inefficient firm selection pre-crisis.

Despite these advances, the spatial dimension of misallocation in Italy remains underexplored, with most studies aggregating at national or sectoral levels without explicitly modeling geographic interdependence (Bartelsman et al., 2013; Linarello and Petrella, 2017). However, when dealing with georeferenced data, nearby units are usually associated in some way, generating spatial autocorrelation (Frischer and Griffith, 2008). This is particularly true in the Italian context, where labor and capital productivity disparities between Northern and Southern regions are well documented in literature (Piacentino and Vassallo, 2011; Emili and Galli, 2025).

A step in this direction is made by Calligaris et al. (2018), who decompose misallocation variance into within-and between geographical zones, but only limiting the analysis on macro-zones (e.g. NUTS 1 level). Other attempts to consider the influence of nearby regions in Italian labor productivity are done applying spatial decompositions. However, these works focus on inequality measures, separating neighbor from non-neighbor effects, to show the role of sector-specific

differentials (Mussini *et al.*, 2019) and industry-mix effects as drivers of regional disparities (Espa et al., 2014). We contribute to the growing literature proposing the application of a spatial technique directly on TFP and misallocation values, allowing to separate spatial patterns from specific performance of the units.

While some work, like Adamopoulos et al. (2022), uses fixed-effects residuals to capture location-specific distortions, these approaches focus on spatial heterogeneity and overlook formal decompositions of spatial autocorrelation. Our paper addresses this gap by aggregating firm-level misallocation measures at the provincial level and employing techniques which account for spatial dependence, including eigenvector-based filtering (Griffith, 2003), to disentangle spatially structured inefficiencies—arising from spillovers, common shocks, or regional frictions—from province-intrinsic ones. This structured decomposition extends previous intuitions, quantifying the role of geography in shaping allocative efficiency and informing targeted policies in heterogeneous economies like Italy's.

In our analysis, we focus on manufacturing firms because misallocation measures are more reliably identified in this sector, where inputs and output are better observed and production technologies are more homogeneous across firms, thereby limiting measurement error and comparability issues that are more severe in services and other sectors (De Dominicis et al., 2013; Restuccia and Rogerson, 2017). Moreover, recent findings stress how positive spatial spillovers are identified in manufacturing sector for both labor and capital productivity (Emili and Galli, 2025). The spatial scale of our analysis is at Italian province level (i.e. European NUTS 3), instead of the regional one (NUTS 2), because spatial influence in TFP could be deeper analyzed if the geographical units considered at a finer scale (Glass and Kenjegalieva, 2024).

The aim of our study goes also in the direction of understanding the possible causes of the spatial patterns that could be detected by spatial filtering. Northern regions, benefiting from superior infrastructure and institutional quality, display higher TFP levels, while southern provinces suffer from greater allocative distortions, leading to productivity gaps where the South's TFP is often 20%–30% lower than the North's. Calligaris (2015) attributes this to elevated misallocation in southern, low-tech, small, and young firms, exacerbated by financial constraints and regulatory frictions that hinder resource reallocation. Empirical studies demonstrate that spatial agglomeration—via localization, diversity, and competition—nonlinearly boosts firm-level TFP, with benefits accruing only above critical thresholds, particularly in northern industrial clusters (Cainelli et al., 2015). Additional evidence points to technological spillovers explaining 20%–30% of North-South TFP gaps, where peripheral southern regions are disadvantaged by limited proximity to innovative hubs (Aiello and Cardamone, 2012). These findings underscore that spatial frictions, such as those from geographic isolation or uneven broadband adoption, amplify TFP penalties in peripheral zones, suggesting a need for place-based policies to mitigate spillovers' uneven distribution (Giannini et al., 2023). Similarly, agglomeration in the South enhances TFP and firm survival through innovation diffusion, though benefits are curtailed by historical underinvestment in connectivity (Bhattacharjee et al., 2023). Northern Italy, instead, benefits from spillovers of technological progress in manufacturing, especially considering governments strategies aimed at boosting digitalization (Camagni et al., 2022).

To overcome these gaps, many policies, especially at European level, are devoted to the spread of subsidies and funds to the worst performing regions. However, the effects of these policies on firms' productivity are debated in literature, since conflicting results emerge regarding the performance of companies located in the target regions (Percoco, 2017; Albanese et al., 2021). In the discussion of our results, we try to interpret the relation between these grants and inefficiency, and to assess when place-based or firm-based policies are better suitable.

## 3. Methods

This section outlines the methodological framework adopted to quantify and disentangle the different dimensions of resource misallocation across Italian provinces. Our analysis proceeds in two steps. First, we estimate firm-level distortions in the allocation of capital and labor within the manufacturing sector, drawing on the seminal framework of Hisieh and Klenow (2009). These firm-specific distortions are then aggregated at the provincial level to construct a synthetic indicator of misallocation that reflects the efficiency of factor allocation within local production systems.

In a second step, we explicitly account for the spatial structure of the data. Since provinces are geographically contiguous and economically interdependent, patterns of misallocation may not be purely idiosyncratic but may also exhibit spatial dependence. Neighboring provinces may display similar degrees of allocative inefficiency due to common institutional settings, shared infrastructure, interprovincial supply chains, or diffusion effects in technology and productivity. Ignoring such spatial interactions could therefore lead to biased inference and obscure the underlying geography of distortions.

Recent work by Adamopoulos et al. (2022) has highlighted the importance of spatial components of misallocation, using village fixed effects to capture location-specific heterogeneity in agricultural settings. Building on this intuition, we extend the analysis by employing an explicit spatial filtering approach that decomposes misallocation into spatially structured and idiosyncratic components, allowing for a finer distinction between geographic spillovers and intrinsic provincial efficiency.

To address this, we complement the firm-level analysis with a spatial decomposition of the provincial misallocation measure. We test for spatial autocorrelation in misallocation values using Moran's I and, when dependence is detected, we apply a spatial filtering procedure based on the eigenvector approach of Griffith (2003). This technique allows us to separate the spatially structured component of misallocation—reflecting regional spillovers or neighbourhood effects—from its idiosyncratic, province-specific component. The resulting filtered measure captures the intrinsic allocative efficiency of each province, net of spatial dependence. This twofold analytical strategy provides a clearer picture of how both local and spatial dynamics contribute to the observed geography of misallocation in manufacturing sector across Italian provinces.

### 3.1. Misallocation analysis

In order to measure resource misallocation at the provincial level, we adapt the framework of Hisieh and Klenow (2009), in which allocative inefficiency is inferred from dispersion in marginal revenue products across firms within narrowly defined sectors. Under standard assumptions of monopolistic competition, Cobb-Douglas technology, and common factor prices within sectors, an efficient allocation requires the marginal revenue products of capital and labor to be equalized across firms. Equivalently, revenue productivity (TFPR) must be constant within sector.

Deviations from this condition reflect the presence of firm-specific distortions that prevent inputs from being allocated according to underlying physical productivity. These distortions may arise from taxes, credit constraints, regulatory frictions, entry and exit barriers, or other institutional features that affect firms asymmetrically. When such wedges are present, some firms operate at a scale that is too small relative to the efficient benchmark, while others operate at a scale that is too large. Misallocation therefore manifests itself as dispersion in revenue productivity across firms within the same sector.

Formally, firm-level production is assumed to follow a Cobb-Douglas technology:

$$Y_{it} = A_{it} K_{it}^{\alpha_s} L_{it}^{1-\alpha_s} \tag{1}$$

where $Y_{it}$ denotes output, $K_{it}$ capital, $L_{it}$ labor, and $A_{it}$ physical productivity (TFPQ) of firm $i$ at time $t$. The capital share parameter $\alpha$ is estimated at the two-digit industry level within manufacturing sector.

Physical productivity is therefore given by:

$$A_{it} = \frac{Y_{it}}{K_{it}^{\alpha_s} L_{it}^{1-\alpha_s}} \tag{2}$$

Following Hisieh and Klenow (2009), misallocation is measured using revenue productivity (TFPR), defined as:

$$TFPR_{it} = \frac{P_{it} Y_{it}}{K_{it}^{\alpha_s} L_{it}^{1-\alpha_s}} = P_{it} A_{it} \tag{3}$$

where $P_{it}$ denotes the firm-specific output price. Under efficient allocation and common markups within sector, TFPR must be equalized across firms in the same sector. Dispersion in TFPR is therefore interpreted as evidence of allocative distortions.[1]

Importantly, TFPR dispersion does not measure differences in physical productivity (TFPQ). Rather, conditional on sector-level parameters, a firm with higher TFPR is interpreted as being relatively distorted and therefore operating at a scale that is too small compared to the efficient benchmark. Conversely, a firm with lower TFPR operates at an inefficiently large scale. In equilibrium, eliminating distortions would reallocate inputs across firms until TFPR is equalized within each sector.

Let $TFPR_{it}$ denote the revenue productivity of firm $i$ at time $t$, and let $\overline{\log TFPR}_{st}$ denote the average log$TFPR$ in sector $s$ at time $t$. We define firm-level misallocation as the log deviation:

$$Misallocation_{it} = \log TFPR_{it} - \overline{\log TFPR}_{st} \tag{4}$$

Positive values indicate firms that are relatively too small given their fundamentals (high TFPR), while negative values indicate firms that are relatively too large (low TFPR). Sectoral dispersion of this object is the sufficient statistic for the aggregate efficiency losses emphasized in Hsieh and Klenow (2009).

### 3.2. Gains from Reallocation

To quantify the aggregate efficiency losses associated with observed distortions, we use the framework of Hisieh and Klenow (2009) in order to compute the counterfactual gains from reallocation comparing observed output with the level that would prevail under an efficient allocation in which revenue productivity is equalized across firms within each sector.

Under the assumptions outlined above, the ratio of observed to efficient output within a sector can be expressed as:

$$\frac{Y_t}{Y_t^{efficient}} = \prod_{s=1}^{S} \left[ \sum_{i \in s} \left( \frac{A_{it}}{\overline{A}_{st}} \frac{\overline{TFPR}_{st}}{TFPR_{it}} \right)^{\sigma-1} \right]^{\frac{\theta_s}{\sigma-1}} \tag{5}$$

Here, $\sigma$ denotes the elasticity of substitution across firms, which we set to $\sigma = 3$ in the baseline specification and to $\sigma = 5$ as a robustness check as in Hisieh and Klenow (2009).

A higher elasticity of substitution amplifies the aggregate cost of misallocation, as it increases the responsiveness of optimal firm size to differences in marginal revenue products. As a result, a given dispersion in TFPR implies larger deviations from the efficient allocation and therefore larger output losses. $\theta_s$ is the share of sector $s$ in total value added.

We implement this counterfactual at the province–year level, allowing the extent of misallocation to vary across local production systems. This counterfactual corresponds to the standard Hisieh and Klenow (2009) exercise, in which all distortions are removed, and inputs are efficiently reallocated across firms within sectors. It should therefore be interpreted as an upper-bound measure of potential efficiency gains, rather than a policy-specific counterfactual targeting particular sources of distortions. Gains from reallocation are then defined as: $Gain = \left( \frac{Y^{efficient}}{Y} - 1 \right) \times 100$ which measures the percentage increase in output that would arise if distortions were eliminated, and inputs were efficiently reallocated across firms within sectors. This counterfactual outlines the observed dispersion in revenue productivity into an aggregate output loss relative to the efficient allocation. We use this measure to quantify the magnitude of misallocation across provinces and over time, and to assess how much of these losses are associated with the spatial component identified through the filtering procedure.

### 3.3. Spatial filtering approach

In our application, if nearby provinces tend to assume similar values of TFP and misallocation, it could be a signal of positive spatial autocorrelation. We test the extent of spatial autocorrelation in our data relying on the global Moran's I statistic (Moran, 1950). The index is computed using a nearest-neighbour spatial weights matrix (C) based on geographical proximity between provinces. Under the hypothesis of no spatial autocorrelation, the expected value of the Moran's index is $E(I) = 1/(n-1)$, where $n$ is the number of units. An index value significantly higher than its expected value it is a signal of positive spatial dependence. Since global indicators values could hide local clusters with spatial concentration of high-or low-values, we also calculate a local indicator of spatial association (LISA; Anselin, 1995), specifically the local Moran's I.

To transform a spatially dependent variable into an independent variable, spatial filtering techniques are employed. These approaches work on the spatially autocorrelated variables by removing the spatial dependence embedded in them, with the aim of partitioning the original variable into two components: a filtered (non-spatial) one and a spatial one (Griffith, 2003).

Two main approaches exist for screening spatial autocorrelation by means of spatial filtering. The first is based on Getis' statistic $G_i$ (Getis, 1990), while the second was introduced by Griffith (2003) and relies on an eigenvector decomposition of the spatial weights matrix, linked to Moran's I. Getis' technique requires that the input variables be strictly positive and with a natural origin, while Griffith's approach imposes no restrictions on the variables' distribution. Since misallocation can assume positive or negative values, thereby violating Getis' conditions (Getis and Griffith, 2002), in this work we rely on Griffith's technique.

The filtering technique introduced by Griffith is also known as the eigenvector approach, because it is based on an eigenvector decomposition of the spatial weights' matrix. This decomposition is associated with Moran's $I$ and aims to remove nuisances due to spatial dependence (Griffith et al., 2022). The eigenvector decomposition is done over the matrix:

[1] The mapping between TFPR dispersion and allocative inefficiency follows the standard Hsieh–Klenow framework and relies on the maintained assumptions of common markups and static efficiency within sectors. Under these assumptions, TFPR dispersion can be interpreted as evidence of allocative distortions. As discussed in the literature, markup heterogeneity, adjustment costs, or dynamic frictions may also contribute to revenue-productivity dispersion (Asker et al., 2014; De Loecker and Goldberg, 2014; Haltiwanger, 2016). We therefore interpret our measure as revenue-productivity dispersion consistent with allocative distortions, rather than as a direct estimate of structural wedges. As a robustness check, we recompute firm-level misallocation using production-function coefficients estimated at increasingly finer industry levels, namely two-digit, three-digit, and four-digit manufacturing industries (Gopinath et al., 2017). The resulting measures are highly correlated across classifications, with correlations above 0.98, suggesting that the measured dispersion and the resulting spatial patterns are not mechanically driven by the chosen level of sectoral aggregation.

$$\left(\mathrm{I}-\frac{11'}{\mathrm{n}}\right)\mathrm{C}\left(\mathrm{I}-\frac{11'}{\mathrm{n}}\right) \tag{6}$$

where I is an n × n identity matrix; 1 is n × 1 vector of ones; and C is a binary spatial weight matrix (Griffith, 2008). In this way, the spatial part of the variable is obtained to minimize the degree of spatial autocorrelation in the model residuals, where the spatial autocorrelation model for a generic variable *Y* is:

$$y_i = \mu_Y + V_i'\beta_V + \epsilon_i \tag{7}$$

where $y_i$ is the variable at each location i and $\mu_Y$ is the mean of the variable *Y*. $V_i$s are the values associated to unit i included into the matrix of the q < n selected eigenvectors V of the matrix $(I-11'/n)C(I-11'/n)$ and $\beta_V$ is the set of parameters associated to the eigenvectors. Finally, $\epsilon_i$ is an independent and identically distributed error term. The eigenvectors Vs describe latent spatial autocorrelation included in each of variable and it is demonstrated that that each of the eigenvalues of $(I-11'/n)C(I-11'/n)$ is a Moran index value (Tiefelsdorf and Boots, 1995). The *q* eigenvectors involved in the estimation phase are the minimum number for which the spatial autocorrelation in the residuals of equation [7] does not significantly differ from zero (Tiefelsdorf and Griffith, 2007). The linear combination of selected eigenvectors-and related coefficient estimates-defines the spatial filter for the variable of interest (Patuelli et al., 2012).

Once the model in [7] is estimated, we obtain the filtered variable as the residuals of the model prediction:

$$y_l^* = e_i \text{with} e_i = \quad y_i - \widehat{y}_i \tag{8}$$

where the value $\widehat{y}_i$ is the predicted value obtained estimating the parameters of the formula [7]. Accordingly, the value $\widehat{y}_i$ represents the spatial component of the variable. Therefore, in our application, for each province *i*, the original value of misallocation can be rewritten as the sum of the filtered part $y_i^*$ and its spatial component $\widehat{y}_i = s_i$ as:

$$y_i = y_l^* + s_i \tag{9}$$

By applying this decomposition, we retrieve the unit-specific achievements and the spatial effects. This visualization allows to distinguish the intrinsic performance of each province in terms of misallocation from the amount imputable to the influence of the neighbourhood.

## 4. Empirical application

### 4.1. Data

The core of our analysis is based on microdata for Italian manufacturing firms over the period 2015–2024. These are from AIDA database, the Italian subset of the global data covering digital balance sheets, Orbis (Caragliu and Landoni, 2024), which provides balance sheet, registry, product data, and income statement information. AIDA database provides very broad coverage of the Italian corporate sector, including more than 6.8 million firms, and it is used in several similar works (e.g., Card et al., 2014; Marzucchi et al., 2015; Serafinelli, 2019; Marin and Modica, 2021). AIDA (Bureau van Dijk) provides near-complete coverage of Italian limited liability companies (*società di capitale*). It does not include sole proprietorships (*imprese individuali*), partnerships (*società di persone*), most self-employed professionals, banks, insurance companies, or public-sector entities. Its coverage is widely recognized as suitable for empirical analyses in Italy (Lotti and Marin, 2013; Bocci and Smith, 2026).

For each firm, we collect value added (*Y*), capital stock (*K*), total employment (*L*), and total labor costs (*W*). Output and capital are deflated using industry-specific producer price indices, while labor input is measured either as the number of employees or total deflated wages, depending on the specification. We use annual sectoral deflators from the Italian National Accounts (ISTAT, September 2024 release). The output deflator is constructed as the ratio of value added at current prices to chain-linked value added (reference year 2020) for the industrial aggregate including manufacturing, energy, utilities, and construction, labor costs are deflated using the output deflator. The capital deflator is constructed analogously using gross fixed capital formation (GFCF) at current and chain-linked prices for the same sectoral aggregation.

Table 1 reports firm-level summary statistics (all variables in logs). The data reveal substantial heterogeneity across firms: the standard deviation of log value added is 1.61, and that of log capital is 2.40, reflecting the highly skewed size distribution of Italian manufacturing firms. Table 2 reports firm characteristics by macro-region and size class. The results highlight a strongly skewed size distribution and a monotonic increase in both output and revenue productivity with firm size, while average TFP differences across macro-regions remain limited. This suggests that structural heterogeneity is primarily driven by firm scale rather than systematic North–South gaps at the firm level.

Using these variables, we compute total factor productivity (TFP) and total factor productivity in revenue terms (TFPR) following the Hsieh–Klenow framework. As shown in Table 3, the standard deviation of log TFPR equals 0.604, with a 90–10 gap of 1.086 log points. This implies that firms at the 90th percentile of TFPR exhibit nearly three times the revenue productivity of firms at the 10th percentile, indicating economically meaningful distortions in the allocation of inputs. Dispersion in log TFP is even larger (SD = 0.753), confirming substantial technological heterogeneity across firms.

To explore the structure of distortions, Table 4 reports TFPR dispersion by firm size class. Misallocation is markedly higher among micro firms (SD = 0.674) and declines sharply for small and medium firms, suggesting that the aggregate dispersion is largely driven by the smallest establishments. By contrast, Table 5 shows that TFPR dispersion is remarkably similar across macro-regions (North, Centre, and South), with standard deviations ranging from 0.594 to 0.610. This indicates that the North–South divide does not originate from systematically different firm-level dispersion, but rather from the spatial aggregation and interaction of local distortions.

Firm-level measures are then averaged at the provincial level to construct indicators of local allocative efficiency and all results about spatial and idiosyncratic components are an aggregation (mean) over the time period considered, to replicate a cross-section context as common in spatial econometric literature (Fischer and Griffith, 2008; Anselin and Arribas-Bel, 2013). Table 6 summarizes the distribution of provincial means. The dispersion across provinces (SD = 0.132 for TFPR) is substantially smaller than firm-level dispersion, implying that most misallocation arises within provinces rather than between them. These aggregated indicators constitute the basis for the subsequent spatial analysis.

### 4.2. Results

Fig. 1 displays the spatial distribution of total factor productivity

**Table 1**
Firm-level summary statistics. All variables are expressed in logarithms. Y denotes value added, K total capital, L employment, W wage bill. TFP and TFPR are sector-level (two-digit ATECO) residual-based measures computed following the Calligaris et al. (2016) framework.

| | Mean | SD | p25 | p50 | p75 | N |
|---|---|---|---|---|---|---|
| Y | 12.370 | 1.611 | 11.318 | 12.308 | 13.336 | 2926,486 |
| K | 11.454 | 2.398 | 9.896 | 11.448 | 13.061 | 2926,486 |
| L | 1.790 | 1.215 | 1.099 | 1.609 | 2.485 | 2926,486 |
| W | 11.585 | 1.660 | 10.534 | 11.583 | 12.609 | 2926,486 |
| TFP | 0.000 | 0.753 | −0.338 | 0.030 | 0.395 | 2926,486 |
| TFPR | 0.000 | 0.604 | −0.246 | −0.029 | 0.231 | 2926,486 |

**Table 2**
Firm characteristics by macro-region and size class. All variables are expressed in logarithms. TFP and TFPR are sector-level (two-digit) residual-based measures.

| | Y | K | L | W | TFP | TFPR |
|---|---|---|---|---|---|---|
| *North* | | | | | | |
| Micro | 11.590 | 10.648 | 1.113 | 10.688 | −0.045 | −0.035 |
| Small | 13.606 | 12.906 | 2.857 | 12.916 | 0.014 | 0.040 |
| Medium | 15.492 | 15.078 | 4.481 | 14.778 | 0.012 | 0.158 |
| Large | 17.280 | 17.330 | 6.198 | 16.538 | −0.169 | 0.229 |
| *Centre* | | | | | | |
| Micro | 11.505 | 10.448 | 1.112 | 10.653 | −0.077 | −0.059 |
| Small | 13.541 | 12.685 | 2.851 | 12.884 | 0.003 | 0.034 |
| Medium | 15.403 | 14.885 | 4.464 | 14.735 | −0.015 | 0.131 |
| Large | 17.256 | 17.375 | 6.178 | 16.528 | −0.201 | 0.186 |
| *South* | | | | | | |
| Micro | 11.621 | 10.577 | 1.106 | 10.735 | 0.002 | −0.029 |
| Small | 13.638 | 12.809 | 2.862 | 12.958 | 0.058 | 0.053 |
| Medium | 15.508 | 14.925 | 4.481 | 14.804 | 0.054 | 0.173 |
| Large | 17.421 | 17.241 | 6.308 | 16.703 | −0.092 | 0.277 |

**Table 3**
Dispersion of log productivity measures. Statistics are computed on firm-level residual-based measures following the Hsieh–Klenow framework. Dispersion in log TFPR captures the extent of resource misallocation.

| | TFP | TFPR |
|---|---|---|
| Standard deviation | 0.753 | 0.604 |
| Variance | 0.567 | 0.365 |
| 75–25 gap | 0.733 | 0.477 |
| 90–10 gap | 1.590 | 1.086 |

**Table 4**
Dispersion of log TFPR by firm size class. Size classes are defined according to employment thresholds. TFPR is computed as a sector-level (two-digit) residual-based measure following the Calligaris et al. (2016) framework.

| Size class | SD | Variance | p10 | p90 | N |
|---|---|---|---|---|---|
| Micro | 0.674 | 0.454 | −0.589 | 0.635 | 1979,227 |
| Small | 0.411 | 0.169 | −0.303 | 0.483 | 793,441 |
| Medium | 0.409 | 0.168 | −0.200 | 0.607 | 131,618 |
| Large | 0.439 | 0.193 | −0.169 | 0.749 | 22,200 |
| Total | 0.604 | 0.365 | −0.499 | 0.587 | 2926,486 |

**Table 5**
Dispersion of log TFPR by macro-region. TFPR is computed as a sector-level (two-digit) residual-based measure following the Calligaris et al. (2016) framework.

| Macro-region | SD | Variance | p10 | p90 | N |
|---|---|---|---|---|---|
| North | 0.594 | 0.353 | −0.497 | 0.573 | 841,307 |
| Centre | 0.594 | 0.353 | −0.518 | 0.534 | 215,715 |
| South | 0.610 | 0.372 | −0.498 | 0.598 | 1869,289 |
| Total | 0.604 | 0.365 | −0.499 | 0.587 | 2926,311 |

**Table 6**
Provincial-level summary statistics. Variables represent province-level averages of firm-level log TFP and log TFPR.

| | Mean | SD | Min | Max | N |
|---|---|---|---|---|---|
| TFP | −0.010 | 0.216 | −0.736 | 0.990 | 107 |
| TFPR | −0.015 | 0.132 | −0.893 | 0.562 | 107 |

(TFP, panel a) and resource misallocation (panel b) across Italian provinces. A clear geographical pattern emerges: northern provinces systematically record higher TFP values, indicating greater average productivity among manufacturing firms, whereas southern provinces exhibit substantially lower productivity levels. Misallocation, shown in panel b, follows a related but not identical distribution. It is generally more pronounced in northern and central provinces, where firms appear inefficiently small despite higher productivity—suggesting that local frictions constrain the optimal reallocation of inputs. In contrast, many southern provinces combine low productivity with firms operating at inefficiently large scales, reflecting weak selection and barriers to adjustment.

Fig. 1 about here.

Overall, these maps confirm a persistent North–South divide in productivity, accompanied by differences in the degree and nature of misallocation. While the northern manufacturing system is on average more productive, it also displays pockets of allocative inefficiency; conversely, some southern provinces show relatively lower misallocation given their structural conditions. This intra-regional variation indicates that the geography of productivity and inefficiency is not uniform within macro-areas, providing a first indication that spatial dependence and local dynamics play a non-negligible role in shaping allocative outcomes. To formally assess the presence of spatial dependence, we compute global Moran's I statistics for both TFP and misallocation using a spatial weights matrix based on geographic proximity. The results indicate strong positive spatial autocorrelation in both cases, confirming that neighbouring provinces tend to exhibit similar levels of productivity and allocative efficiency, as shown in the Moran scatter plot (Fig. 2). Moreover, we present significance maps of Local Moran (Fig. 3) to identify local pockets of geographical agglomeration. For TFP, this manifests in well-defined clusters of high-productivity provinces in the North and low-productivity provinces in the South, with the remarkable case of Rome as the unique significant high-low, i.e. a province with high TFP value situated among a zone of low values (Fig. 3a). Misallocation also displays significant, though comparatively weaker, spatial clustering: provinces with higher or lower distortions are often geographically proximate, suggesting the presence of regional spillovers and shared structural constraints. The corresponding scatter plot (Fig. 2b) shows greater dispersion around the trend line, implying that beyond these spatial effects, substantial province-specific characteristics remain. Coherently, the LISA map of misallocation (Fig. 3b) shows a more fragmented figure with respect to the TFP one, whit clusters of inefficiently small firms in the North-Est and some dispersed pockets of inefficiently large firms in Centre-South and islands.

These findings confirm that both productivity and misallocation exhibit significant spatial autocorrelation, albeit with different intensities. The coexistence of strong clustering in TFP and more localized patterns in misallocation motivates the following decomposition analysis, where each variable is separated into its spatially structured and idiosyncratic components. This allows us to quantify how much of Italy's allocative inefficiency is driven by geography and interregional spillovers, and how much reflects province-specific distortions.

Applying the eigenvector-based spatial filtering procedure to province-level TFP, we decompose it into a spatial component and an idiosyncratic component, respectively representing geographical spillovers and province-specific deviations net of spatial effects. Fig. 4 illustrates the results, with panel (a) showing the spatial component and panel (b) the idiosyncratic one. The spatial component displays a pronounced North–South gradient: positive values are concentrated in northern provinces, reflecting clustered productivity advantages, while negative values dominate in the South, indicative of spatially correlated inefficiencies. The idiosyncratic component, instead, is more dispersed and heterogeneous, mixing positive and negative deviations across regions. Notable positive outliers emerge in some northwest- ern provinces, while scattered negative deviations appear elsewhere, suggesting that local factors—such as firm composition or regional dynamics—introduce variability without a dominant geographic pattern.

The spatial component is clearly dominant in magnitude and, in some cases, closely aligned with the overall TFP variation, consistent

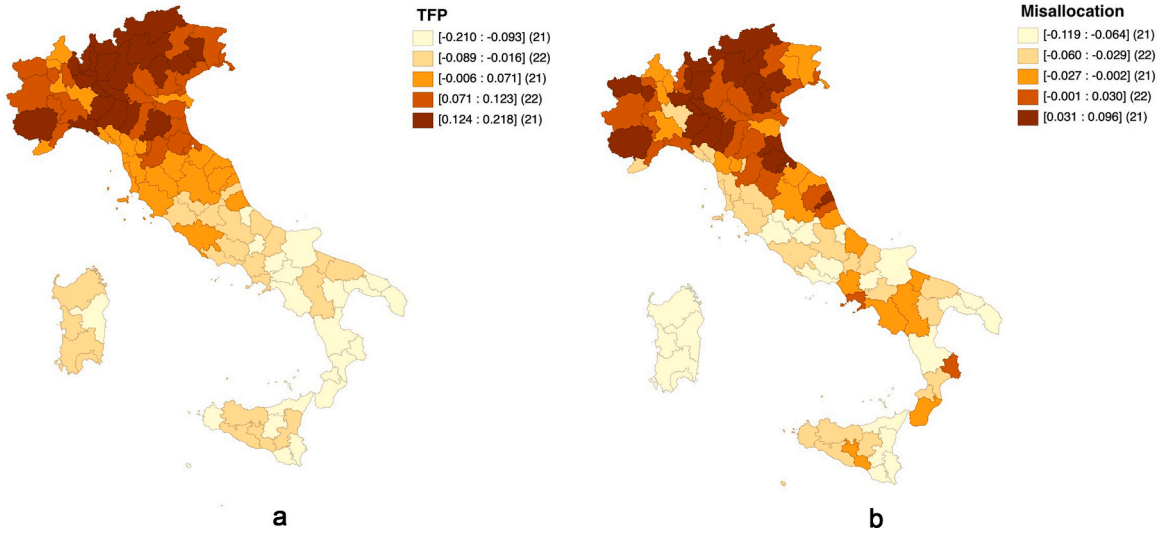



**Fig. 1.** Spatial distribution of total factor productivity (TFP) and resource misallocation across Italian provinces. In panel (a) Total Factor Productivity (TFP) quintile map, in panel (b) Resource Misallocation quintile map.

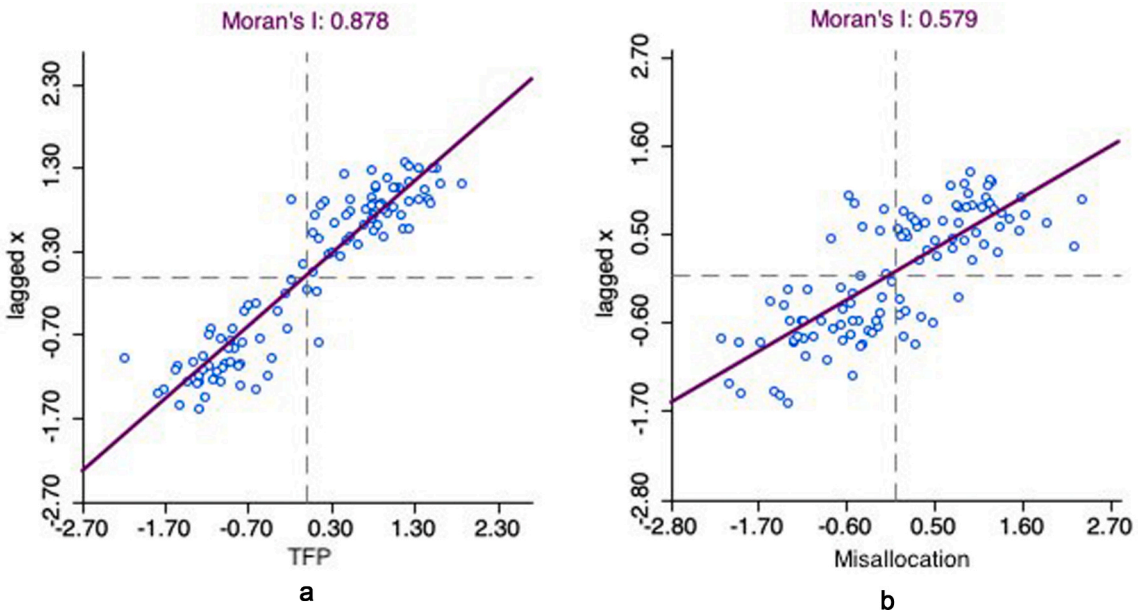



**Fig. 2.** Moran scatter plots. In panel (a) Moran scatter plot for TFP, in panel (b) Moran scatter plot for Misallocation.

with the high Moran's I value (0.878), implying that geography accounts for the bulk of productivity disparities. This component preserves the core North–South cleavage but smooths local fluctuations, isolating the geographically interdependent factors that drive clustering. The idiosyncratic component, while smaller, captures local deviations from this trend—provinces whose productivity exceeds or falls short of neighborhood expectations—highlighting the interplay between broader spatial dynamics and localized distortions in shaping productivity outcomes. Summary statistics about the distribution of the spatial components are available in Table 7, while the complete shares of spatial components in TFP and misallocation by Province are collected in Appendix A, together with the temporal evolution of these shares between 2015 and 2024, which highlights how aggregating over time TFP and misallocation measures does not cause misleading results.

The application of the same decomposition to misallocation yields comparable insights. Fig. 5 reports the spatial and idiosyncratic components for misallocation. The spatial component again exhibits a clear North–South pattern, with positive values concentrated in northern provinces—reflecting geographically clustered inefficiencies where productive firms remain inefficiently small—and negative values prevailing in the South, where low- productivity firms operate at inefficiently large scales. The idiosyncratic component, by contrast, is more scattered, showing alternating positive and negative deviations across regions. Some provinces adjacent to high-productivity clusters, such as Milan or Bologna, register negative idiosyncratic values—interpretable as areas where firms are inefficiently large relative to their neighbors, possibly due to spillover advantages that allow less efficient firms to persist. Conversely, certain central and southern provinces display positive idiosyncratic values, indicating inefficiently small firms despite surrounding inefficiencies, potentially reflecting isolation from industrial hubs or limited access to production networks.

The spatial component of misallocation is higher in magnitude, respecting the specific one, consistent with its moderate Moran's I (0.579). It confirms that geography accounts for a substantial portion of

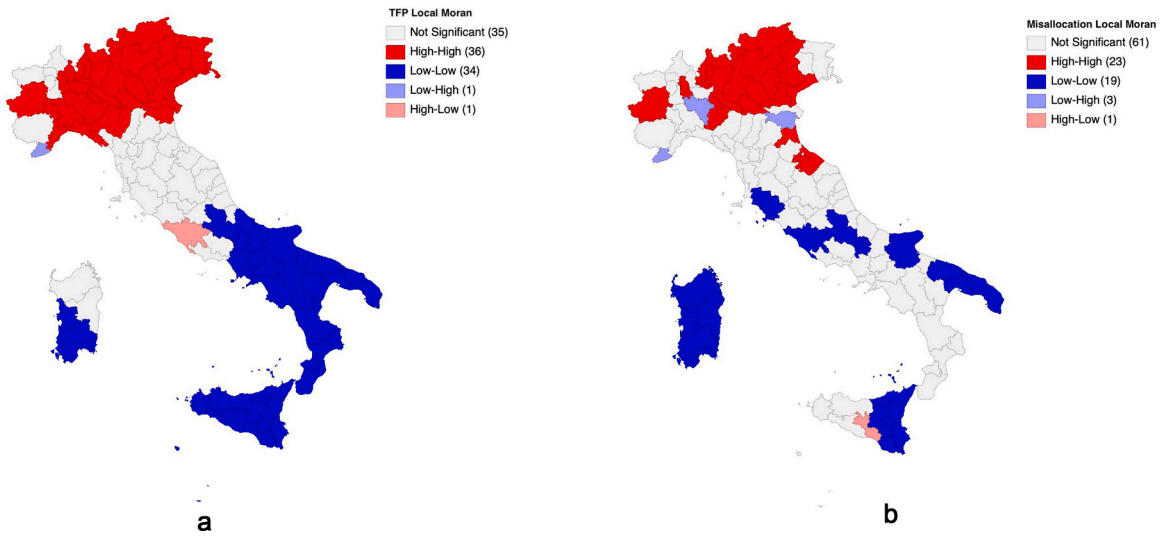



**Fig. 3.** Significance maps of Local Moran Index. I panel (a) Total Factor Productivity Local Moran index, in panel (b) Resource Misallocation Local Moran index.

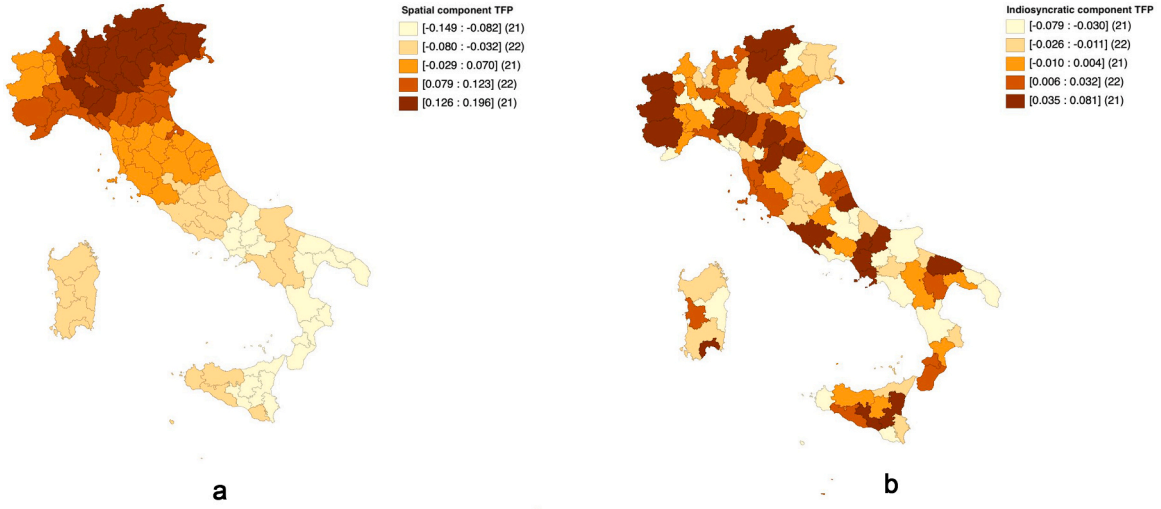



**Fig. 4.** Spatial decomposition of provincial TFP. Panel (a) shows the spatially structured component. Panel (b) depicts the idiosyncratic component.

**Table 7**
Spatial components distribution in proportion of the total.

| | Min | 1st. quart. | Median | Mean | 3rd. quart | Max |
|---|---|---|---|---|---|---|
| TFP | 0.078 | 0.638 | 0.781 | 0.747 | 0.880 | 0.995 |
| Misallocation | 0.050 | 0.396 | 0.676 | 0.610 | 0.789 | 0.996 |

allocative disparities, though less than for productivity. Its structure reinforces the persistent regional divide, with high-misallocation clusters in northern industrial hubs such as Lombardy, Emilia-Romagna, and Veneto, and low-misallocation concentrations in southern regions including Sicily and Calabria. The idiosyncratic component instead highlights intra-regional anomalies, unexpectedly high local misallocation in select central provinces or relative efficiency in isolated northern ones, revealing where local conditions diverge from broader spatial patterns.

Taken together, these decompositions show that the geography of productivity and inefficiency in Italy reflects both spatially correlated mechanisms and local idiosyncrasies. The spatial components, on average, account for large part of overall variation, reproducing the North–South divide, while the idiosyncratic parts capture localized deviations that introduce heterogeneity within each macro-area.

Following previous attempts in literature (Cainelli et al., 2015; Calligaris et al., 2018) we quantify the aggregate efficiency losses implied by the observed dispersion in revenue productivity and find that eliminating distortions would increase output by approximately 21% under the baseline specification $\sigma = 3$, and up to 34% when assuming a higher elasticity of substitution $\sigma = 5$. These magnitudes are economically large and broadly consistent with estimates for developed economies in the existing literature, although somewhat smaller than the upper bounds reported for highly distorted environments. Importantly, the increase in gains with $\sigma$ reflects the standard amplification mechanism of higher substitutability across firms that implies larger efficiency losses from misallocation (intuitively, when firms are closer substitutes, inputs can be more easily reallocated toward more productive producers, so that any misallocation becomes more costly in terms of forgone output). The results are therefore both quantitatively relevant and theoretically consistent (Table 8). This counterfactual corresponds to the standard Hsieh and Klenow (2009) exercise, in which all distortions are removed, and inputs are reallocated efficiently across firms within sectors.

Moving a step forward, our analysis can decompose these gains into spatial and idiosyncratic components. At the aggregate level, the spatial

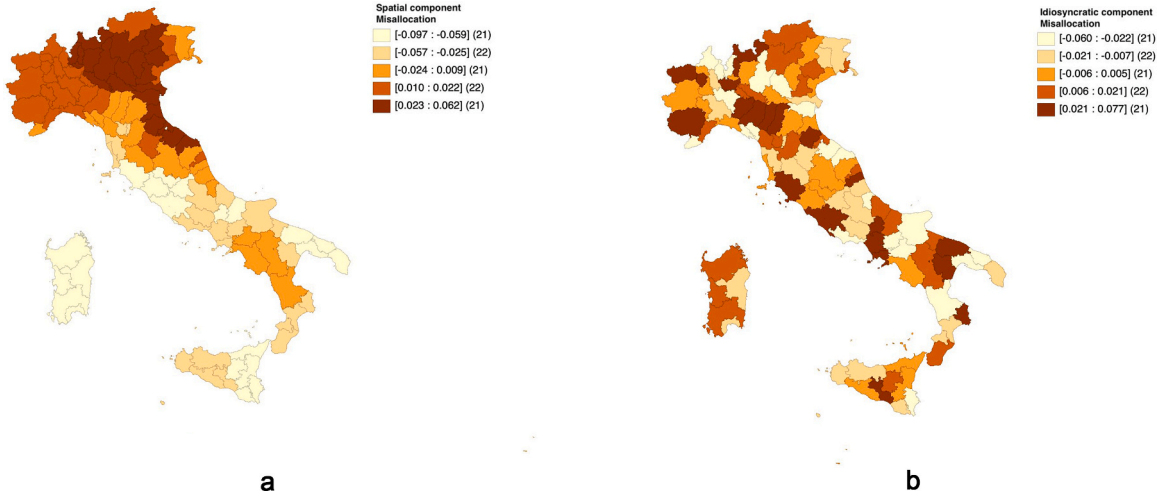



**Fig. 5.** Spatial decomposition of provincial misallocation. Panel (a) shows the spatially structured component. Panel (b) depicts the idiosyncratic component.

**Table 8**
Average gains from reallocation under alternative values of the elasticity of substitution.

| | $\sigma = 3$ | $\sigma = 5$ |
|---|---|---|
| Aggregate | | |
| Total gains (%) | 20.72 | 34.36 |
| Spatial share | 0.66 | 0.66 |
| Spatial component | 13.64 | 22.62 |
| Idiosyncratic component | 7.08 | 11.73 |
| Centre | | |
| Total gains (%) | 23.17 | 39.22 |
| Spatial share | 0.53 | 0.53 |
| Spatial component | 12.18 | 20.62 |
| Idiosyncratic component | 10.99 | 18.60 |
| North | | |
| Total gains (%) | 18.20 | 33.07 |
| Spatial share | 0.62 | 0.62 |
| Spatial component | 11.29 | 20.52 |
| Idiosyncratic component | 6.91 | 12.55 |
| South | | |
| Total gains (%) | 18.13 | 32.50 |
| Spatial share | 0.61 | 0.61 |
| Spatial component | 11.02 | 19.77 |
| Idiosyncratic component | 7.10 | 12.74 |

component accounts for roughly two-thirds of total gains, indicating that a substantial fraction of allocative inefficiency is not purely firm-specific but instead reflects geographically correlated distortions. The geographic dimension of these results reveals substantial heterogeneity. While gains from reallocation are present across all macro-areas, they are largest in Central regions, where potential output increases exceed 23% under the baseline specification. At the same time, the composition of misallocation differs markedly across space. In Central regions, a relatively larger share of inefficiency is idiosyncratic, suggesting that firm-level distortions play a more prominent role. This pattern is consistent with production systems characterized by a high density of small and medium-sized firms, where heterogeneity in managerial practices, access to finance, and firm-level constraints may generate dispersion in revenue productivity. In contrast, in both Northern and Southern regions, the spatial component accounts for a larger fraction of total gains, indicating that distortions tend to be correlated across firms within the same local environment.

While aggregate results are stable across alternative levels of sectoral aggregation, disaggregating at the industry level (two-digit) uncovers some differences in the underlying sources of inefficiency across sectors (all results are tabled in Appendix B). Importantly, a high spatial share reflects the fact that firms operating in that sector are disproportionately located in provinces where distortions are largely common across firms within the same local environment (e.g., metal products industry, paper manufacture, textile industry, and so on). In these cases, the majority, misallocation arises primarily from constraints that affect all firms in a given location in a similar way, such as local credit conditions, the structure of local labor markets (LLM), infrastructure quality, or access to intermediate inputs. As a result, differences in productivity across firms within the same province are relatively limited, while variation across provinces becomes the dominant source of inefficiency.

Conversely, industries characterized by a low spatial share exhibit a pattern in which misallocation is primarily driven by idiosyncratic, firm-level distortions (e.g., leather manufacture and wood and cork manufacture). In these sectors, firms operating within the same province face markedly different conditions, reflecting heterogeneity in managerial practices, access to finance, organizational capabilities, or firm-specific constraints. In such environments, the allocation of resources is less tied to geographic location and more influenced by within-province dispersion in firm characteristics.

### 4.3. Discussion

Our findings suggest that local economic environments play a central role in shaping the allocation of resources. Spatial distortions may arise from a variety of mechanisms, including local credit constraints, differences in financial development across provinces, labor market frictions, and the structure of local labor markets (LLM), which can limit the mobility of workers and constrain firms' ability to adjust input use. In addition, imperfect infrastructure, limited access to intermediate inputs, and barriers to knowledge diffusion may generate correlated wedges across nearby firms, leading to systematic misallocation at the local level. Looking at TFP gains, in the North, this pattern is consistent with highly integrated production systems, where firms operating within the same local networks are exposed to common input prices, financial conditions, and labor market constraints, leading to similar distortions in factor allocation. In the South, the larger spatial component instead reflects more pervasive structural frictions—such as limited access to credit, weaker infrastructure, and thinner markets—which affect firms within the same area in a systematic and uniform way.

These results motivate an interesting visual analysis, which jointly interprets the spatial and idiosyncratic components through a bubble-graph framework of "winners" and "losers," quantifying the relative importance of geography and local distortions in shaping provincial performance.

The bubble graph (Fig. 6) summarizes the joint distribution of the spatial and idiosyncratic components, offering a synthetic view of how

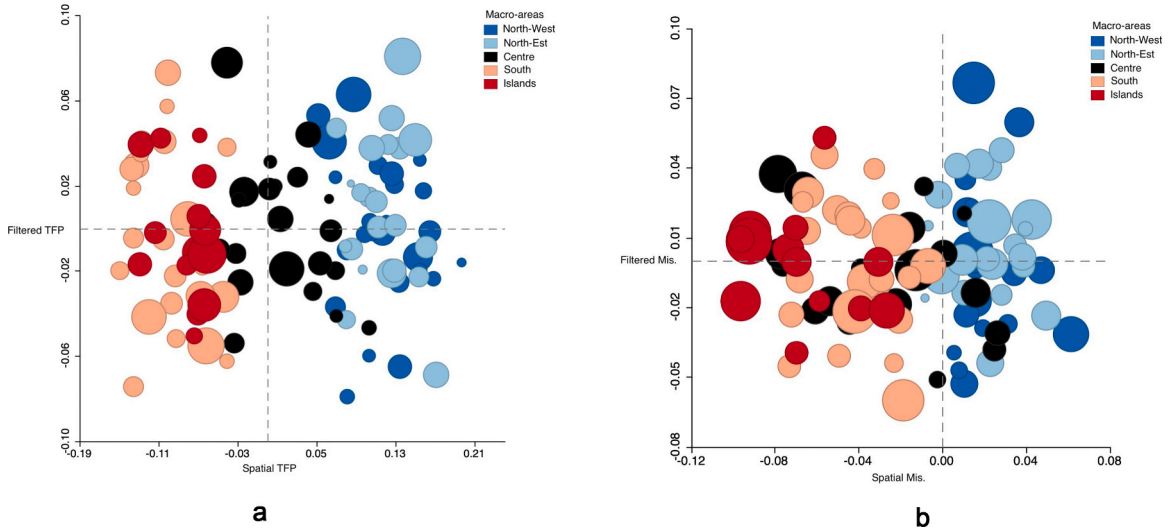



**Fig. 6.** Bubble plots comparing the spatial and idiosyncratic components of TFP and misallocation across Italian provinces. The quadrants identify "winners" and "losers" in terms of geography-adjusted performance, highlighting the joint role of spatial spillovers and local distortions in shaping provincial outcomes. In panel (a) Bubble plot TFP, in panel (b) Bubble plot Misallocation.

provinces benefit from or are penalized by their geographic context. Panel (a) plots provinces according to the spatial and idiosyncratic components of TFP. The upper-right quadrant includes provinces that are both intrinsically productive and embedded in high-productivity environments, those correctly positioned in both geographic and economic terms. The lower-right quadrant groups provinces that, despite low idiosyncratic productivity, benefit from favorable surroundings characterized by strong spatial spillovers ("winners"). Conversely, the upper-left quadrant identifies "losers": provinces that exhibit high intrinsic productivity but are in disadvantaged areas surrounded by low-productivity neighbors. Finally, the lower-left quadrant includes provinces with both low idiosyncratic productivity and negative spatial spillovers, representing the weakest local manufacturing systems.

Panel (b) applies the same framework to misallocation, combining its spatial and idiosyncratic components. The interpretation is less immediate, as higher misallocation values denote provinces where firms are, on average, inefficiently small, whereas lower values indicate provinces where firms are inefficiently large. Economic efficiency corresponds to the origin (0,0), where both components are minimal. The upper-right quadrant therefore represents provinces with inefficiently small firms located in regions dominated by similar inefficiencies, while the lower-left quadrant corresponds to areas where firms are inefficiently large in equally distorted environments. The lower-right quadrant includes provinces where firms are inefficiently large at the local level but embedded in regions of inefficiently small firms, and the upper-left quadrant captures the opposite case—provinces with inefficiently small firms surrounded by inefficiently large ones. This two-dimensional representation highlights how geography and local firm dynamics jointly shape allocative outcomes, illustrating that spatial context can either amplify or mitigate local inefficiencies.

From one side, some possible causes for these patterns of spatial misallocation can be identified in the higher housing prices in the zones characterized by higher productivity. In fact, Hsieh and Moretti (2019) find that misallocation could arise due to the constraints on housing supply in the most productive cities, while Bryan and Morten (2019) highlight that misallocation of labor is influenced by barriers to mobility. This occurrence drives to a limitation of workers which causes an increase of spatial misallocation of labor, observed in our analysis as the presence of spatial patterns of inefficiently small firms in the zones characterized by hot spots of high productivity.

Fig. 6 about here.

From another point of view, spatial misallocation derived by geographical externalities could be caused by distortions due to government intervention about taxation or welfare policies (Fajgelbaum et al., 2019). For instance, capital market distortions and disparities in labor productivity are found in relation with government policies devoted to reducing regional income disparities (Brandt et al., 2013). The regions targeted by subsidies are, usually, the ones with low productivity firms, which consequently became inefficiently large (Bachtrögler et al., 2020). The main example of these policies is the Structural and Cohesion Funds of EU, aimed at promoting employment and boosting regional productivity. However, Cohesion Funds reduce socio-economic disparities, but there is no evidence of their positive impact on firms' growth (Fratesi and Wishlade, 2017) and neither on their TFP (Albanese et al., 2021). Instead of generic and supra-national interventions, the dominance of spatial distortions in several regions suggests that place-based policies can play a crucial role in improving allocative efficiency (Okubo, 2012). Interventions aimed at relaxing local constraints, such as improving infrastructure, enhancing access to credit, and facilitating labor mobility, are therefore likely to generate the largest efficiency gains, as they directly target the dominant spatial component of misallocation. While firm-level distortions remain quantitatively relevant, particularly in Central regions, their contribution is smaller in magnitude, implying that policies targeting idiosyncratic frictions are likely to yield more limited aggregate effects compared to place-based interventions.

Also the within sector distinction carries direct implications for policy design. In industries where the spatial component dominates, place-based interventions are likely to be most effective, as they target the common constraints affecting firms within a given location. Policies aimed at improving local infrastructure, easing credit conditions at the regional level, or enhancing labor mobility can generate broad-based efficiency gains by reducing geographically correlated distortions (Chakravorty, 2000; Agrawal et al., 2022). In contrast, in industries where idiosyncratic distortions prevail, policies should instead focus on firm-level interventions, such as improving access to finance for individual firms, promoting managerial upgrading, or facilitating entry and exit (Baldwin and Okubo, 2006).

## 5. Conclusions

The decomposition of productivity and misallocation into spatial and idiosyncratic components reveals a nuanced geography of disparities within Italian manufacturing, carrying direct implications for regional

and industrial policy. While the existing literature typically models distortions as firm-specific, our findings show that a large share of allocative inefficiency is geographically structured. This has direct implications for policy: if misallocation is predominantly idiosyncratic, interventions should target firm-level frictions, such as credit constraints or managerial inefficiencies; if instead it is spatially driven, as our evidence suggests, place-based policies addressing local environments, infrastructure, housing constraints, and regional institutions become central to improving allocative efficiency.

This study advances the literature on resource misallocation by being the first to apply eigenvector spatial filtering to province-level measures of productivity and misallocation. More broadly, the paper contributes by introducing a tractable empirical framework to disentangle spatially correlated distortions from firm-specific ones, thereby providing a clearer mapping between observed misallocation and its underlying economic mechanisms. Using province-level data for Italian manufacturing sector, we document three main results.

First, both total factor productivity and misallocation exhibit strong and statistically significant spatial autocorrelation. Productivity displays highly persistent geographic clustering, with a pronounced North–South gradient, while misallocation also shows spatial dependence, albeit with more localized and fragmented patterns. This establishes that allocative inefficiencies are not randomly distributed across space but are systematically correlated across neighboring provinces. From an economic perspective, this implies that firms operating in the same local environment are exposed to common constraints—such as local labor market frictions, credit conditions, infrastructure quality, and institutional settings—that jointly affect their scale and input allocation. As a result, inefficiencies emerge not only from firm-specific distortions but from shared local conditions that limit efficient reallocation.

Second, decomposing both productivity and misallocation into spatial and idiosyncratic components reveals that the spatial component accounts for the bulk of the observed variation, particularly for productivity. For misallocation, the spatial component remains quantitatively important, explaining a large share of allocative disparities across provinces. This finding implies that a significant portion of observed misallocation reflects geographically correlated distortions—common local environments, spillovers, and regional constraints—rather than purely firm-specific wedges. Economically, this suggests that firms do not adjust freely to their optimal scale because local conditions—such as limited labor mobility, segmented credit markets, or weak production networks—systematically distort factor allocation within regions.

Third, the joint distribution of spatial and idiosyncratic components highlights substantial heterogeneity in how provinces interact with their geographic environment. Some provinces benefit from positive spatial spillovers despite weak intrinsic performance, while others exhibit strong local fundamentals but are penalized by adverse surroundings. For misallocation, spatial context can either amplify or mitigate local inefficiencies, generating systematic patterns such as clusters of inefficiently small firms in high-productivity areas and inefficiently large firms in low-productivity regions. From an economic standpoint, this indicates that spillovers and local interactions affect not only productivity levels but also the direction of misallocation: in high-productivity areas, congestion forces or mobility constraints may prevent firms from expanding, while in low-productivity regions, weak selection mechanisms allow less efficient firms to survive at inefficiently large scales.

Some limitations should be acknowledged and motivate future research. A promising extension would integrate firm-level data on EU Horizon or national innovation programs to examine how targeted R&D subsidies affect micro-level distortions, potentially uncovering heterogeneous local responses that aggregate data conceal. Methodologically, future work could refine the analysis by adopting the variance decomposition in our framework, to consider additional sectors beyond the manufacturing one, for a clearer separation of within- and between-sector inefficiencies and their spatial propagation. Furthermore, future research will improve the aggregation phase by weighing firm level productivity and misallocation for their relevance in the areas. Taken together, our findings suggest that spatial misallocation is a key dimension of Italy's productivity gap—one that requires policies simultaneously attentive to location and firm heterogeneity. Continued efforts to integrate spatial econometrics with firm-level microdata will be essential to identify the mechanisms through which geography shapes allocative efficiency and to design interventions that promote convergence through, rather than against, market selection.

## CRediT authorship contribution statement

**D'Isidoro Andrea:** Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Matteo Rapagna:** Writing – original draft, Software, Methodology, Formal analysis, Conceptualization.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## APPENDIX A. Additional details about the shares of spatial components

**Table A.1**
Shares of Spatial Components in TFP and Misallocation by Province

| Province | Spatial Mis. | Spatial TFP | Province | Spatial Mis. | Spatial TFP | Province | Spatial Mis. | Spatial TFP |
|---|---|---|---|---|---|---|---|---|
| Agrigento | 0.99 | 0.92 | Firenze | 0.34 | 0.90 | Parma | 0.56 | 0.99 |
| Alessandria | 0.48 | 0.98 | Foggia | 0.52 | 0.48 | Pavia | 0.29 | 0.71 |
| Ancona | 0.39 | 0.61 | Forlì-Cesena | 0.66 | 0.53 | Perugia | 0.16 | 0.67 |
| Arezzo | 0.35 | 0.49 | Frosinone | 0.37 | 0.60 | Pesaro e Urbino | 0.78 | 0.51 |
| Ascoli Piceno | 0.54 | 0.76 | Genova | 0.76 | 0.97 | Pescara | 0.46 | 0.98 |
| Asti | 0.22 | 0.68 | Gorizia | 0.73 | 0.79 | Piacenza | 0.35 | 0.39 |
| Avellino | 0.85 | 0.97 | Grosseto | 0.32 | 0.83 | Pisa | 0.35 | 0.78 |
| Bari | 0.45 | 0.81 | Imperia | 0.69 | 0.57 | Pistoia | 0.77 | 0.56 |
| Barletta-Andria-Trani | 0.68 | 0.58 | Isernia | 0.14 | 0.51 | Pordenone | 0.78 | 0.63 |
| Belluno | 0.73 | 0.79 | L'Aquila | 0.72 | 0.78 | Potenza | 0.43 | 0.87 |
| Benevento | 0.95 | 0.71 | La Spezia | 0.81 | 0.58 | Prato | 0.68 | 0.95 |
| Bergamo | 0.55 | 0.65 | Latina | 0.11 | 0.63 | Ragusa | 0.75 | 0.82 |
| Biella | 0.92 | 0.99 | Lecce | 0.63 | 0.38 | Ravenna | 0.78 | 0.59 |
| Bologna | 0.36 | 0.74 | Lecco | 0.90 | 0.73 | Reggio di Calabria | 0.95 | 0.85 |

(*continued on next page*)

**Table A.1** (*continued*)

| Province | Spatial Mis. | Spatial TFP | Province | Spatial Mis. | Spatial TFP | Province | Spatial Mis. | Spatial TFP |
|---|---|---|---|---|---|---|---|---|
| Bolzano | 0.92 | 0.74 | Livorno | 0.56 | 0.83 | Reggio nell'Emilia | 0.72 | 0.83 |
| Brescia | 0.56 | 0.63 | Lodi | 0.93 | 0.28 | Rieti | 0.14 | 0.76 |
| Brindisi | 0.66 | 0.92 | Lucca | 0.34 | 0.97 | Rimini | 0.74 | 0.83 |
| Cagliari | 0.62 | 0.64 | Macerata | 0.69 | 0.78 | Roma | 0.74 | 0.90 |
| Caltanissetta | 0.85 | 0.61 | Mantova | 0.12 | 0.10 | Rovigo | 0.68 | 0.35 |
| Campobasso | 0.52 | 0.72 | Massa Carrara | 0.87 | 0.84 | Salerno | 0.66 | 0.65 |
| Caserta | 0.83 | 0.72 | Matera | 0.05 | 0.69 | Sassari | 0.77 | 0.68 |
| Catania | 0.55 | 0.76 | Messina | 0.70 | 0.82 | Savona | 0.91 | 0.83 |
| Catanzaro | 0.94 | 0.76 | Milano | 0.99 | 0.89 | Siena | 0.66 | 0.97 |
| Chieti | 0.79 | 0.97 | Modena | 0.24 | 0.90 | Siracusa | 0.55 | 0.74 |
| Como | 0.69 | 0.85 | Monza e della Brianza | 0.07 | 0.90 | Sondrio | 0.64 | 0.82 |
| Cosenza | 0.53 | 0.88 | Napoli | 0.85 | 0.92 | Sud Sardegna | 0.38 | 0.83 |
| Cremona | 0.24 | 0.74 | Novara | 0.49 | 0.64 | Taranto | 0.88 | 0.86 |
| Crotone | 0.85 | 0.86 | Nuoro | 0.35 | 0.98 | Teramo | 0.76 | 0.96 |
| Cuneo | 0.45 | 0.88 | Oristano | 0.85 | 0.64 | Terni | 0.70 | 0.52 |
| Enna | 0.16 | 0.58 | Padova | 0.91 | 0.72 | Torino | 0.98 | 0.73 |
| Fermo | 0.83 | 0.98 | Palermo | 0.84 | 0.87 | Trapani | 0.79 | 0.60 |

.

The results about spatial shares of TFP and misallocation by provinces are an aggregation (mean) over the time period considered. Here follows Figures A1 and A2 in which are averaged the provinces' shares of spatial components for each year, together with the confidence interval bounds at 99% around the mean of aggregated values.

The variability around the mean of TFP spatial shares is higher with respect to that of misallocation. While for misallocation data it is detected one year value below the confidence interval (2019), for TFP spatial shares all years' values are included between the boundaries. However, in Figure A1 (TFP spatial shares) we can observe that probably the Covid−19 shock caused an inversion of trend in the evolution of spatial component of TFP, since from 2015 to 2019 this quantity seems to growth, and from 2020 to the end it decreases, while always remaining within the confidence interval around the aggregate value.

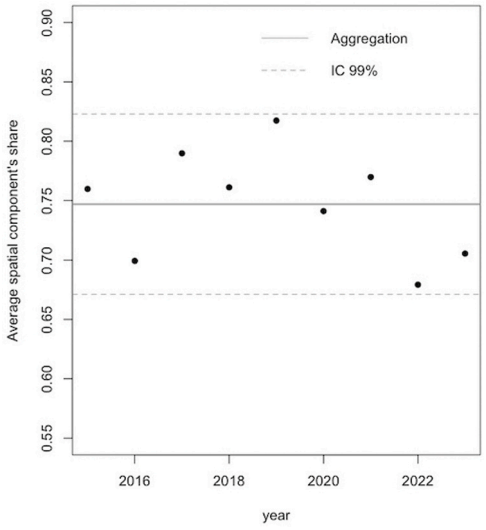



**Figure A1.** Average proportion of TFP spatial components' share per year

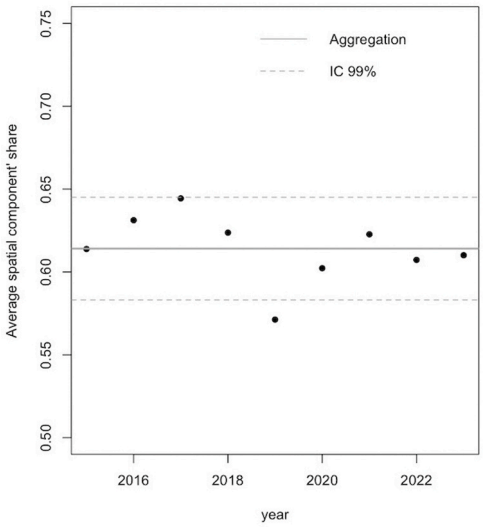



**Figure A2.** Average proportion of misallocation spatial components' share per year

## APPENDIX B. Gains from reallocation by two-digit industries

Gains from reallocation are computed following Hsieh and Klenow (2009) as the percentage increase in output under efficient allocation. Spatial share measures the fraction of misallocation attributable to geographically correlated distortions. Industries are defined at the two-digit level.

While aggregate measures of misallocation are largely invariant to the level of sectoral aggregation, the decomposition into spatial and idiosyncratic components reveals that the economic mechanisms underlying inefficiency differ across industries. These findings highlight that misallocation is shaped by the interaction between industry structure and geographic environment, rather than being solely determined by either dimension in isolation.

**Table B.1**
Average gains from reallocation under alternative values of the elasticity of substitution. Gains are expressed as percentage increases in output relative to the two-digit sector. The spatial share is computed as the ratio of the spatial component to total gains

| Industry (two-digit) | $\sigma = 3$ Gain (%) | $\sigma = 3$ Spatial Share | $\sigma = 5$ Gain (%) | $\sigma = 5$ Spatial Share |
|---|---|---|---|---|
| Food ind. (10) | 15.81 | 0.765 | 30.08 | 0.986 |
| Beverage ind. (11) | 16.96 | 0.460 | 32.16 | 0.526 |
| Textile ind. (13) | 14.96 | 0.703 | 29.78 | 0.339 |
| Wearing manufacture (14) | 17.59 | 0.759 | 32.78 | 0.230 |
| Leather manufacture (15) | 19.00 | 0.044 | 49.44 | 0.252 |
| Wood and cork manufacture (16) | 15.93 | 0.220 | 34.65 | 0.193 |
| Paper manufacture (17) | 17.57 | 0.871 | 30.51 | 0.282 |
| Printing and recording (18) | 14.95 | 0.562 | 33.50 | 0.979 |
| Chemical manufacture (20) | 15.72 | 0.591 | 30.37 | 0.986 |
| Rubber and plastic ind. (22) | 17.38 | 0.839 | 29.38 | 0.843 |
| Other non-metallic ind. (23) | 14.83 | 0.693 | 30.05 | 0.643 |
| Metallurgy (24) | 17.53 | 0.424 | 28.03 | 0.537 |
| Metal products ind. (25) | 16.63 | 0.980 | 33.82 | 0.914 |
| Manufacture of computers (26) | 16.80 | 0.469 | 37.07 | 0.888 |
| Electrical and non ind. (27) | 17.79 | 0.933 | 29.67 | 0.589 |
| Machinery and equipment (28) | 16.40 | 0.762 | 33.04 | 0.987 |
| Motor vehicles (29) | 15.71 | 0.470 | 34.06 | 0.389 |
| Other transport equipment (30) | 18.84 | 0.686 | 29.64 | 0.722 |
| Manufacture of furniture (31) | 16.51 | 0.606 | 34.12 | 0.683 |
| Other manufacturing (32) | 16.79 | 0.674 | 30.66 | 0.045 |
| Repair and installation (33) | 18.99 | 0.943 | 31.69 | 0.883 |

## References

Adamopoulos, T., Brandt, L., Leight, J., Restuccia, D., 2022. Misallocation, selection, and productivity: a quantitative analysis with panel data from China. Econometrica 90 (3), 1261–1282. https://doi.org/10.3982/ECTA16598.

Agrawal, D.R., Hoyt, W.H., Wilson, J.D., 2022. Local policy choice: theory and empirics. J. Econ. Lit. 60 (4), 1378–1455. https://doi.org/10.1257/jel.20201490.

Aiello, F., Cardamone, P., 2012. Regional economic divide and the role of technological spillovers in Italy: evidence from microdata. Struct. Change Econ. Dyn. 23 (3), 205–220. https://doi.org/10.1016/j.strueco.2012.03.001.

Albanese, G., de Blasio, G., Locatelli, A., 2021. Does EU regional policy promote local TFP growth? Evidence from the Italian Mezzogiorno. Pap. Reg. Sci. 100 (2), 327–349. https://doi.org/10.1111/pirs.12574.

Anselin, L., 1995. Local indicators of spatial association—LISA. Geogr. Anal. 27 (2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x.

Anselin, L., Arribas-Bel, D., 2013. Spatial fixed effects and spatial dependence in a single cross-section. Pap. Reg. Sci. 92 (1), 3–18.

Asker, J., Collard-Wexler, A., De Loecker, J., 2014. Dynamic inputs and resource (mis) allocation. J. Political Econ. 122 (5), 1013–1063. https://doi.org/10.1086/677072.

Bachtrögler, J., Fratesi, U., Perucca, G., 2020. The influence of the local context on the implementation and impact of EU Cohesion Policy. Reg. Stud. 54 (1), 21–34. https://doi.org/10.1080/00343404.2018.1551615.
Bai, Y., 2026. Agglomeration and sector composition across cities: evidence from China. Pap. Reg. Sci., 100145 https://doi.org/10.1016/j.pirs.2026.100145.
Baldwin, R.E., Okubo, T., 2006. Heterogeneous firms, agglomeration and economic geography: spatial selection and sorting. J. Econ. Geogr. 6 (3), 323–346. https://doi.org/10.1093/jeg/lbi020.
Banerjee, A.V., Duflo, E., 2005. Growth theory through the lens of development economics. In: Handbook of Economic Growth, 1. Elsevier, pp. 473–552. https://doi.org/10.1016/S1574-0684(05)01007-5.
Bartelsman, E., Haltiwanger, J., Scarpetta, S., 2013. Cross-country differences in productivity: the role of allocation and selection. In: American Economic Review, 103, pp. 305–334. https://doi.org/10.1257/aer.103.1.305.
Bhattacharjee, A., Maietta, O.W., Mazzotta, F., 2023. Spatial agglomeration, innovation and firm survival for Italian manufacturing firms. Spat. Econ. Anal. 18 (3), 318–345. https://doi.org/10.1080/17421772.2023.2176538.
Bils, M., Klenow, P.J., Ruane, C., 2021. Misallocation or mismeasurement? J. Monet. Econ. 124, S39–S56. https://doi.org/10.1016/j.jmoneco.2021.09.004.
Blien, U., Suedekum, J., Wolf, K., 2006. Local employment growth in West Germany: a dynamic panel approach. Labour Econ. 13 (4), 445–458. https://doi.org/10.1016/j.labeco.2006.02.004.
Bocci, C., Smith, P.A., 2026. Small area estimation for business surveys: a comparison of transformation-based unit level models. qlag016 J. R. Stat. Soc. Ser. C Appl. Stat.. https://doi.org/10.1093/jrsssc/qlag016.
Brandt, L., Tombe, T., Zhu, X., 2013. Factor market distortions across time, space and sectors in China. Rev. Econ. Dyn. 16 (1), 39–58. https://doi.org/10.1016/j.red.2012.10.002.
Bryan, G., Morten, M., 2019. The aggregate productivity effects of internal migration: evidence from Indonesia. J. Political Econ. 127 (5), 2229–2268. https://doi.org/10.1086/701810.
Cainelli, G., Fracasso, A., Vittucci Marzetti, G., 2015. Spatial agglomeration and productivity in Italy: a panel smooth transition regression approach. Pap. Reg. Sci. 94, S39–S67. https://doi.org/10.1111/pirs.12103.
Calligaris, S., 2015. Misallocation and total factor productivity in Italy: Evidence from firm-level data. Labour 29 (4), 367–393. https://doi.org/10.1111/labr.12067.
Calligaris, S., Del Gatto, M., Hassan, F., Ottaviano, G., Schivardi, F., 2016. Italy's productivity conundrum: a study on resource misallocation in Italy. Publications Office of the European Union. https://hdl.handle.net/11564/683670.
Calligaris, S., Del Gatto, M., Hassan, F., Ottaviano, G.I.P., Schivardi, F., 2018. The productivity puzzle and misallocation: an Italian perspective. Econ. Policy 33 (96), 635–684. https://doi.org/10.1093/epolic/eiy014.
Camagni, R., Capello, R., Perucca, G., 2022. Beyond productivity slowdown: quality, pricing and resource reallocation in regional competitiveness. Pap. Reg. Sci. 101 (6), 1307–1331. https://doi.org/10.1111/pirs.12696.
Capello, R., 2009. Spatial spillovers and regional growth: a cognitive approach. Eur. Plan. Stud. 17 (5), 639–658. https://doi.org/10.1080/09654310902778045.
Caragliu, A., Landoni, P., 2024. Firm cooperation policies: the impact of territorial spillovers. Ann. Reg. Sci. 73 (1), 363–396. https://doi.org/10.1007/s00168-024-01273-2.
Card, D., Devicienti, F., Maida, A., 2014. Rent-sharing, holdup, and wages: evidence from matched panel data. Rev. Econ. Stud. 81 (1), 84–111. https://doi.org/10.1093/restud/rdt030.
Chakravorty, S., 2000. How does structural reform affect regional development? Resolving contradictory theory with evidence from India. Econ. Geogr. 76 (4), 367–394. https://doi.org/10.1111/j.1944-8287.2000.tb00149.x.
Cui, Y., 2025. Special economic zones and land misallocation: evidence from Chinese cities. Pap. Reg. Sci. 104 (2), 100084. https://doi.org/10.1016/j.pirs.2025.100084.
De Dominicis, L., Arbia, G., De Groot, H.L.F., 2013. Concentration of manufacturing and service sector activities in Italy: accounting for spatial dependence and firm size distribution. Reg. Stud. 47 (3), 405–418. https://doi.org/10.1080/00343404.2011.579593.
De Loecker, J., Goldberg, P.K., 2014. Firm performance in a global market. Annu. Rev. Econ. 6 (1), 201–227. https://doi.org/10.1146/annurev-economics-080113-104741.
Desmet, K., Rossi-Hansberg, E., 2013. Urban accounting and welfare. Am. Econ. Rev. 103 (6), 2296–2327. https://doi.org/10.1257/aer.103.6.2296.
Dias, D.A., Marques, C.R., Richmond, C., 2016. Misallocation and productivity in the lead up to the eurozone crisis. J. Macroecon. 49, 46–70. https://doi.org/10.1016/j.jmacro.2016.04.009.
Duguet, E., L'horty, Y., Sari, F., 2023. Agglomeration effects and unemployment to work: evidence from French data. Pap. Reg. Sci. 102 (1), 129–167. https://doi.org/10.1111/pirs.12718.
Emili, S., Galli, F., 2025. Capturing inter and intra sectoral productivity spillovers in industrial filière: a system of dynamic spatial panel data models. J. Reg. Sci. 65 (3), 639–653. https://doi.org/10.1111/jors.12757.
Espa, G., Filipponi, D., Giuliani, D., Piacentino, D., 2014. Decomposing regional business change at plant level in Italy: a novel spatial shift-share approach. Pap. Reg. Sci. 93, S113–S135. https://doi.org/10.1111/pirs.12044.
Fajgelbaum, P.D., Morales, E., Suárez Serrato, J.C., Zidar, O., 2019. State taxes and spatial misallocation. Rev. Econ. Stud. 86 (1), 333–376. https://doi.org/10.1093/restud/rdy050.
Fratesi, U., Wishlade, F.G., 2017. The impact of European Cohesion Policy in different contexts. Reg. Stud. 51 (6), 817–821. https://doi.org/10.1080/00343404.2017.1326673.
Getis, A., 1990. Screening for spatial dependence in regression analysis. Pap. Reg. Sci. 69 (1), 69–81. https://doi.org/10.1111/j.1435-5597.1990.tb01204.x.
Getis, A., Griffith, D.A., 2002. Comparative spatial filtering in regression analysis. Geogr. Anal. 34 (2), 130–140. https://doi.org/10.1111/j.1538-4632.2002.tb01080.x.
Giannini, M., Martini, B., Fiorelli, C., 2023. How does firms' broadband adoption affect regional tfp in Italy? Econ. Polit. 40 (3), 1025–1050. https://doi.org/10.1007/s40888-022-00269-5.
Glass, A.J., Kenjegalieva, K., 2024. The role of inefficiency in a productivity puzzle: regional evidence for Great Britain. J. Reg. Sci. 64 (4), 1287–1322. https://doi.org/10.1111/jors.12702.
Gopinath, G., Kalemli-Özcan, Karabarbounis, L., Villegas-Sanchez, C., 2017. Capital allocation and productivity in south Europe. Q. J. Econ. 132 (4), 1915–1967. https://doi.org/10.1093/qje/qjx024.
Griffith, D.A., 2003. Spatial filtering. In Spatial autocorrelation and spatial filtering: gaining understanding through theory and scientific visualization. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 91–130. https://doi.org/10.1007/978-3-540-24806-4_4.
Griffith, D.A., 2008. Spatial-filtering-based contributions to a critique of geographically weighted regression (gwr). Environ. Plan. A 40 (11), 2751–2769. https://doi.org/10.1068/a38218.
Griffith, D.A., Chun, Y., Hauke, J., 2022. A Moran eigenvector spatial filtering specification of entropy measures. Pap. Reg. Sci. 101 (1), 259–280. https://doi.org/10.1111/pirs.12646.
Haltiwanger, J., 2016. Firm dynamics and productivity: Tfpq, tfpr, and demand-side factors. Econom. ía 17 (1), 3–26. https://doi.org/10.1353/eco.2016.a634029.
Hilber, C.A., Lyytikäinen, T., 2017. Transfer taxes and household mobility: distortion on the housing or labor market? J. Urban. Econ. 101, 57–73. https://doi.org/10.1016/j.jue.2017.06.002.
Hopenhayn, H.A., 2014. Firms, misallocation, and aggregate productivity: A review. Annu. Rev. Econ. 6 (1), 735–770. https://doi.org/10.1146/annurev-economics-082912-110223.
Hsieh, C.T., Moretti, E., 2019. Housing constraints and spatial misallocation. Am. Econ. J. Macroecon. 11 (2), 1–39. https://coi.org/10.1257/mac.20170388.
Hsieh, C.-T., Klenow, P.J., 2009. Misallocation and manufacturing tfp in China and India. Q. J. Econ. 124 (4), 1403–1448. https://doi.org/10.1162/qjec.2009.124.4.1403.
Huang, Z., Shi, T., Tong, D., 2025. Understanding the role of government in regional industrial evolution: evidence from land supply in China. Pap. Reg. Sci. 104 (1), 100070. https://doi.org/10.1016/j.pirs.2024.100070.
Linarello, A., Petrella, A., 2017. Productivity and reallocation: evidence from the universe of Italian firms. Int. Product. Monit. 32, 116–136. https://doi.org/10.2139/ssrn.2910391.
López-Rodríguez, J., Martínez-López, D., Pociña-Sánchez, B., 2025. Threshold effects of agglomeration on local business taxation: evidence from Spain. Pap. Reg. Sci., 100117 https://doi.org/10.1016/j.pirs.2025.100117.
Lotti, F., Marin, G., 2013. Matching of PATSTAT applications to AIDA firms: discussion of the methodology and results. Bank. Italy Occas. Pap. (166). https://doi.org/10.2139/ssrn.2283111.
Lucas, R.E., Rossi–Hansberg, E., 2002. On the internal structure of cities. Econometrica 70 (4), 1445–1476. https://doi.org/10.1111/1468-0262.00338.
Marin, G., Modica, M., 2021. Local demand shocks and firms' survival: an application to the Italian economy during the Great Recession. Pap. Reg. Sci. 100 (3), 745–776. https://doi.org/10.1111/pirs.12587.
Marzucchi, A., Antonioli, D., Montresor, S., 2015. Industry–research co-operation within and across regional boundaries. What does innovation policy add? Pap. Reg. Sci. 94 (3), 499–525. https://doi.org/10.1111/pirs.12079.
Midrigan, V., Xu, D.Y., 2014. Finance and misallocation: Evidence from plant-level data. Am. Econ. Rev. 104 (2), 422–458. https://doi.org/10.1257/aer.104.2.422.
Moll, B., 2014. Productivity losses from financial frictions: can self-financing undo capital misallocation? Am. Econ. Rev. 104 (10), 3186–3221. https://doi.org/10.1257/aer.104.10.3186.
Moran, P.A.P., 1950. Notes on continuous stochastic phenomena. Biometrika 37 (1–2), 17–23. https://doi.org/10.2307/2332142.
Moretti, E., Yi, M., 2024. *Size matters: Matching externalities and the advantages of large labor markets* (No. w32250. National Bureau of Economic Research. https://doi.org/10.3386/w32250.
Muolo, A., Bruno, E., Castellano, R., Salvati, L., Punzo, G., 2026. Does labour market area affect local unemployment rates? Evidence from Mono-centric and Polycentric Italies, 2006-2022. Pap. Reg. Sci., 100141 https://doi.org/10.1016/j.pirs.2026.100141.
Mussini, M., 2019. A spatial decomposition of the shift-share components of labour productivity inequality in Italy. Pap. Reg. Sci. 98 (1), 283–307. https://doi.org/10.1111/pirs.12362.
Okubo, T., 2012. Antiagglomeration subsidies with heterogeneous firms. J. Reg. Sci. 52 (2), 285–299. https://doi.org/10.1111/j.1467-9787.2011.00736.x.
Patuelli, R., Schanne, N., Griffith, D.A., Nijkamp, P., 2012. Persistence of regional unemployment: application of a spatial filtering approach to local labor markets in Germany. J. Reg. Sci. 52 (2), 300–323. https://doi.org/10.1111/j.1467-9787.2012.00759.x.
Percoco, M., 2017. Impact of European cohesion policy on regional growth: does local economic structure matter? Reg. Stud. 51 (6), 833–843. https://doi.org/10.1080/00343404.2016.1213382.
Piacentino, D., Vassallo, E., 2011. Exploring the sources of labour productivity growth and convergence in the Italian regions: some evidence from a production frontier approach. Ann. Reg. Sci. 46 (2), 469–486. https://doi.org/10.1007/s00168-009-0345-0.

Redding, S.J., Rossi-Hansberg, E., 2017. Quantitative spatial economics. Annu. Rev. Econ. 9, 21–58. https://doi.org/10.1146/annurev-economics-063016-103713.
Restuccia, D., Rogerson, R., 2008. Policy distortions and aggregate productivity with heterogeneous establishments. Rev. Econ. Dyn. 11 (4), 707–720. https://doi.org/10.1016/j.red.2008.05.002.
Restuccia, D., Rogerson, R., 2013. Misallocation and productivity. Rev. Econ. Dyn. 16 (1), 1–10. https://doi.org/10.1016/j.red.2012.11.003.
Restuccia, D., Rogerson, R., 2017. The causes and costs of misallocation. J. Econ. Perspect. 31 (3), 151–174. https://doi.org/10.1257/jep.31.3.151.
Serafinelli, M., 2019. Good" firms, worker flows, and local productivity. J. Labor. Econ. 37 (3), 747–792. https://doi.org/10.1086/702628.
Tiefelsdorf, M., Boots, B., 1995. The exact distribution of Moran's I. Environ. Plan. A 27 (6), 985–999. https://doi.org/10.1068/a270985.
Tiefelsdorf, M., Griffith, D.A., 2007. Semiparametric filtering of spatial autocorrelation: the eigenvector approach. Environ. Plan. A 39 (5), 1193–1221. https://doi.org/10.1068/a37378.