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GRANULAR SOURCES OF THE ITALIAN BUSINESS CYCLE

by Nicolò Gnocato* and Concetta Rondinelli**

Abstract

A recent strand of literature has investigated the granular sources of the business cycle, i.e. to what extent firm-level dynamics have an impact on aggregate fluctuations. From a conceptual point of view, in the presence of fat-tailed firm-size distributions, shocks to large firms may not average out and may then have a direct effect on aggregate fluctuations; in addition, firm-to-firm linkages can propagate shocks to individual firms, leading to movements at the aggregate level. Using Cerved and INPS data, we test the granular hypothesis on a large sample of Italian firms, covering the period 1999-2014. Idiosyncratic Total Factor Productivity (TFP) shocks are found to explain around 30 per cent of aggregate TFP volatility; furthermore, the contribution of these linkages to firm-specific aggregate volatility is more important than that of the direct effect, especially for the manufacturing sector.

JEL Classification: D24, E32, L25.
Keywords: aggregate fluctuations, firm-level dynamics, productivity.

Contents

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1 Introduction[1]

The predominant tradition in macroeconomics has long assumed that idiosyncratic shocks to individual firms average out and thus have negligible effects at the aggregate level (Lucas, 1977). Therefore, micro dynamics would not contribute to business-cycle fluctuations, these latter being the result only, for instance, of aggregate changes to monetary, fiscal, and exchange rate policy, or aggregate productivity shocks.

Two recent strands of literature have started challenging this perspective, and investigating the hypothesis that macroeconomic fluctuations result (also) from many microeconomic shocks; according to a first perspective, if the firm size distribution is extremely fat-tailed, idiosyncratic shocks to individual (large) firms will not average out and, instead, lead to movements in the aggregates (Gabaix, 2011). According to a second perspective, idiosyncratic shocks to a single sector/firm can have sizeable aggregate effects if the sector/firm is interconnected with others in the economy through input-output linkages: these linkages propagate microeconomic shocks, leading to positive endogenous comovement (Acemoglu et al., 2012).

There is, however, still little empirical evidence on the direct role of individual (large) firms and firm-level input-output linkages in explaining aggregate fluctuations.

The pioneering contribution by Gabaix (2011) develops the view that a large part of aggregate fluctuations may arise from idiosyncratic shocks to individual (large) firms. Since modern economies are indeed dominated by large firms, idiosyncratic shocks to these firms can lead to non-trivial aggregate shocks. Using annual U.S. Compustat data from 1951 to 2008 regarding the 100 largest firms in the economy, he claims that idiosyncratic shocks to the top 100 firms seem to explain a large fraction (about one-third, depending on the specification) of GDP fluctuations.

Carvalho and Gabaix (2013) investigate the hypothesis that macroeconomic fluctuations are ultimately the result of many microeconomic shocks. They define *fundamental volatility* as the volatility that would arise from an economy made entirely of idiosyncratic sectoral or firm-level shocks; the explanatory power of fundamental volatility is found to be quite good, supporting the view that the key to macroeconomic volatility might be found in microeconomic shocks.

The direct role of shocks to individual firms and their propagation through input-output linkages are emphasized by di Giovanni et al. (2014); their work incorporates as well the international dimension by considering individual firms' sales to each destination market rather than total firm sales: the growth rate of a firm's sales to a single destination market is decomposed additively into a macroeconomic shock, a sectoral shock, and a firm-level shock. The firm-specific component is found to contribute substantially to aggregate sales volatility, mattering about as much as the component capturing shocks that are common across firms within a sector or country. They then

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decompose the firm-specific component to provide evidence on the two mechanisms that generate aggregate fluctuations from microeconomic shocks highlighted in the recent literature; firm-linkages are found to be approximately three times as important as the direct effect of firm shocks in driving aggregate sales fluctuations.

In this paper we empirically analyse the firm-level sources of aggregate fluctuations for the Italian case. The Italian *manufacturing* productive system has two features of interest in this respect: on the one hand, the small size of firms, which would in principle weaken the granular hypothesis; on the other hand, the strong geographical agglomeration of firms by sector of economic activity (in so-called "districts"), which could enhance the idiosyncratic sources of aggregate fluctuations.

Our approach is related to that by di Giovanni et al. (2014), but departs from it in two respects, both dictated by data availability considerations. While they use a database covering the *universe* of French firms and focus on firm-destination sales as their unit of observation, the Italian micro-data only allows us to focus on a *sample* of firms, whose balance sheets are retrieved from the Cerved database for the period 1999–2014.[2]

In the spirit of Melitz (2003) and Eaton et al. (2011), di Giovanni et al. (2014) set up a multi-sector model explicitly focusing on firm-destination sales, implying, as mentioned above, an additive decomposition of the growth rate of sales of an individual firm to a single destination market into a macroeconomic shock (common to all firms), a sectoral shock (common to all firms in a particular sector), and a firm-specific shock.

Our simpler, underlying model, focusing on firm-level Total Factor Productivity (TFP), moves from the basic insight by Hulten (1978) —later reprised by Gabaix (2011) and Carvalho and Gabaix (2013) in the granularity literature— that aggregate TFP growth can be expressed in terms of Domar aggregation. This provides an additive decomposition —in the spirit of di Giovanni et al. (2014)— of aggregate TFP volatility into a common-sector component and a firm-specific component, and allows to decompose the latter, in turn, into a "direct" and a "linkages" component.

Idiosyncratic TFP shocks are found to explain around 30% of aggregate TFP volatility, and the contribution of the linkages component to firm-specific aggregate volatility is found to be more relevant than that of the direct effect. Additionally, more interconnected couples of sectors display, as expected, higher linkages volatilities.[3]

The remainder of the paper is organized as follows. Section 2 sketches in deeper detail the underlying model, while its empirical implementation is detailed in Section 3. Section 4 describes the data. Section 5 presents the main results. Section 6 provides some robustness checks of the main results. Section 7 concludes. Some additional details are presented in the Appendices.

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[2] The absence of a *universe* of Italian firms might be problematic especially if a missing firm has a fundamental link with the rest of the economy. We are however confident that our sample is representative of the universe of Italian firms, as illustrated in Appendix A where we show a high correlation in the relevant variables between the Cerved-INPS sample and the Invind dataset.

[3] Exploiting the network of ownership relations, Burlon (2015) studies how aggregate volatility is influenced by the propagation of idiosyncratic shocks across Italian firms over the period 2005-2013. He shows that the volatility implied by the model may account for a sizeable percentage of GDP fluctuations.

2 The Granular Hypothesis: Conceptual Background

Consider an economy populated by n competitive firms, producing intermediate and final goods using capital, labor and other intermediate inputs sourced from one another. If a Hicks-neutral, idiosyncratic productivity shock $\dot{\omega}_i = d\omega_i/\omega_i$ hits firm i then, according to Hulten (1978), the corresponding shock to aggregate TFP is given by

$$\dot{\Omega} = \frac{d\Omega}{\Omega} = \sum_{i=1}^{n} \left(\frac{Q_i}{Y}\right) \dot{\omega}_i \tag{1}$$

where Q_i denotes firm i's gross production value, Y denotes nominal aggregate value added, and Q_i/Y is a so-called "Domar" weight (Hulten, 1978). The sum of these weights is greater than or equal to one. The intuitive reason behind this weighting is that a change in firm i's efficiency creates extra output which can increase both aggregate value added and intermediate goods' supplies.[4]

Following Carvalho and Gabaix (2013), if we allow firm-level TFP shocks to be cross-sectionally correlated across firms $i, j = 1, ..., n$ (due, for instance, to input linkages or local labor market interactions) then we have

$$\sigma^2_{\dot{\Omega}_t} = \sigma^2_{F_t} = \sum_{i,j=1,\ldots,n} \left(\frac{Q_{it}}{Y_t}\right)\left(\frac{Q_{jt}}{Y_t}\right) \rho_{ij}\sigma_i\sigma_j \tag{2}$$

where $\rho_{ij} = \frac{\operatorname{cov}(\dot{\omega}_i, \dot{\omega}_j)}{\sigma_i \sigma_j}$, $\sigma_i = \sqrt{\operatorname{var}(\dot{\omega}_i)}$, and where $\operatorname{var}(\dot{\omega}_i)$ and $\operatorname{cov}(\dot{\omega}_i, \dot{\omega}_j)$ are, respectively, the diagonal and off-diagonal elements of the $n \times n$ variance-covariance matrix of firm-level TFP shocks $(\rho_{ij}\sigma_i\sigma_j)$. Then, $\sigma^2_{F_t}$ can accordingly be decomposed into:

i. A term given by the sum of the diagonal terms, weighted by their corresponding squared Domar weights, which Carvalho and Gabaix (2013) define as their baseline, *fundamental* volatility, Gabaix (2011) as *granular* volatility, and di Giovanni et al. (2014) as the *direct* effect of shocks to firms on aggregate volatility.

ii. A term given by the sum of the off-diagonal terms, weighted by the product of the shares of each firm's production value in aggregate value added.

$$\sigma^2_{F_t} = \sum_{i,j=1,\ldots,n} \left(\frac{Q_{it}}{Y_t}\right)\left(\frac{Q_{jt}}{Y_t}\right) \rho_{ij}\sigma_i\sigma_j = \sum_{i=1}^{n} \left(\frac{Q_{it}}{Y_t}\right)^2 \sigma_i^2 + \sum_{i \neq j}\sum_{j} \left(\frac{Q_{it}}{Y_t}\right)\left(\frac{Q_{jt}}{Y_t}\right) \operatorname{cov}(\dot{\omega}_i, \dot{\omega}_j) \tag{3}$$

2.1 Variance Contribution to Aggregate TFP Shocks (*direct effect*)

As shown by Gabaix (2011), when the firm size distribution is sufficiently fat-tailed, idiosyncratic shocks to individual firms do not wash out at the aggregate level, because shocks to large firms do not cancel out with shocks to smaller units.

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[4] Baqaee and Farhi (2017) move beyond Hulten's theorem's first order approximation, generalising the result for distorted economies.

To illustrate in the simplest way the role of the *direct* component, suppose shocks are uncorrelated across firms ($\text{cov}(\dot{\omega}_i, \dot{\omega}_j) = 0 \quad \forall i, j$), so that the only sources of aggregate volatility are the diagonal components

$$\sigma_{F_t}^2 = \sum_{i=1}^{n} \left(\frac{Q_{it}}{Y_t} \right)^2 \sigma_i^2.$$

Suppose, also, that the variance of shocks is the same across all firms in the economy, i.e. $\sigma_i^2 = \sigma^2 \quad \forall i$. Then, we can write

$$\sigma_{F_t}^2 = \sigma^2 \sum_{i=1}^{n} \left(\frac{Q_{it}}{Y_t} \right)^2 = \sigma^2 \times H_t$$

where $H_t = \sum_{i=1}^{n} (Q_{it}/Y_t)^2$ denotes the Herfindahl index of the economy. The more fat-tailed is the firm-size distribution, the larger will be the Herfindahl index and the greater will be the aggregate TFP volatility originating from idiosyncratic shocks. On the opposite, extreme case where the economic activity is symmetrically distributed across firms ($Q_{it} = Y_t/n$), we have $\sigma_{F_t} = \sigma/\sqrt{n}$ and the contribution of idiosyncratic shocks to aggregate volatility decays rapidly as n increases.

2.2 Covariance Contribution to Aggregate TFP Shocks (*linkages effect*)

The covariance term in (3),

$$\sum_{i \neq j} \sum_{j} \left(\frac{Q_{it}}{Y_t} \right) \left(\frac{Q_{jt}}{Y_t} \right) \text{cov}(\dot{\omega}_i, \dot{\omega}_j),$$

captures the contribution of comovement across firms in explaining aggregate volatility. Cross-firm correlations can arise, for instance, from input-output linkages and/or local labor market interactions.

Indeed, as shown by Acemoglu et al. (2012), idiosyncratic shocks to single sectors/firms can be propagated through input-output linkages, leading to positive endogenous comovement and, in turn, to aggregate fluctuations. However, there may be further interdependencies, other than input-output linkages, responsible for this comovement, such as the aforementioned local labor market interactions. As observing comovement is, therefore, a necessary but not sufficient condition for the presence of input-output (IO) relations, in Section 5.3.2 we will provide some evidence on the actual inter-relation between IO linkages and comovement.

3 Empirical Framework

Following Gabaix (2011), we define the productivity growth rate as

$$g_{it} = \omega_{it} - \omega_{i,t-1}$$

where ω_{it} is the log of firm-level productivity.[5] Our baseline measure is firm-level TFP, estimated as the residual in a value added based Cobb-Douglas production function, i.e.

$$\hat{\omega}_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} \tag{4}$$

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[5] Notice that we are focusing on the intensive margin of aggregate productivity growth (i.e. on those firms whose productivity is observed both at t and $t-1$).

where y_{it} is (log) firm i's real value added at time t, l_{it} the (log) number of employees, k_{it} the log of firm i's real capital stock at time t, and β_l and β_k labor and capital elasticities.[6]

To test whether idiosyncratic, rather than common shocks drive aggregate dynamics, we need to isolate the idiosyncratic component of firm-level productivity growth. Common shocks are computed as sectoral averages of firm-level TFP growth rates; the firm-specific shock e_{it} is then computed as the deviation from this average. In practice, the cross-section of g_{it}'s in a given year t is regressed on a set of sector fixed effects (sector dummies δ_{st}), retaining the residual e_{it} as the firm-specific shock

$$g_{it} = \delta_{st} + e_{it} \tag{5}$$

3.1 Granular Residual

Following Gabaix (2011), we define the granular residual as the sum of firm-specific shocks, weighted by size:[7]

$$E_t \equiv \sum_i \left(\frac{Y_{i,t-1}}{Y_{t-1}} \right) e_{it} \tag{6}$$

In addition, we also define a similar measure based on common shocks at sector level, rather than on idiosyncratic shocks:

$$\Delta_t \equiv \sum_s \left(\frac{Y_{s,t-1}}{Y_{t-1}} \right) \delta_{st} \tag{7}$$

where $Y_s = \sum_{i \in s} Y_i$.

3.2 Contributions to Aggregate TFP Volatility

Aggregate TFP growth at the intensive margin (i.e. among firms that kept producing between any two periods) can be approximated, to a first-order, by

$$g_{\Omega_t} = \sum_i \left(\frac{Y_{i,t-1}}{Y_{t-1}} \right) g_{it} = \sum_s \left(\frac{Y_{s,t-1}}{Y_{t-1}} \right) \delta_{st} + \sum_i \left(\frac{Y_{i,t-1}}{Y_{t-1}} \right) e_{it} \tag{8}$$

Following di Giovanni et al. (2014), we work with a simpler stochastic process where, for a given time period τ, weights are fixed at their $\tau - 1$ values and combined with shocks from period t

$$g_{\Omega_{t|\tau}} = \sum_s \left(\frac{Y_{s,\tau-1}}{Y_{\tau-1}} \right) \delta_{st} + \sum_i \left(\frac{Y_{i,\tau-1}}{Y_{\tau-1}} \right) e_{it} \tag{9}$$

Then, the variance of aggregate TFP growth is

$$\sigma^2_{\Omega_\tau} = \sigma^2_{\Delta_\tau} + \sigma^2_{F_\tau} + \mathrm{COV}_\tau \tag{10}$$

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[6] Elasticities β_l and β_k are econometrically estimated. A well-known issue in doing so is that whenever a firm has prior knowledge about its productivity, and responds to positive expected shocks by increasing input usage, OLS estimates will be biased. The baseline procedure we use to overcome this issue and obtain consistent estimates of β_l and β_k is that proposed by Ackerberg et al. (2015); more details in Appendix C.

[7] Since our baseline TFP measure is value added based, the correct weights to use here are value added weights, while Domar weights are the correct weights when the TFP measure is gross output based. The results of the two aggregations are conceptually the same in Hulten's (1978) framework.

where common-sectoral volatility is estimated as $\sigma^2_{\Delta_\tau} = \text{Var}\left[\sum_s \left(\frac{Y_{s,\tau-1}}{Y_{\tau-1}}\right)\delta_{st}\right]$, firm-specific volatility as $\sigma^2_{F_\tau} = \text{Var}\left[\sum_i \left(\frac{Y_{i,\tau-1}}{Y_{\tau-1}}\right) e_{it}\right]$, and the covariance of shocks from different levels of aggregation as $\text{COV}_\tau = \text{Cov}\left[\sum_s \left(\frac{Y_{s,\tau-1}}{Y_{\tau-1}}\right)\delta_{st}, \sum_i \left(\frac{Y_{i,\tau-1}}{Y_{\tau-1}}\right) e_{it}\right]$.

For instance, for each $\tau = 1, ..., T$, $\sigma^2_{F_\tau}$ is the sample variance of the T realizations $(t = 1, ..., T)$ of $\sum_i \left(\frac{Y_{i,\tau-1}}{Y_{\tau-1}}\right) e_{it}$, e.g. $\sigma^2_{F_{\tau=1}} = \text{Var}\left(\sum_i \left(\frac{Y_{i0}}{Y_0}\right) e_{it}\right)$, and so on. This approach, of constructing aggregate variances under weights that are fixed period-by-period, follows Carvalho and Gabaix (2013) and di Giovanni et al. (2014).

In what follows, we use the standard deviation as our measure of volatility, and present the results in terms of relative standard deviations when discussing contributions to aggregate volatility.

3.2.1 Channels for Firms' Contributions

As outlined in (3), firm-specific volatility, $\sigma^2_{F_\tau}$, can be decomposed into a variance (or *direct*) and a covariance (or *linkages*) contribution. Therefore, we estimate, for t and τ=2000–2014:

$$\sigma^2_{F_\tau} = \underbrace{\sum_i \left(\frac{Y_{i,\tau-1}}{Y_{\tau-1}}\right)^2 \text{Var}(e_{it})}_{\text{DIRECT}} + \underbrace{\sum_{i\neq j}\sum_j \left(\frac{Y_{i,\tau-1}}{Y_{\tau-1}}\right)\left(\frac{Y_{j,\tau-1}}{Y_{\tau-1}}\right)\text{Cov}(e_{it}, e_{jt})}_{\text{LINK}} \tag{11}$$

and look at relative standard deviations $\sqrt{\text{DIRECT}}/\sigma_{F_\tau}$ and $\sqrt{\text{LINK}}/\sigma_{F_\tau}$ to assess the relative contributions of the *direct* and *linkages* channels respectively.

However, we must recall that simply observing positive covariances (aggregated into the LINK term) provides a necessary but not sufficient condition for the existence of input-output linkages: there may be other interdependencies responsible for this comovement, such as local labor market interactions. Moreover, if TFP is measured with error, as it inevitably happens, this may lead to comovement as well (Carvalho and Gabaix, 2013). As already mentioned, in Section 5.3.2 we will provide some evidence on the actual inter-relation between IO linkages and comovement.

4 Data and Descriptive Statistics

The main data source used for the following empirical analysis is the Cerved database, collected by Cerved Group, which comprises balance sheet information for almost all joint stock (S.p.a.), partnership limited by shares (S.a.p.a.), and limited liability (S.r.l.) Italian companies since 1993.[8]

As the number of employees is not reported on balance sheets on a mandatory basis, the Cerved data have been merged with information about employment coming from INPS, the Italian National Social Security Institute, whose dataset comprises the universe of Italian companies with at least one employee.[9] Firm-level real capital stocks are recovered by means of a Perpetual Inventory Method (outlined in detail in Appendix B). Lastly, *firms* with gaps in relevant variables are excluded from the

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[8] That is, almost all so-called "società di capitale" are included in the dataset, whereas so-called "società di persone" are completely excluded.

[9] We refer to this merged dataset as Cerved-INPS, whose coverage is reported in Appendix A.

analysis,[10] and the growth rate of TFP, g_{it}, is winsorized at 5% on both tails to tackle measurement error in the micro-data and account for extreme events such as mergers and acquisitions.[11] The final sample, ranging from 1999 to 2014, is an unbalanced panel of 3,597,015 firm-year observations, whose summary statistics are reported in Table 4.1, while summary statistics for selected years in the panel are reported in Appendix A.2. As far as the full panel is concerned, the average firm in our sample has a value added of 1267.33 thousand euros (at constant 2010 prices), 22 employees,[12] a capital stock of 1344.78 thousand euros, and a TFP of 33.34 euros of value added generated per employee and euro of capital stock.

Table 4.1: Summary Statistics

	Obs.	Mean	St. Dev.	p10	p25	p50	p75	p90
Value Added	3,597,015	1267.33	25335.86	48.43	105.61	257.59	663.35	1759.31
Employees	3,597,015	22.38	287.54	1	2.75	6.17	14.17	34.92
Capital Stock	3,597,015	1344.78	36252.45	13.13	37.26	116.62	423.25	1484.65
TFP	3,597,015	33.34	72.90	11.72	18.03	26.46	38.15	55.96

Notes: Value Added and Capital Stock at constant 2010 prices (thousand euros). TFP: thousand euros of value added generated per employee and per thousand euros of capital stock (constant 2010 prices). Employees: average number of workers employed across the year according to INPS. *Sources:* Cerved-INPS.

4.1 Properties of Shocks

Looking more in detail at some properties of firm-level shocks, we report in Table 4.2 averages of firm-level standard deviations of shocks by size quintile and, in Table 4.4, the same averages by 2-digit sector. Larger firms have, on average, lower TFP volatility; this implies that the direct effect of idiosyncratic shocks in (3) is potentially dampened, as to incresed size (i.e. Q_{it}/Y_t) corresponds, on average, lower volatility (as measured by σ_i). Average TFP volatility varies across sectors as well (Table 4.4), ranging between a low of 0.2405 for social work activities, and a high of 0.4140 for manufacturing of coke and refined petroleum products.

Table 4.3 reports averages and correlations between the different components of firm-level TFP growth, g_{it}. Simply observing high correlation, at firm-level, between g_{it} and e_{it} does not automatically mean that idiosyncratic shocks matter more at the aggregate level (they could average out); on the other hand, observing that e_{it}'s average is 0, does not automatically mean that

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[10] That is, if a firms has one or more missing observations on either (log) TFP or the weight, we remove the entire firm from the sample. This avoids alterations in the results deriving from firms jumping in and out of the dataset.

[11] In doing so, we follow the recent literature. Gabaix (2011) winsorizes growth rates in his Compustat sample at 20%, while di Giovanni et al. (2014) trim observations displaying growth rates greater/less than ± 100% (i.e. they winsorize g_{it} at ± 1). In our baseline specification g_{it}, after winsorization at 5% on both tails, ranges between -0.7 and 0.61. Overall results are, though, robust to winsorizing at 1%.

[12] This average might seem high given the typical small size of Italian business. Firstly, the median number of employees in our sample is 6. Secondly, the Cerved database is itself tilted towards larger firms. Lastly, smaller firms might be more extensively involved in the exclusion of firms with gaps in the relevant variables used to obtain our final sample, as it is more likely that they fail to be consecutively observed. We must also stress, however, that since aggregates should be primarily driven by larger units, the exclusion of smaller units should not represent a big issue.

idiosyncratic shocks *do not* matter at the aggregate level; to answer whether they matter or not, we have to account for the firm-size distribution (by means of aggregation).

Table 4.2: FIRM-LEVEL VOLATILITY BY SIZE

St.Dev.	Whole Economy	Manufacturing
Average	0.2938	0.2709
Size Percentile		
0–20	0.3729	0.3441
21–40	0.3211	0.2837
41–60	0.2843	0.2582
61–80	0.2576	0.2407
81–100	0.2298	0.2249

Notes: The table reports averages of firm-level TFP volatilities ($\sigma_i = \sqrt{\text{var}(g_{it})}$) by size quintile (defined in terms of number of employees). *Sources:* Cerved-INPS.

Table 4.3: SUMMARY STATISTICS AND CORRELATIONS OF SHOCKS

	Obs.	Mean	St.Dev.	Correlation
Actual (g_{it})	3,178,447	-0.0201	0.3096	1.0000
Firm-specific (e_{it})	3,178,447	0.0000	0.3056	0.9870
Common (δ_{st})	1,140	-0.0202	0.0496	0.1608

Notes: The table reports sample averages and standard deviations of g_{it}, e_{it} and δ_{st}, and correlations between g_{it} and g_{it}, e_{it} and δ_{st}. *Sources:* Cerved-INPS.

4.2 Aggregate TFP Growth

Figure 4.1 reports the aggregate TFP growth of firms in our sample, as obtained from aggregation of firm-level TFP (i.e. $g_{\Omega_t} = \sum_i (Y_{i,t-1}/Y_{t-1}) g_{it}$), and compares it to the growth rate of GDP and the Solow residual, as reported at the aggregate level by Istat, the Italian national statistical office.

The Italian productivity and GDP growth slowdowns during the past two decades clearly emerge from the Istat trends. In this respect, our sample shows trends in TFP growth rates that are qualitatively similar, but even more tilted toward negative growth rates. Additionally, the crisis sub-period (2008–2014) presents higher volatility than the pre-crisis sub-period (2000–2007). Lastly, the manufacturing sector displays higher volatility than the economy as a whole.

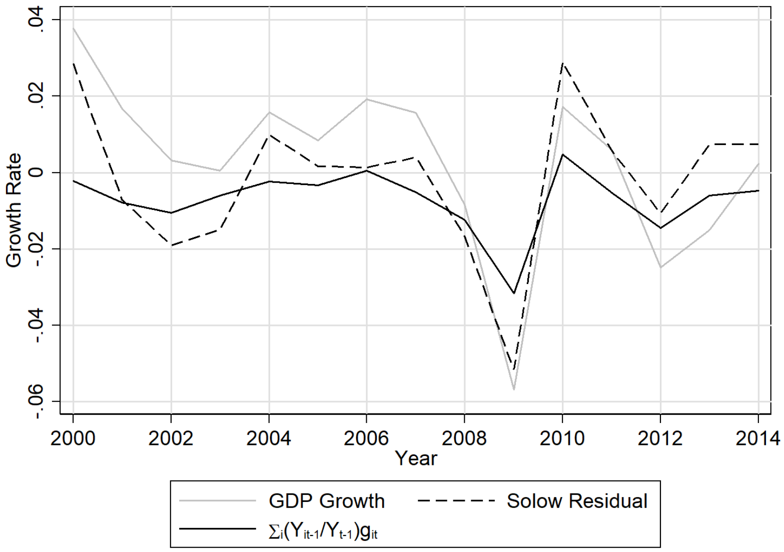
Table 4.4: Firm-level Volatility by Sector

ATECO	Activity Description	St.Dev.	ATECO	Activity Description	St.Dev.
01–03	Agriculture, Forestry and Fishing	0.3331	45–47	Wholesale and Retail Trade	0.3032
05–09	Mining and Quarring	0.3295	49–53	Transport and Storage	0.2877
10–12	Food, Beverages and Tobacco	0.2692	55–56	Accommodation and Food Service	0.3017
13–15	Textiles, Wearing Apparel and Leather	0.2869	58–60	Publishing, Audiovisuals and Broadcasting	0.3497
16–18	Wood and Paper Products, and Printing	0.2619	61	Telecommunications	0.3744
19	Coke and Refined Petroleum	0.4140	62–63	Computer and Information Services	0.2721
20	Chemicals and Chemical Products	0.2615	64–66	Financial and Insurance	0.3240
21	Pharmaceuticals	0.2590	68	Real Estate	0.3800
22–23	Rubber, Plastics and Mineral Products	0.2641	69–71	Professional Activities	0.3068
24–25	Basic Metals and Metal Products	0.2673	72	Research and Development	0.3361
26	Computer, Electronic and Optical Products	0.2856	73–75	Advertising	0.3355
27	Electrical Equipment	0.2690	77–82	Administrative and Support Services	0.3019
28	Machinery and Equipment	0.2660	85	Education	0.3289
29–30	Transport Equipment	0.2831	86	Health	0.2812
31–33	Manufacturing n.e.c.	0.2743	87–88	Social Work	0.2405
35	Electricity, Gas, Steam and A.C. Supply	0.3549	90–93	Arts, Entertainment and Recreation	0.3549
36–39	Water Supply, Sewage, Waste Management	0.2902	94–96	Other Services	0.3013
41–43	Construction	0.3040			

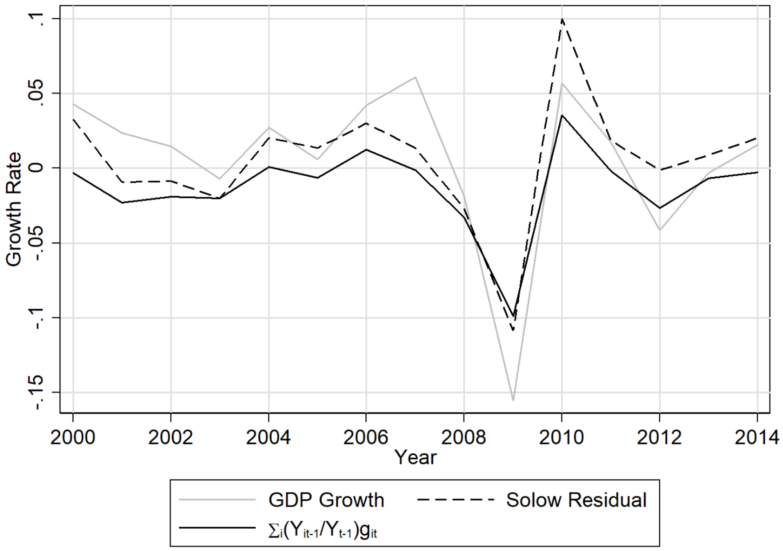
Notes: The table reports averages of firm-level TFP volatilities ($\sigma_i = \sqrt{\mathrm{var}(g_{it})}$) by sector of economic activity (defined in terms of the ATECO 2007 classification, the Italian version of Nace Rev.2). "n.e.c." = "not elsewhere classified." *Sources:* Cerved-INPS.

Figure 4.1: AGGREGATE TFP GROWTH

(a) Whole Economy



(b) Manufacturing



Notes: The Figure displays the aggregate TFP growth of firms in our sample —as obtained from aggregation of firm-level TFP shocks —$g_{\Omega t} = \sum_i \left(\frac{Y_{i,t-1}}{Y_{t-1}}\right) g_{it}$— (solid black line), the growth rate of GDP (gray line; Istat) and the Solow residual (dashed black line; Istat).
Sources: Cerved-INPS and Istat.

5 Baseline Results

5.1 Granular Residual

As a preliminary exercise, we replicate Gabaix's Granular Residual in our sample,[13] and investigate its explanatory power (top of Table 5.1). Additionally, we also use our measure based on Common-Sector shocks in (7), investigating its explanatory power as well (bottom of Table 5.1).

The results in Table 5.1 tell us that idiosyncratic shocks are able to explain a non-trivial fraction of aggregate volatility, both when looking at Istat aggregates (GDP growth and Solow Residual in columns (1) and (2) on top of Table 5.1) and when focusing on the Aggregate TFP growth of our sample (column (3)).[14] However, Common-Sector shocks are unambiguously prevalent in explaining aggregate volatility (bottom of Table 5.1).

The contribution of the Granular Residual to aggregate TFP volatility (about 30% adjusted R^2 in column (3) on top Table 5.1) is potentially inclusive of both direct effects of shocks to larger firms and the propagation of shocks through firm-to-firm linkages. In order to assess the relative importance of these two channels, we shall depart from the time-varying weights used to construct the Granular Residual, and adopt a simpler stochastic process with time-invariant weights as in Carvalho and Gabaix (2013) and di Giovanni et al. (2014), allowing us to exploit the decomposition depicted in (3).

5.2 Contributions to Aggregate TFP Volatility

We firstly assess the relative contribution of idiosyncratic shocks to aggregate TFP volatility —as opposed to that of Common-Sector shocks— when adopting a specification based on time-invariant weights. The results in Figure 5.1 and Table 5.2 are coherent with those obtained from the Granular Residual, telling us that idiosyncratic shocks explain about 30-40% of aggregate TFP volatility (in terms of relative standard deviations), while common-sector shocks explain about 80% of it.

Focusing on the pre- (2000–2007) and post-crisis (2008–2014) sub-periods, this latter is, on average, a period of greater volatility in terms of all actual aggregate TFP growth and both its firm-specific and common-sector components. Moreover, the average impact of the firm specific component is slightly reduced in the crisis period as opposed to the pre-crisis period.

A potential caveat to highlight is that using annual (balance sheet) data may induce sector fixed effects to capture part of the firm-specific contribution to aggregate volatility. For instance, if a shock hits a certain firm at the beginning of the year, and this shock is propagated to other firms in the same sector over the year, our evidence from end-year data will only capture this propagation as a sector fixed effect. This may lead to an underestimation of the firm-specific component and a correspondingly over-estimated common-sector component.

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[13] We compute the Granular Residual on our full sample, rather than on the top 100 Compustat firms as done by Gabaix (2011).

[14] Repeating the exercise by focusing on the top 10% (or 1%) firms in the sample reduces the explanatory power of the Granular Residual. This can be reconciled with the fact that the *linkages* component is predominant in driving idiosyncratic firm dynamics, as we shall see in Section 5.3.2; when looking only at the biggest firms in the sample, we focus our attention more on the *direct* component, and the importance of the granular residual is accordingly reduced by failing to take into account firm-to-firm linkages as fully as possible.

Table 5.1: EXPLANATORY POWER OF IDIOSYNCRATIC AND COMMON SHOCKS

I. Explanatory Power of Idiosyncratic Shocks

	(1) GDP Growth$_t$		(2) Solow Residual$_t$		(3) g_{Ω_t}	
E_t	5.456**	5.814**	5.280**	5.286**	2.605**	2.766**
	(2.351)	(2.465)	(1.969)	(2.218)	(0.858)	(0.925)
E_{t-1}	0.184	-0.598	-2.085	-2.062	-0.719	-0.812
	(2.263)	(2.444)	(1.895)	(2.199)	(0.826)	(0.917)
E_{t-2}		2.068		0.021		0.815
		(2.393)		(2.153)		(0.898)
(Intercept)	0.021	0.026	0.008	0.009	-0.000	0.003
	(0.012)	(0.017)	(0.010)	(0.015)	(0.005)	(0.006)
N	14	13	14	13	14	13
R^2	0.333	0.389	0.418	0.416	0.465	0.509
adj. R^2	0.211	0.186	0.312	0.222	0.367	0.346

II. Explanatory Power of Common-Sector Shocks

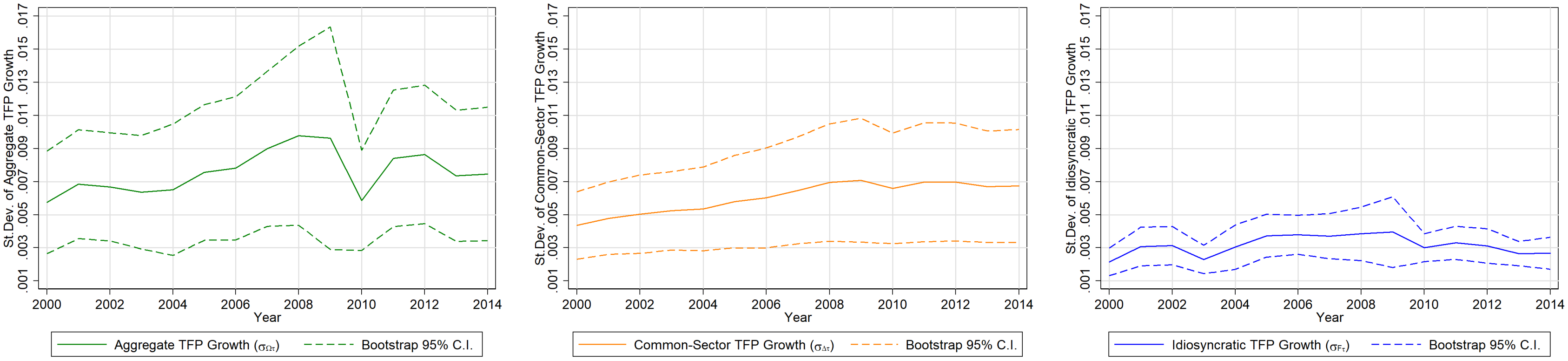
	(1) GDP Growth$_t$		(2) Solow Residual$_t$		(3) g_{Ω_t}	
Δ_t	2.603***	2.651***	2.304***	2.218***	1.142***	1.144***
	(0.363)	(0.359)	(0.337)	(0.401)	(0.081)	(0.098)
Δ_{t-1}	0.691*	0.630*	-0.152	-0.182	0.018	0.016
	(0.362)	(0.334)	(0.336)	(0.374)	(0.081)	(0.091)
Δ_{t-2}		0.081		-0.210		0.002
		(0.357)		(0.400)		(0.098)
(Intercept)	0.012***	0.011**	0.004	0.003	-0.003***	-0.003**
	(0.003)	(0.004)	(0.003)	(0.004)	(0.001)	(0.001)
N	14	13	14	13	14	13
R^2	0.827	0.878	0.814	0.819	0.948	0.948
adj. R^2	0.796	0.837	0.780	0.759	0.938	0.931

Notes: Columns (1) and (2): aggregate GDP and aggregate TFP growth rates (Istat aggregate data). Column (3): aggregate TFP growth resulting from aggregation (Cerved sample). Standard errors in parentheses. Significance: *0.10, **0.05, ***0.01. *Sources:* Cerved-INPS and Istat.

Figure 5.1: VOLATILITY OF AGGREGATE TFP GROWTH AND ITS COMPONENTS

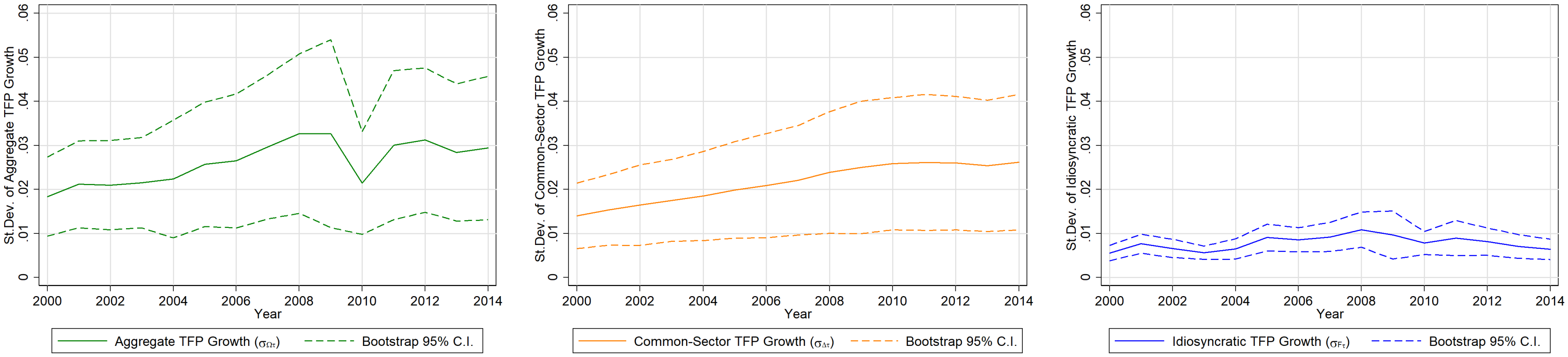
A. Whole Economy

(a) Aggregate (b) Common-Sector (c) Idiosyncratic



B. Manufacturing

(d) Aggregate (e) Common-Sector (f) Idiosyncratic



Notes: The figure presents the estimates of σ_{Ω_τ}, σ_{F_τ}, and σ_{Δ_τ} for the whole economy (top panel) and the manufacturing sector (bottom panel), along with bootstrap 95% confidence intervals. *Sources:* Cerved-INPS.

Table 5.2: AGGREGATE IMPACT OF FIRM-SPECIFIC SHOCKS ON AGGREGATE VOLATILITY

	Whole Economy		Manufacturing	
	St.Dev.	Relative SD	St.Dev.	Relative SD
	A. 2000–2014			
Actual ($\bar{\sigma}_\Omega$)	0.0076	1.0000	0.0261	1.0000
Firm-specific ($\bar{\sigma}_F$)	0.0032	0.4203	0.0079	0.3030
Common-Sector ($\bar{\sigma}_\Delta$)	0.0061	0.8090	0.0215	0.8271
	B. 2000–2007			
Actual ($\bar{\sigma}_\Omega$)	0.0071	1.0000	0.0233	1.0000
Firm-specific ($\bar{\sigma}_F$)	0.0031	0.4394	0.0074	0.3156
Common-Sector ($\bar{\sigma}_\Delta$)	0.0054	0.7644	0.0181	0.7776
	C. 2008–2014			
Actual ($\bar{\sigma}_\Omega$)	0.0082	1.0000	0.0294	1.0000
Firm-specific ($\bar{\sigma}_F$)	0.0032	0.3986	0.0084	0.2886
Common-Sector ($\bar{\sigma}_\Delta$)	0.0069	0.8600	0.0255	0.8836

Notes: The table presents averages $\bar{\sigma}_\Omega$, $\bar{\sigma}_F$, and $\bar{\sigma}_\Delta$ over different periods — e.g. $\bar{\sigma}_F = \frac{1}{T}\sum_\tau \sigma_{F_\tau}$ — and average relative standard deviations with respect to σ_Ω — e.g. $\frac{1}{T}\sum_\tau \frac{\sigma_{F_\tau}}{\sigma_{\Omega_\tau}}$. *Sources:* Cerved-INPS.

5.3 Channels for Firms' Contributions

We now exploit the decomposition of firm-specific volatility, σ_F^2, into a "direct" and a "linkages" component (Figure 5.2 and Table 5.3). The contribution of the linkages component to firm-specific aggregate volatility is more relevant than that of the direct effect ($\sim$ 80% vs $\sim$ 60%), especially when focusing on manufacturing ($\sim$ 90% vs $\sim$ 40%). For both the whole economy and the manufacturing sub-sample, the contribution of the direct effect slightly grows in importance in the crisis sub-period (2008–2014), even if it remains below that of the linkages channel.[15]

In terms of contributions of these two firm-specific channels to *aggregate TFP* volatility, σ_Ω, the direct effect can explain, on average, about 25% of aggregate TFP volatility when looking at the whole economy, but only about 11% when looking at manufacturing alone (consistently with the dominant presence of smaller production units in Italian manufacturing). By contrast, the linkages component explains, on average, around 33% of aggregate TFP volatility as for the whole economy and about 28% as for manufacturing alone.[16]

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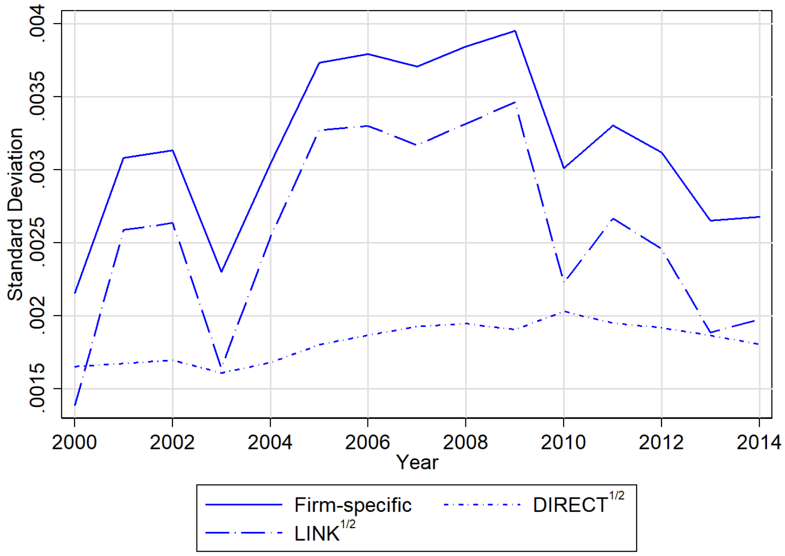
[15] Since firm-level variances are fixed, and so the only sources of variation are given by the sample (re)composition and by the weights, the fact that the direct effect slightly grows in importance in the crisis sub-period is likely due to the fact that the biggest firms in the sample increase their relative weight in the post-crisis period. Indeed, the top 10% firms in our sample (in terms of value added), account, on average, for 13% of GDP in the pre-crisis period (2000–2007), and for 16% of GDP in the post-crisis period (2008–2014), while the top 1% firms account, on average, for 8% of GDP in the pre-crisis period, and for 10% of GDP in the post-crisis period.

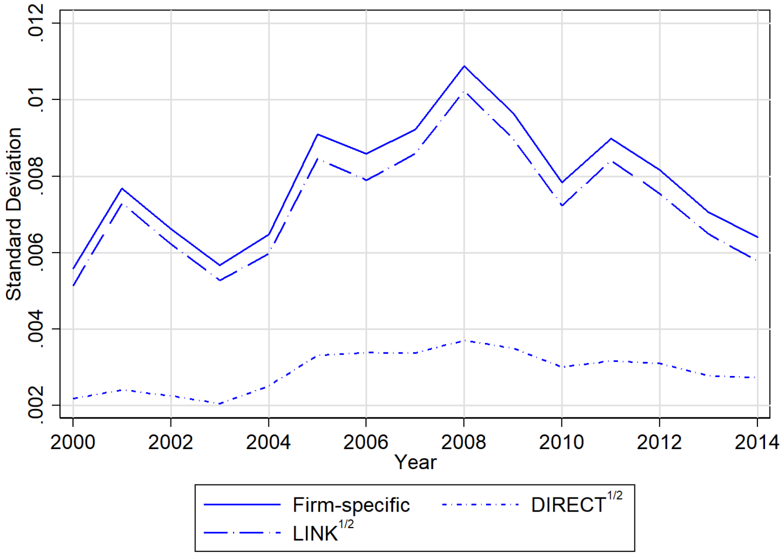
[16] These contributions are average relative standard deviations with respect to σ_Ω, $\frac{1}{T}\sum_\tau \frac{\sqrt{\text{DIRECT}_\tau}}{\sigma_{\Omega_\tau}}$ and

Figure 5.2: Contributions to Firm-specific Volatility

(a) Whole Economy



(b) Manufacturing



Notes: The figure presents yearly decompositions of firm-specific aggregate volatility, σ_{F_τ}, into a direct component, $\sqrt{\text{DIRECT}_\tau}$, measuring the aggregate contribution of firm-specific variances, and a linkages component, $\sqrt{\text{LINK}_\tau}$, measuring the aggregate contribution of covariances across firms. *Sources:* Cerved-INPS.

Table 5.3: CONTRIBUTIONS TO FIRM-SPECIFIC VOLATILITY

	Whole Economy		Manufacturing	
	St.Dev.	Relative SD	St.Dev.	Relative SD
		A. 2000–2014		
Firm-specific	0.0032	1.0000	0.0079	1.0000
Direct	0.0018	0.5894	0.0029	0.3709
Linkages	0.0026	0.7997	0.0073	0.9282
		B. 2000–2007		
Firm-specific	0.0031	1.0000	0.0074	1.0000
Direct	0.0017	0.5745	0.0027	0.3652
Linkages	0.0026	0.8091	0.0069	0.9305
		C. 2008–2014		
Firm-specific	0.0032	1.0000	0.0084	1.0000
Direct	0.0019	0.6064	0.0031	0.3775
Linkages	0.0026	0.7889	0.0078	0.9255

Notes: The table presents averages of σ_F, $\sqrt{\text{DIRECT}}$, and $\sqrt{\text{LINK}}$ over different periods, and average relative standard deviations with respect to σ_F. *Sources:* Cerved-INPS.

5.3.1 Direct Effect's Contribution

In order to illustrate the role of the firm size distribution emphasized by Gabaix (2011), we construct a simple counterfactual by artificially assuming that all firms are of equal size (i.e. $Y_{i,\tau-1}/Y_{\tau-1} = 1/N_{\tau-1} \quad \forall i$). The standard deviation of the counterfactual direct component is, on average, about 3 times smaller than the actual direct component (Table 5.4). This means that the presence of a fat right tail in the firm size distribution does matter when considering the direct contribution of firm-specific shocks to aggregate fluctuations. However, consistently with the typically smaller size of Italian productive units, this number is much smaller than that found by di Giovanni et al. (2014) focusing on French aggregate sales' fluctuations.

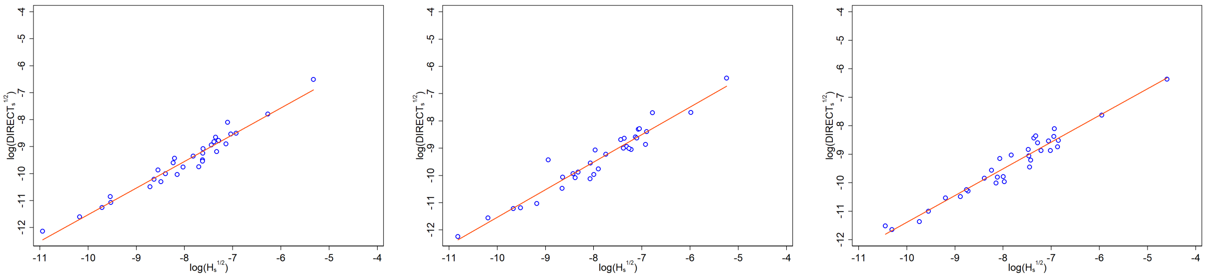
Table 5.4: DIRECT EFFECT'S CONTRIBUTION

	2000–2014		2000–2007		2008–2014	
	St.Dev.	Ratio	St.Dev.	Ratio	St.Dev.	Ratio
Direct	0.0018	1.00	0.0017	1.00	0.0019	1.00
Counterfactual	0.0007	2.78	0.0007	2.45	0.0006	3.16

Notes: The table presents averages over different periods of $\sqrt{\text{DIRECT}}$, its counterfactual implied by symmetric weights, and their ratio. *Sources:* Cerved-INPS.

$\frac{1}{T}\sum_{\tau}\frac{\sqrt{\text{LINK}_\tau}}{\sigma_{\Omega_\tau}}$ respectively.

Figure 5.3: Direct Volatility and the Herfindahl Index



(a) 2001 (b) 2006 (c) 2011

Notes: The figure plots, for different years in the sample, the sectoral (log) $\sqrt{\text{DIRECT}_{r\tau}}$ component against the (log) of $\sqrt{\sum_{i\in r}\left(Y_{i,\tau-1}/Y_{\tau-1}\right)^2}$. *Sources:* Cerved-INPS.

Next, we decompose the direct component in (3) into sectors, where sector r's direct component is

$$\text{DIRECT}_{r\tau} = \sum_{i\in r}\left(\frac{Y_{i,\tau-1}}{Y_{\tau-1}}\right)^2 \text{Var}\left(e_{it}\right)$$

so that $\text{DIRECT}_{\tau} = \sum_r \text{DIRECT}_{r\tau}$. We expect more concentrated sectors (i.e. with higher $H_{r\tau} = \sum_{i\in r}\left(Y_{i,\tau-1}/Y_{\tau-1}\right)^2$) to display larger direct volatilities. This prediction is tested in Figure 5.3: the correlation is strongly positive (observations are tightly clustered around the linear fits in the Figure), but less than perfect because firm-level variances differ both within and between sectors (as emerges in Tables 4.2 and 4.4).

Last, we shall recall that the direct component is intimately related to the presence of fat tails in the firm size distribution. Gabaix (2011), assuming for sake of theoretical exposure that all firms have volatility equal to σ, shows that if firm size is power law distributed, the lower the power law coefficient in absolute terms, the slower will be the rate at which the (direct) contribution of idiosyncratic shocks to aggregate volatility decays as the number of firms increases.[17] Therefore, by estimating power law coefficients from the firm size distribution of our sample, we can shed further light on the direct component, its lower relevance in the manufacturing sector, and its increased relevance in the post-crisis sub-period.

From Figure 5.4 we can see that, consistently with our previous results on the contribution of the direct component, power law coefficients are higher, in absolute value, in the manufacturing sector (which displays, coherently, a lower contribution arising from the direct component), and that they display a decreasing trend, in absolute value, both in the whole economy and in manufacturing (which is coherent with our finding of an increased importance of the direct component in the post-crisis sub-period).

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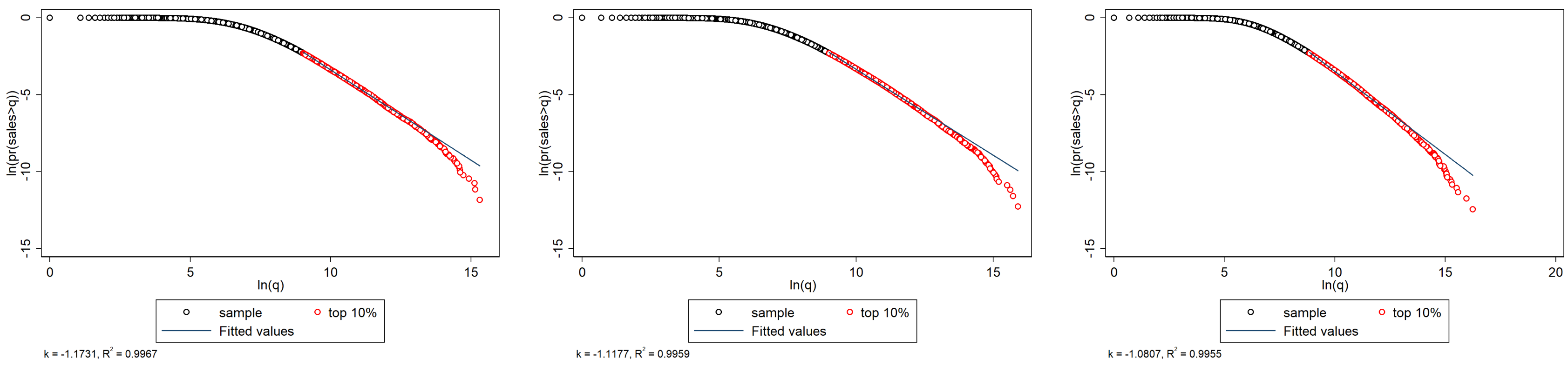
[17] For instance, Gabaix (2011) shows that a power law coefficient $k \geq 2$ implies a rate of decay of aggregate volatility originating from idiosyncratic firm-level shocks equal to $\sqrt{n}$, while a power law coefficient $k = 1$ (a.k.a. Zipf distribution) implies a rate of decay equal to $\ln(n)$.

Figure 5.4: Power Law Estimates of the Firm Size Distribution (Selected Years)

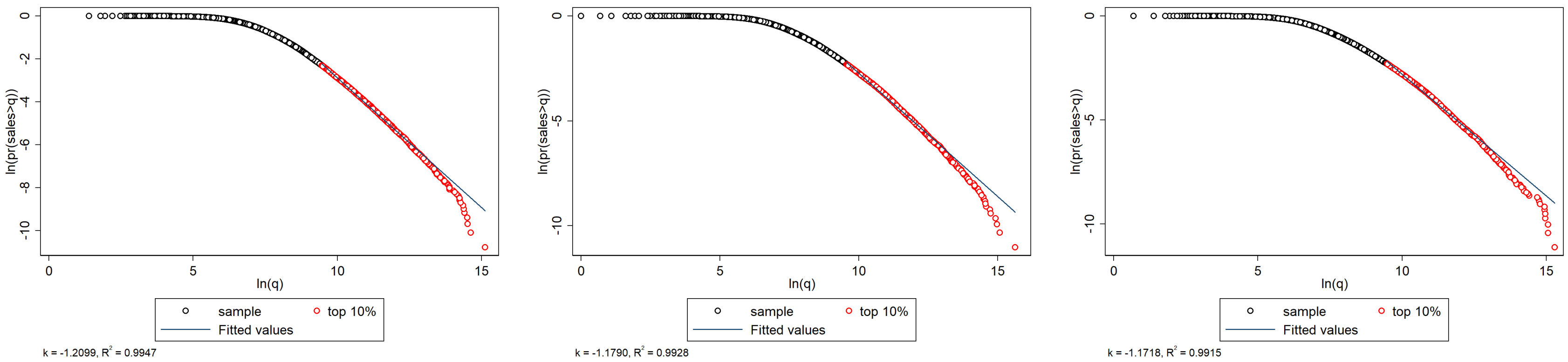
A. Whole Economy

(a) 2000 (b) 2007 (c) 2014



B. Manufacturing

(d) 2000 (e) 2007 (f) 2014



Notes: Power law coefficients k are estimated as in Axtell (2001) from OLS regressions of the form $\ln\left(\Pr\left(sales > q\right)\right) = a + k \cdot \ln\left(q\right) + \epsilon$ on the top 10% firms by sales in selected years and different samples (whole economy and manufacturing). Focusing on the top 10% firms as cutoff is performed on the basis of visual goodness of fit. Gabaix (2009) argues that choosing simple cut-off rules like this is what most researchers do, as there is no clear consensus on how to select the upper tail cutoff; di Giovanni and Levchenko (2013) claim that this is, in fact, a conservative approach, since the estimates obtained without imposing any minimum size cut-off would yield power law coefficients even lower in absolute value, suggesting an even more fat-tailed firm size distribution. *Sources:* Cerved.

5.3.2 Firm Linkages' Contribution

We now test the linkages hypothesis, i.e. whether the comovement captured by the link component arises from input-output linkages. One would ideally test the linkages hypothesis using firm-level measures of interconnections; as these are not available for the Italian economy, we use data on sector pairs from input-output (IO) tables by the Organization for Economic Cooperation and Development (OECD).[18]

We follow di Giovanni et al. (2014), decomposing the LINK component in (3) across sector pairs:

$$\mathrm{LINK}_{rs\tau} = \sum_{i \in r} \sum_{j \in s} \left(\frac{Y_{i,\tau-1}}{Y_{\tau-1}} \right) \left(\frac{Y_{j,\tau-1}}{Y_{\tau-1}} \right) \mathrm{Cov}\left(e_{it}, e_{jt} \right)$$

so that $\mathrm{LINK}_\tau = \sum_r \sum_s \mathrm{LINK}_{rs\tau}$. The mean intensity of IO linkages between sector r and sector s is defined, as in di Giovanni et al. (2014), as:

$$\overline{IO}_{rs} = \frac{1}{2} \left[\left(1 - \lambda_r\right) \rho_{rs} + \left(1 - \lambda_s\right) \rho_{sr} \right]$$

where λ_r is the share of value added in sector r's total output, and ρ_{rs} is the share of inputs sourced domestically from sector s in sector r's total domestic spending on intermediates. If comovement is the result of input-output linkages, we would expect a positive correlation between LINK_{rs} and $\overline{IO}_{rs}$.

As labor market interactions provide another potential cause of comovement between firms, we construct a pseudo-Herfindahl index of concentration of economic activity across Italian provinces to proxy the extent of labor market pooling occurring between each pair of sectors:

$$H_{rs} = \sum_{p=1}^{P} \tilde{z}_p^2$$

with:

$$\tilde{z}_p^2 = \frac{(\sum_{i \in r \cap p} L_i)(\sum_{i \in s \cap p} L_i)}{(\sum_{i \in r} L_i)(\sum_{i \in s} L_i)}$$

where L_i is the number of workers employed by firm i, p indexes Italian provinces, r and s index sectors, the time subscript t is omitted, and where, in order to have a measure of pooling occurring *between* sectors r and s (and not only *within* either one of them), we omit squared terms and keep only interaction terms from:

$$z_p^2 = \left(\frac{\sum_{i \in r, s \cap p} L_i}{\sum_{i \in r, s} L_i} \right)^2 = \frac{(\sum_{i \in r \cap p} L_i)^2 + (\sum_{i \in s \cap p} L_i)^2 + (\sum_{i \in r \cap p} L_i)(\sum_{i \in s \cap p} L_i)}{(\sum_{i \in r} L_i)^2 + (\sum_{i \in s} L_i)^2 + (\sum_{i \in r} L_i)(\sum_{i \in s} L_i)}$$

The resulting pseudo-Herfindahl measure preserves the property of ranging between $1/P$ and 1, but avoids the potential issue of capturing high concentration in only one of the two sectors.

Pairwise correlations are positive and highly significant for both mean IO intensity and our measure of labor market interaction (Top of Table 5.5 and Figure 5.5); the pairwise correlations

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[18] Available at `stats.oecd.org/Index.aspx?DataSetCode=IOTS`.

Table 5.5: DETERMINANTS OF LINKAGES VOLATILITY

I. Pairwise Correlations

LINK_{rs}	2001	2006	2011
$\overline{IO}_{rs}$	0.4788^{***}	0.4273^{***}	0.3684^{***}
H_{rs}	0.2861^{***}	0.2170^{***}	0.3329^{***}

II. Standardized Beta Coefficients

LINK_{rs}	2001	2006	2011
$\overline{IO}_{rs}$	0.432^{***}	0.400^{***}	0.284^{***}
H_{rs}	0.132^{***}	0.078^{*}	0.228^{***}
N	528	528	528
R^2	0.244	0.188	0.181
adj. R^2	0.242	0.185	0.178

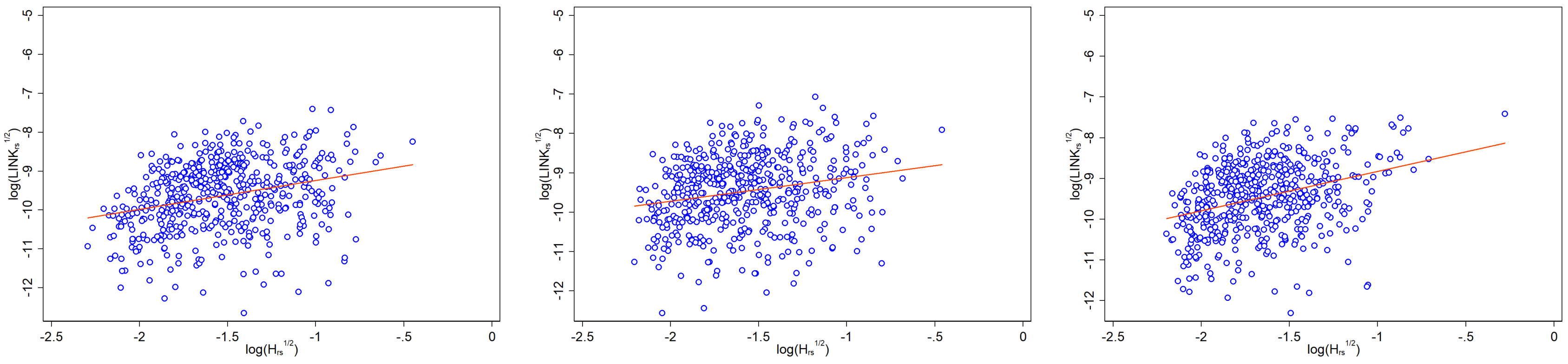
Notes: The tables report, for different years in the sample, pairwise correlation coefficients between (log) $\sqrt{\text{LINK}_{rs}}$ and (log) $\overline{IO}_{rs}$ or (log) $\sqrt{H_{rs}}$ (top table), and standardized beta coefficients from regressions of (log) $\sqrt{\text{LINK}_{rs}}$ on (log) $\overline{IO}_{rs}$ and (log) $\sqrt{H_{rs}}$. Significance: $^{*}0.10$, $^{**}0.05$, $^{***}0.01$. *Sources:* Cerved-INPS.

coefficients in Table 5.5 display a medium correlation between linkages volatilities and mean input-output intensity, and a low correlation between linkages volatilities and our measure of labor market pooling. These results can be visually gathered from Figure 5.5, where we can see that the observations are more clustered around their linear fits when considering mean IO intensities. Partial contributions, highlighted by means of standardized beta coefficients (Bottom of Table 5.5), coherently display a higher relevance and significance for mean IO intensity than for the labor market pooling indicator. A possible issue implying the reduced significance of labor market pooling when looking at partial contributions, is that such a measure of agglomeration possibly proxies, in part, input-output linkages as well; this is true, in particular, whenever firms preferably source/sell intermediate inputs from/to other firms located in proximity (as it is more likely for non-tradable sectors). Lastly, looking at the evolution of the correlations over time, the diminishing importance of mean IO intensity in explaining comovement across firms between sectors possibly derives from increased outsourcing of intermediate inputs from the global market, and correspondingly reduced sourcing from domestic firms.

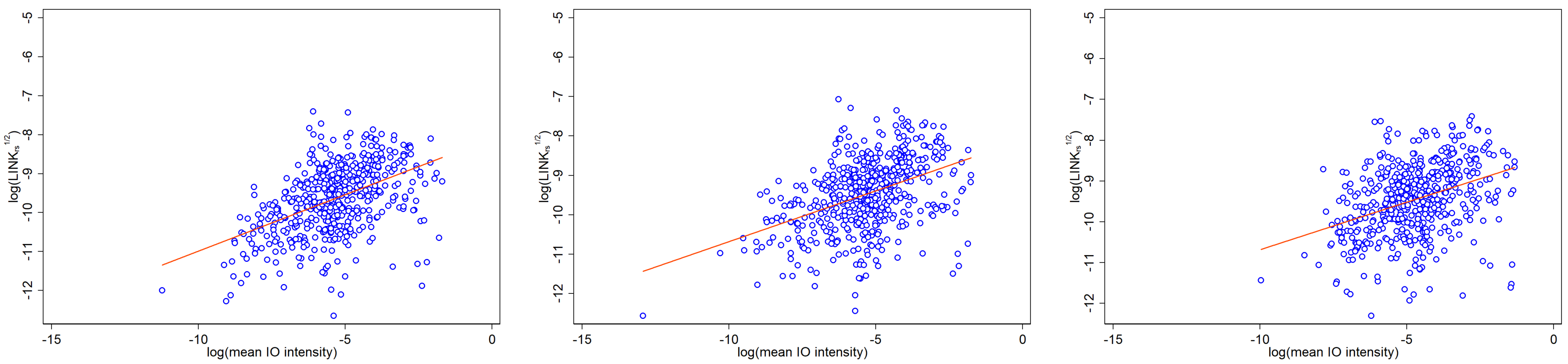
In sum, the results in this section suggest that the linkages component is not just an aggregate by-product of measurement error of TFP at the micro level, since more interconnected pairs of sectors (as measured from OECD IO tables, or labor market concentration) significantly display higher linkages volatilities.

Figure 5.5: DETERMINANTS OF LINKAGES VOLATILITY

A. Linkages Volatility and Labor Market Concentration


(a) 2001 (b) 2006 (c) 2011

B. Linkages Volatility and Mean Input-Output Intensity


(d) 2001 (e) 2006 (f) 2011

Notes: The figure plots, for different years in the sample, the (log) $\sqrt{\text{LINK}_{rs}}$ against an index of labor market concentration between sectors r and s (top panels), and against the (log) of the mean IO intensity between sectors r and s (bottom panels). *Sources:* Cerved-INPS.

6 Extensions and Robustness

6.1 Labor Productivity (LP)

Our baseline measure of firm-level productivity is firm-level TFP. As a robustness check, we use a different and more parsimonious measure: labor productivity (LP), proxied by the log of real value added per employee, $\text{lp}_{it} = \ln(Y_{it}/L_{it})$. Therefore, we isolate idiosyncratic shocks e'_{it} from $\Delta\text{lp}_{it} = \delta'_{st} + e'_{it}$ and, in addition, in a two-step procedure where, in the first step, we control for the growth rate in the capital stock per employee, $\Delta kl_{it} = \Delta\ln(K_{it}/L_{it})$ in $\Delta\text{lp}_{it} = \Delta kl_{it} + u_{it}$, retaining the residual as the growth rate in labor productivity not to be accrued to increases in the capital stock per employee (which should come closer to the growth rate of TFP), i.e. $\Delta\text{lp}'_{it} = u_{it}$. In the second step we then isolate idiosyncratic shocks from this latter proxy: $\Delta\text{lp}'_{it} = \delta''_{st} + e''_{it}$.

As shown in Table 6.1, TFP and LP growth are highly correlated, both in actual terms and in their idiosyncratic components; moreover, as expected, the correlation is even higher and almost perfect when controlling for the growth rate in the capital stock per employee. Accordingly, results are robust to using this different proxy for productivity shocks (Table 6.2).

Table 6.1: Correlation Between Shocks From Different Specifications

I. Productivity Growth

	TFP	LP	LP’
Corr. with TFP growth	1.0000	0.9203	0.9881

II. Idiosyncratic Component

	e_{it}	e'_{it}	e''_{it}
Corr. with Idiosyncratic TFP growth	1.0000	0.9189	0.9881

Notes: The table reports, on the top panel, sample correlations between Δtfp_{it} and Δtfp_{it}, Δlp_{it} and $\Delta\text{lp}'_{it}$, and, on the bottom panel, between their corresponding idiosyncratic components. *Sources:* Cerved-INPS.

6.2 Gross–Output Based Production Function

When estimating a value added based production function,[19] one forces the elasticity of output with respect to materials to be equal to 1 (i.e. there is a 1:1 relationship between gross output and intermediate inputs). For instance, a 10% increase in (value added based) TFP would mean that, for given K and L, *both* gross output and intermediate inputs have gone up by 10%. By contrast, a 10% increase in gross output based TFP would mean that for given K, L *and* M, *only* gross output has gone up by 10%.

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[19] The value added based production function is $y_{it} = \beta_l l_{it} + \beta_k k_{it} + \omega_{it}$, where on the right hand side we have value added $y_{it} = q_{it} - m_{it}$. The gross output based production function includes intermediate inputs, m_{it}, on the right hand side $q_{it} = \alpha_l l_{it} + \alpha_k k_{it} + \alpha_m m_{it} + \tilde{\omega}_{it}$).

Table 6.2: AGGREGATE IMPACT OF FIRM-SPECIFIC SHOCKS ON AGGREGATE VOLATILITY (LP BASED, CONTROLLING FOR Δkl_{it})

	Whole Economy		Manufacturing	
	St.Dev.	Relative SD	St.Dev.	Relative SD
A. 2000–2014				
Actual ($\bar{\sigma}_{\Omega}$)	0.0075	1.0000	0.0262	1.0000
Firm-specific ($\bar{\sigma}_{F}$)	0.0031	0.4094	0.0078	0.3007
Common-Sector ($\bar{\sigma}_{\Delta}$)	0.0061	0.8146	0.0217	0.8284
B. 2000–2007				
Actual ($\bar{\sigma}_{\Omega}$)	0.0071	1.0000	0.0233	1.0000
Firm-specific ($\bar{\sigma}_{F}$)	0.0030	0.4279	0.0073	0.3133
Common-Sector ($\bar{\sigma}_{\Delta}$)	0.0054	0.7637	0.0181	0.7785
C. 2008–2014				
Actual ($\bar{\sigma}_{\Omega}$)	0.0081	1.0000	0.0296	1.0000
Firm-specific ($\bar{\sigma}_{F}$)	0.0031	0.3883	0.0084	0.2863
Common-Sector ($\bar{\sigma}_{\Delta}$)	0.0069	0.8728	0.0257	0.8855

Notes: The table summarizes the results from adopting a more parsimonious proxy for productivity growth, based on value added per employee controlling for the growth rate in the capital stock per employee. Results are reported in terms of averages $\bar{\sigma}_{\Omega}$, $\bar{\sigma}_{F}$, and $\bar{\sigma}_{\Delta}$ over different periods, and average relative standard deviations with respect to σ_{Ω}. *Sources:* Cerved-INPS.

A direct implication of this is that firm-Level TFP shocks derived from a value added based production function specification are larger, by construction, than shocks derived from a gross output based specification. While this is conceptually taken into account, when proceeding with aggregation, by using value added weights in the former case, and Domar weights in the latter case (as in Hulten, 1978), there still is the potential that idiosyncratic TFP shocks derived from a gross output based specification are not found to have a significant impact on aggregate fluctuations. To control for this issue, we repeat the exercise by adopting a gross output based specification, and proceeding with Domar aggregation.[20]

Idiosyncratic shocks isolated from gross output based TFP explain about 26% of aggregate TFP volatility, as far as the whole economy is concerned: a lower (but still non-trivial) fraction than that found from the value added based, baseline specification (40%). As for the manufacturing sector, the relative fall in the explanatory power of idiosyncratic shocks is more contained when turning to the gross output based specification (25% vs the 30% obtained in the value added based specification); this can be reconciled with the fact that the notion of Total Factor Productivity itself is more meaningful for the manufacturing sector than for services sectors.

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[20] That this, with reference to section 3.2, $\tilde{g}_{\Omega_{t|\tau}} = \sum_i \left(\frac{Q_{i,\tau-1}}{Y_{\tau-1}}\right) \tilde{g}_{it} = \sum_s \left(\frac{Q_{s,\tau-1}}{Y_{\tau-1}}\right) \tilde{\delta}_{st} + \sum_i \left(\frac{Q_{i,\tau-1}}{Y_{\tau-1}}\right) \tilde{e}_{it}$, where $\tilde{g}_{it} = \tilde{\omega}_{it} - \tilde{\omega}_{i,t-1}$, and $\tilde{\omega}_{it} = q_{it} - \hat{\alpha}_m m_{it} - \hat{\alpha}_l l_{it} - \hat{\alpha}_k k_{it}$, and so on.

Table 6.3: AGGREGATE IMPACT OF FIRM-SPECIFIC SHOCKS ON AGGREGATE VOLATILITY (GROSS OUTPUT BASED SHOCKS)

	Whole Economy		Manufacturing	
	St.Dev.	Relative SD	St.Dev.	Relative SD
A. 2000–2014				
Actual ($\bar{\sigma}_\Omega$)	0.0080	1.0000	0.0279	1.0000
Firm-specific ($\bar{\sigma}_F$)	0.0021	0.2624	0.0068	0.2460
Common-Sector ($\bar{\sigma}_\Delta$)	0.0075	0.9413	0.0260	0.9304
B. 2000–2007				
Actual ($\bar{\sigma}_\Omega$)	0.0072	1.0000	0.0237	1.0000
Firm-specific ($\bar{\sigma}_F$)	0.0019	0.2650	0.0059	0.2505
Common-Sector ($\bar{\sigma}_\Delta$)	0.0066	0.9138	0.0213	0.8955
C. 2008–2014				
Actual ($\bar{\sigma}_\Omega$)	0.0089	1.0000	0.0327	1.0000
Firm-specific ($\bar{\sigma}_F$)	0.0023	0.2593	0.0078	0.2408
Common-Sector ($\bar{\sigma}_\Delta$)	0.0086	0.9727	0.0315	0.9703

Notes: The table presents averages $\bar{\sigma}_\Omega$, $\bar{\sigma}_F$, and $\bar{\sigma}_\Delta$ over different periods — e.g. $\bar{\sigma}_F = \frac{1}{T}\sum_\tau \sigma_{F_\tau}$ — and average relative standard deviations with respect to σ_Ω — e.g. $\frac{1}{T}\sum_\tau \frac{\sigma_{F_\tau}}{\sigma_{\Omega_\tau}}$. *Sources:* Cerved-INPS.

6.3 Heterogeneous Responses to Common Shocks

In our baseline model, we do not allow firms to react to common shocks in different ways, and we might therefore incorrectly interpret as idiosyncratic shocks what are, instead, heterogeneous responses to common shocks. In order to control for these heterogeneous responses, we follow di Giovanni et al.'s (2014) extension and isolate idiosyncratic shocks from the following augmented model, where sector fixed effects are interacted with firm-level characteristics $\mathbf{Z}_{it} = (z_{1it}, ..., z_{kit}, ..., z_{Kit})'$

$$g_{it} = \delta_{st} + \sum_{k=1}^{K} \delta_{st} \times z_{kit} + \boldsymbol{\beta}'\mathbf{Z}_{it} + e_{it}$$

Firm-level characteristics include: (i) firm size (number of employees quartile dummies), (ii) firm age (dummy for whether the firm is more or less than 5 years old),[21] (iii) markups (estimated at firm-level as proposed by De Loecker and Warzynski, 2012).[22]

Results are robust to controlling for heterogeneous responses to common shocks, both when using a value-added based specification (top of Table 6.4) and a gross-output based specification (bottom of Table 6.4).

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[21] Fort et al. (2013) find young/small US businesses to be more sensitive to cyclical volatility than older/larger businesses.

[22] The procedure by De Loecker and Warzynski (2012) is detailed in Appendix D.

Table 6.4: AGGREGATE IMPACT OF FIRM-SPECIFIC SHOCKS ON AGGREGATE VOLATILITY (DIFFERING SENSITIVITY)

I. Value Added Based Specification

			Differing Sensitivity by:							
	Benchmark		(i) Size		(ii) Age		(iii) Markup*		(iv) All	
Average:	St.Dev.	Rel.SD	St.Dev.	Rel.SD	St.Dev.	Rel.SD	St.Dev.	Rel.SD	St.Dev.	Rel.SD
A. 2000–2014										
Actual ($\bar{\sigma}_\Omega$)	0.0076	1.0000	0.0076	1.0000	0.0076	1.0000	0.0076	1.0000	0.0076	1.0000
Firm-specific ($\bar{\sigma}_F$)	0.0031	0.4181	0.0031	0.4107	0.0031	0.4120	0.0031	0.4107	0.0030	0.3990
B. 2000–2007										
Actual ($\bar{\sigma}_\Omega$)	0.0071	1.0000	0.0071	1.0000	0.0071	1.0000	0.0071	1.0000	0.0071	1.0000
Firm-specific ($\bar{\sigma}_F$)	0.0031	0.4375	0.0030	0.4206	0.0030	0.4218	0.0030	0.4247	0.0028	0.3950
C. 2008–2014										
Actual ($\bar{\sigma}_\Omega$)	0.0082	1.0000	0.0082	1.0000	0.0082	1.0000	0.0082	1.0000	0.0082	1.0000
Firm-specific ($\bar{\sigma}_F$)	0.0032	0.3959	0.0032	0.3994	0.0032	0.4008	0.0032	0.3948	0.0032	0.4036

II. Gross Output Based Specification

			Differing Sensitivity by:									
	Benchmark		(i) Size		(ii) Age		(iii) Markup*		(iv) Markup**		(v) All	
Avg:	St.Dev.	Rel.SD	St.Dev.	Rel.SD	St.Dev.	Rel.SD	St.Dev.	Rel.SD	St.Dev.	Rel.SD	St.Dev.	Rel.SD
A. 2000–2014												
$\bar{\sigma}_\Omega$	0.0080	1.0000	0.0080	1.0000	0.0080	1.0000	0.0080	1.0000	0.0080	1.0000	0.0080	1.0000
$\bar{\sigma}_F$	0.0021	0.2621	0.0021	0.2650	0.0021	0.2664	0.0022	0.2773	0.0025	0.3133	0.0022	0.2694
B. 2000–2007												
$\bar{\sigma}_\Omega$	0.0072	1.0000	0.0072	1.0000	0.0072	1.0000	0.0072	1.0000	0.0072	1.0000	0.0072	1.0000
$\bar{\sigma}_F$	0.0019	0.2650	0.0019	0.2648	0.0019	0.2669	0.0020	0.2824	0.0023	0.3236	0.0020	0.2785
C. 2008–2014												
$\bar{\sigma}_\Omega$	0.0089	1.0000	0.0089	1.0000	0.0089	1.0000	0.0089	1.0000	0.0089	1.0000	0.0089	1.0000
$\bar{\sigma}_F$	0.0023	0.2588	0.0023	0.2651	0.0023	0.2657	0.0024	0.2713	0.0027	0.3016	0.0023	0.2590

Notes: The tables summarize the results from controlling for differing sensitivity to common shocks. Results are reported in terms of averages $\bar{\sigma}_\Omega$, $\bar{\sigma}_F$, and $\bar{\sigma}_\Delta$ over different periods, and average relative standard deviations with respect to σ_Ω. * Labor-based markups, ** Materials-based markups (more details in Appendix D).
Sources: Cerved-INPS.

7 Conclusions

Using a sample of Italian firms retrieved from the Cerved and Inps databases for the period 1999–2014, and adopting a version of the methodology by di Giovanni et al. (2014) modified and adapted for data availability, we investigate the granular sources of the Italian business cycle, i.e. the question of whether firm-level dynamics have an impact on aggregate fluctuations. On the one hand, shocks to large firms may not average out, leading to aggregate fluctuations (Gabaix, 2011); on the other hand, shocks to individual firms can be propagated through input-output linkages, leading as well to movements at the aggregate level (Acemoglu et al., 2012).

This topic is particularly worth investigating in Italy, which is characterized by an average small size of firms, which in principle could weaken the granular hypothesis, and a strong geographical agglomeration of firms by sector of activity, which could strengthen the idiosyncratic sources of aggregate fluctuations.

Even if common shocks are prevalent in explaining aggregate TFP volatility, the contribution of firm-specific shocks is found to be non-trivial: the aggregate impact of idiosyncratic productivity shocks on aggregate TFP volatility is around 30 to 40% across different specifications. Further, by exploiting the decomposition of the firm-specific component of aggregate TFP volatility proposed by Carvalho and Gabaix (2013) and di Giovanni et al. (2014) we find that the contribution of the linkages component to firm-specific aggregate volatility is more relevant than that of the direct effect ($\sim 80\%$ vs $\sim 60\%$), especially when focusing on manufacturing ($\sim 90\%$ vs $\sim 40\%$). Moreover, the contribution of the direct effect —though remaining well below that of the linkages channel— slightly grows in importance during the crisis.

The direct and linkages components are not mere aggregate by-products of measurement error of TFP at the micro level. A counterfactual direct component —implied by artificially setting firms of equal size— would have an impact 3 times smaller; more concentrated sectors show higher direct volatilities as well. Additionally, more interconnected couples of sectors (as measured from OECD IO tables) show higher linkages volatilities.

Taken together, the results suggest that even in an economy such as the Italian one —dominated by many small firms— firm-level idiosyncratic dynamics do have an impact on aggregate fluctuations. Thus, an analysis of micro-level dynamics is essential for a better understanding of aggregate dynamics.

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Appendices

A The Cerved-INPS Dataset

Tables A.1 and A.2 and Figure A.1 report the distribution of firms by 2-digit ATECO sectors in selected years, both with reference to the full Cerved-INPS merged dataset, and to the sub-sample used in the analysis after the cleaning procedure detailed in Section 4. The distributions from the full and cleaned datasets are not found to be statistically different according to Wilcoxon rank-sum and Kolmogorov-Smirnov tests.[23]

A.1 Representativeness

Table A.3 reports the coverage of the Cerved-INPS dataset, both with reference to the full dataset, and with focus on the sub-sample used in the analysis, i.e. after the exclusion of firms with gaps in the relevant variables (in parentheses). Coverage is expressed in terms of aggregate shares of value added or employment relative to the aggregate data reported by the Italian national statistical office (Istat).

A.2 Summary Statistics for Selected Years

Table A.4 replicates the summary statistics reported in Table 4.1 for selected years in the panel.

A.3 Comparison with the Invind Dataset

Through the contribution of its local branches, the Bank of Italy has conducted, since 1972, sample surveys on industrial companies, and, from 2002, on non-financial private service companies as well (*Indagine Sulle Imprese Industriali e dei Servizi — Invind*). Each year the survey gathers information on investments, gross sales, workforce and other economic variables relating to Italian industrial and service firms with 20 or more employees.[24]

The aim of the Invind surveys is to quickly access main information about the economic activity and to econometrically analyse firms' behaviour. Moreover, these surveys allow the Bank of Italy to acquire information about firms' investment decisions, employment structure, working hours and wages, export activities, and debt.

Table A.5 reports the correlation between the variables from the Cerved-INPS and the Invind datasets, for those firm-year observations which appear in both datasets and those variables which are reported in both of them.

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[23] Also the distribution of *workers* across sectors is statistically unchanged after our cleaning procedure.

[24] Reports of recent surveys are available at `www.bancaditalia.it/pubblicazioni/indagine-imprese/`.

Table A.1: Distribution of Firms by 2-digit Sector (Selecected Years, Sec. 01 to 46)

	A. 2000		B. 2007		C. 2014	
Sec.	Full [%]	Sample [%]	Full [%]	Sample [%]	Full [%]	Sample [%]
01	2,825 [00.89]	1,136 [00.73]	3,052 [00.66]	1,279 [00.54]	3,362 [00.69]	1,438 [00.57]
02	181 [00.06]	76 [00.05]	217 [00.05]	93 [00.04]	228 [00.05]	103 [00.04]
03	684 [00.22]	277 [00.18]	925 [00.20]	340 [00.14]	793 [00.16]	306 [00.12]
05	4 [00.00]	0 [00.00]	4 [00.00]	0 [00.00]	4 [00.00]	0 [00.00]
06	7 [00.00]	0 [00.00]	10 [00.00]	0 [00.00]	16 [00.00]	0 [00.00]
07	6 [00.00]	0 [00.00]	3 [00.00]	0 [00.00]	1 [00.00]	0 [00.00]
08	1,376 [00.43]	668 [00.43]	1,465 [00.32]	768 [00.32]	1,213 [00.25]	697 [00.28]
09	14 [00.00]	0 [00.00]	20 [00.00]	0 [00.00]	20 [00.00]	0 [00.00]
10	6,124 [01.93]	3,307 [02.12]	7,790 [01.70]	4,502 [01.90]	9,046 [01.85]	5,219 [02.07]
11	849 [00.27]	388 [00.25]	1,017 [00.22]	490 [00.21]	1,045 [00.21]	546 [00.22]
12	33 [00.01]	0 [00.00]	23 [00.01]	0 [00.00]	13 [00.00]	0 [00.00]
13	4,747 [01.50]	2,497 [01.60]	4,638 [01.01]	2,666 [01.12]	3,781 [00.77]	2,483 [00.98]
14	6,696 [02.11]	2,886 [01.85]	6,500 [01.42]	3,077 [01.30]	5,360 [01.10]	2,815 [01.12]
15	3,934 [01.24]	2,135 [01.37]	4,202 [00.91]	2,522 [01.06]	4,200 [00.86]	2,575 [01.02]
16	2,243 [00.71]	1,242 [00.79]	3,388 [00.74]	1,960 [00.83]	3,360 [00.69]	2,061 [00.82]
17	1,737 [00.55]	1,074 [00.69]	1,893 [00.41]	1,223 [00.52]	1,820 [00.37]	1,262 [00.50]
18	3,474 [01.09]	2,043 [01.31]	4,124 [00.90]	2,550 [01.07]	3,621 [00.74]	2,363 [00.94]
19	171 [00.05]	82 [00.05]	172 [00.04]	90 [00.04]	158 [00.03]	91 [00.04]
20	2,682 [00.84]	1,655 [01.06]	2,877 [00.63]	1,869 [00.79]	2,782 [00.57]	1,850 [00.73]
21	466 [00.15]	275 [00.18]	484 [00.11]	280 [00.12]	430 [00.09]	263 [00.10]
22	4,873 [01.53]	3,037 [01.94]	5,434 [01.18]	3,565 [01.50]	5,084 [01.04]	3,512 [01.39]
23	5,472 [01.72]	2,940 [01.88]	6,366 [01.39]	3,591 [01.51]	5,717 [01.17]	3,542 [01.40]
24	1,599 [00.50]	989 [00.63]	1,612 [00.35]	1,025 [00.43]	1,474 [00.30]	1,036 [00.41]
25	15,478 [04.88]	9,856 [06.30]	21,374 [04.65]	14,299 [06.03]	22,496 [04.60]	15,205 [06.03]
26	3,045 [00.96]	1,711 [01.09]	3,403 [00.74]	2,024 [00.85]	3,192 [00.65]	2,002 [00.79]
27	3,600 [01.13]	2,187 [01.40]	4,097 [00.89]	2,581 [01.09]	3,836 [00.78]	2,488 [00.99]
28	11,124 [03.50]	6,819 [04.36]	12,329 [02.68]	7,998 [03.37]	11,719 [02.40]	7,944 [03.15]
29	1,612 [00.51]	954 [00.61]	1,727 [00.38]	1,045 [00.44]	1,502 [00.31]	936 [00.37]
30	1,177 [00.37]	584 [00.37]	1,763 [00.38]	845 [00.36]	1,568 [00.32]	781 [00.31]
31	4,671 [01.47]	2,425 [01.55]	5,496 [01.20]	3,102 [01.31]	4,600 [00.94]	2,893 [01.15]
32	3,305 [01.04]	1,767 [01.13]	3,976 [00.87]	2,351 [00.99]	3,596 [00.74]	2,265 [00.90]
33	3,071 [00.97]	1,779 [01.14]	4,713 [01.03]	2,975 [01.25]	5,348 [01.09]	3,200 [01.27]
35	579 [00.18]	325 [00.21]	1,065 [00.23]	477 [00.20]	1,915 [00.39]	754 [00.30]
36	174 [00.05]	94 [00.06]	300 [00.07]	189 [00.08]	273 [00.06]	178 [00.07]
37	353 [00.11]	204 [00.13]	530 [00.12]	333 [00.14]	556 [00.11]	341 [00.14]
38	1,814 [00.57]	1,012 [00.65]	2,894 [00.63]	1,646 [00.69]	3,436 [00.70]	1,990 [00.79]
39	149 [00.05]	74 [00.05]	245 [00.05]	138 [00.06]	288 [00.06]	164 [00.06]
41	22,324 [07.03]	9,178 [05.87]	41,105 [08.95]	18,494 [07.79]	34,943 [07.15]	15,648 [06.20]
42	2,607 [00.82]	1,272 [00.81]	3,708 [00.81]	1,919 [00.81]	3,983 [00.81]	2,234 [00.89]
43	12,253 [03.86]	6,522 [04.17]	24,163 [05.26]	14,327 [06.04]	28,231 [05.78]	16,061 [06.36]
45	9,212 [02.90]	3,534 [02.26]	13,453 [02.93]	5,911 [02.49]	14,882 [03.04]	7,242 [02.87]
46	45,445 [14.31]	21,729 [13.90]	57,344 [12.49]	29,219 [12.31]	58,789 [12.03]	31,641 [12.54]

Notes: The table reports the distribution of firms by 2-digit ATECO sectors 01 to 46 in selected years, both with reference to the full CERVED-INPS merged dataset (*Full* columns), and to the sub-sample used in the analysis after the cleaning procedure detailed in Section 4 (*Sample* columns). *Sources:* Cerved-INPS.

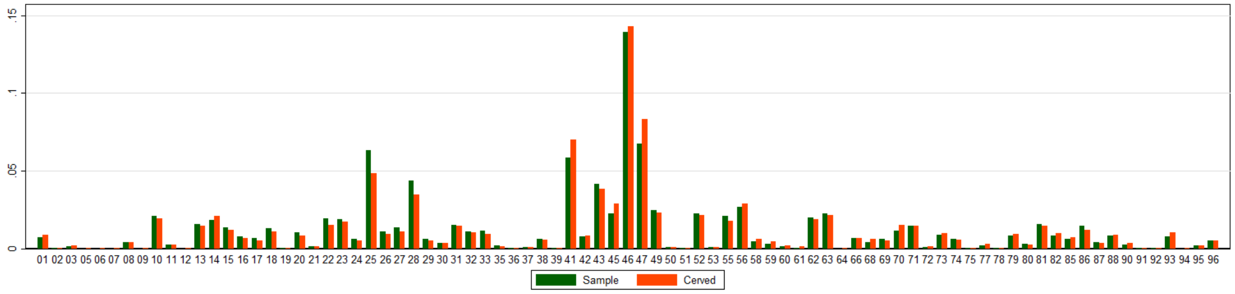
Table A.2: Distribution of Firms by 2-digit Sector (Selecected Years, Sec. 47 to 96)

	A. 2000		B. 2007		C. 2014	
Sec.	Full [%]	Sample [%]	Full [%]	Sample [%]	Full [%]	Sample [%]
47	26,539 [08.36]	10,522 [06.73]	40,737 [08.87]	17,622 [07.43]	45,221 [09.25]	21,091 [08.36]
49	7,432 [02.34]	3,854 [02.47]	11,853 [02.58]	6,545 [02.76]	13,933 [02.85]	7,442 [02.95]
50	368 [00.12]	177 [00.11]	448 [00.10]	193 [00.08]	430 [00.09]	212 [00.08]
51	115 [00.04]	35 [00.02]	141 [00.03]	42 [00.02]	95 [00.02]	29 [00.01]
52	6,956 [02.19]	3,553 [02.27]	8,988 [01.96]	4,393 [01.85]	9,111 [01.86]	4,027 [01.60]
53	298 [00.09]	152 [00.10]	384 [00.08]	190 [00.08]	516 [00.11]	210 [00.08]
55	5,692 [01.79]	3,269 [02.09]	8,962 [01.95]	5,029 [02.12]	10,626 [02.17]	5,561 [02.20]
56	9,240 [02.91]	4,198 [02.69]	20,029 [04.36]	9,302 [03.92]	26,842 [05.49]	11,105 [04.40]
58	2,015 [00.63]	731 [00.47]	2,386 [00.52]	922 [00.39]	2,068 [00.42]	860 [00.34]
59	1,478 [00.47]	526 [00.34]	1,857 [00.40]	722 [00.30]	1,874 [00.38]	726 [00.29]
60	757 [00.24]	270 [00.17]	1,013 [00.22]	337 [00.14]	840 [00.17]	300 [00.12]
61	435 [00.14]	122 [00.08]	930 [00.20]	367 [00.15]	1,018 [00.21]	410 [00.16]
62	5,959 [01.88]	3,098 [01.98]	8,186 [01.78]	4,708 [01.98]	9,297 [01.90]	4,973 [01.97]
63	6,863 [02.16]	3,537 [02.26]	9,822 [02.14]	5,428 [02.29]	10,952 [02.24]	5,667 [02.25]
64	12 [00.00]	0 [00.00]	11 [00.00]	0 [00.00]	10 [00.00]	0 [00.00]
66	2,123 [00.67]	1,073 [00.69]	4,055 [00.88]	1,968 [00.83]	3,984 [00.82]	1,926 [00.76]
68	1,944 [00.61]	649 [00.42]	4,675 [01.02]	1,650 [00.70]	4,576 [00.94]	1,703 [00.67]
69	1,728 [00.54]	992 [00.63]	2,814 [00.61]	1,696 [00.71]	2,876 [00.59]	1,577 [00.62]
70	4,795 [01.51]	1,795 [01.15]	7,580 [01.65]	3,230 [01.36]	8,637 [01.77]	3,405 [01.35]
71	4,640 [01.46]	2,317 [01.48]	7,471 [01.63]	4,080 [01.72]	8,532 [01.75]	4,544 [01.80]
72	434 [00.14]	158 [00.10]	742 [00.16]	252 [00.11]	1,038 [00.21]	374 [00.15]
73	3,196 [01.01]	1,437 [00.92]	4,356 [00.95]	2,090 [00.88]	4,405 [00.90]	2,069 [00.82]
74	1,900 [00.60]	968 [00.62]	3,371 [00.73]	1,953 [00.82]	4,862 [00.99]	2,524 [01.00]
75	27 [00.01]	14 [00.01]	72 [00.02]	37 [00.02]	105 [00.02]	50 [00.02]
77	959 [00.30]	330 [00.21]	2,447 [00.53]	908 [00.38]	2,686 [00.55]	1,102 [00.44]
78	247 [00.08]	111 [00.07]	379 [00.08]	181 [00.08]	388 [00.08]	166 [00.07]
79	3,017 [00.95]	1,315 [00.84]	3,675 [00.80]	1,677 [00.71]	3,393 [00.69]	1,532 [00.61]
80	853 [00.27]	493 [00.32]	1,240 [00.27]	656 [00.28]	1,311 [00.27]	595 [00.24]
81	4,741 [01.49]	2,451 [01.57]	6,842 [01.49]	3,524 [01.49]	8,092 [01.66]	3,485 [01.38]
82	3,118 [00.98]	1,315 [00.84]	5,556 [01.21]	2,512 [01.06]	6,424 [01.31]	2,754 [01.09]
85	2,424 [00.76]	969 [00.62]	3,718 [00.81]	1,576 [00.66]	5,048 [01.03]	2,035 [00.81]
86	3,938 [01.24]	2,293 [01.47]	5,893 [01.28]	3,434 [01.45]	7,637 [01.56]	4,093 [01.62]
87	1,124 [00.35]	692 [00.44]	1,792 [00.39]	1,049 [00.44]	2,490 [00.51]	1,237 [00.49]
88	2,833 [00.89]	1,292 [00.83]	4,374 [00.95]	1,916 [00.81]	5,149 [01.05]	1,955 [00.77]
90	1,103 [00.35]	420 [00.27]	1,414 [00.31]	549 [00.23]	1,452 [00.30]	595 [00.24]
91	223 [00.07]	77 [00.05]	311 [00.07]	114 [00.05]	338 [00.07]	125 [00.05]
92	102 [00.03]	32 [00.02]	566 [00.12]	260 [00.11]	1,205 [00.25]	428 [00.17]
93	3,299 [01.04]	1,246 [00.80]	5,215 [01.14]	2,065 [00.87]	6,152 [01.26]	2,454 [00.97]
94	10 [00.00]	0 [00.00]	3 [00.00]	0 [00.00]	0 [00.00]	0 [00.00]
95	625 [00.20]	313 [00.20]	872 [00.19]	515 [00.22]	1,036 [00.21]	551 [00.22]
96	1,744 [00.55]	811 [00.52]	4,198 [00.91]	1,837 [00.77]	5,500 [01.13]	2,321 [00.92]
Total	317,496 [100]	156,340 [100]	459,279 [100]	237,292 [100]	488,830 [100]	252342 [100]

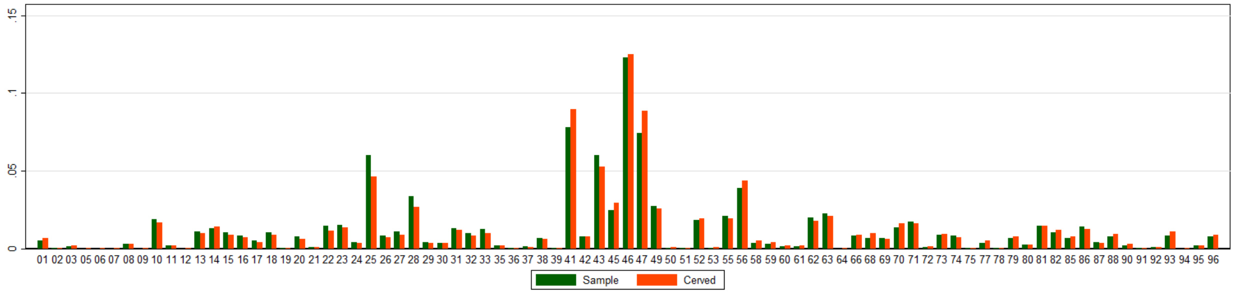
Notes: The table reports the distribution of firms by 2-digit ATECO sectors 47 to 96 in selected years, both with reference to the full CERVED-INPS merged dataset (columns *Full*), and to the sub-sample used in the analysis after the cleaning procedure detailed in Section 4 (*Sample* columns). *Sources:* Cerved-INPS.

Figure A.1: Distribution of Firms by 2-digit Sector (Selecedted Years)

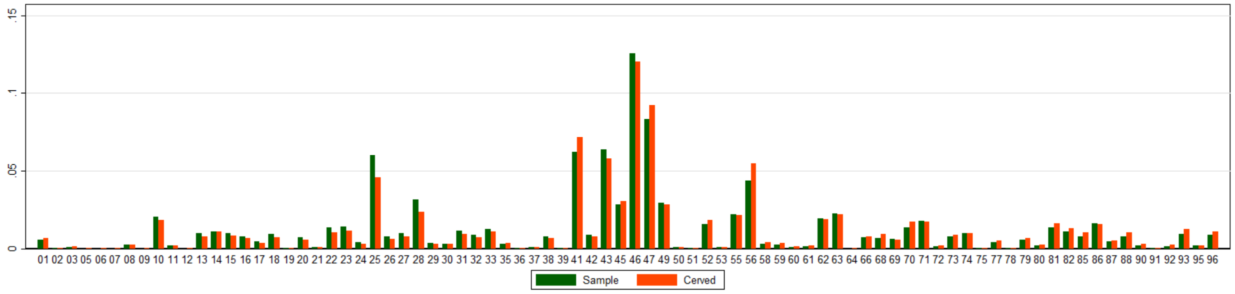
A. 2000



B. 2007



C. 2014



Notes: The figure reports the distribution of firms by 2-digit ATECO sectors in selected years, both with reference to the full CERVED-INPS merged dataset (Green bars), and to the sub-sample used in the analysis after the cleaning procedure detailed in Section 4 (Orange bars). *Sources:* Cerved-INPS.

Table A.3: COVERAGE OF THE CERVED DATASET (1999–2014)

	Whole Economy %		Manufacturing %	
Year	Value Added	Employees	Value Added	Employees
1999	27 (15)	36 (21)	73 (42)	72 (44)
2000	28 (17)	38 (23)	75 (46)	74 (47)
2001	28 (18)	39 (25)	69 (48)	76 (50)
2002	28 (18)	40 (26)	68 (48)	75 (50)
2003	29 (18)	40 (26)	70 (48)	75 (50)
2004	29 (19)	42 (27)	71 (49)	76 (50)
2005	29 (19)	42 (27)	71 (50)	76 (51)
2006	30 (20)	43 (28)	73 (52)	75 (51)
2007	31 (21)	44 (28)	73 (52)	76 (52)
2008	30 (21)	44 (29)	72 (52)	76 (53)
2009	31 (21)	46 (30)	74 (54)	78 (54)
2010	32 (22)	46 (31)	74 (56)	79 (56)
2011	32 (23)	46 (32)	74 (57)	79 (57)
2012	32 (23)	46 (32)	73 (57)	78 (57)
2013	32 (23)	47 (32)	75 (59)	79 (59)
2014	32 (22)	46 (31)	76 (59)	80 (58)
Average	30 (20)	43 (28)	73 (52)	77 (52)

Notes: The table reports, for each year of the period 1999–2014, the coverage of the full Cerved-INPS dataset, and that of the sub-sample used in the analysis (in parentheses). Coverage is expressed in terms of the sum over all firms in the dataset of either value added or employees relative to the corresponding aggregate as reported by Istat. *Sources:* Cerved-INPS and Istat.

Table A.4: Summary Statistics for Selected Years in the Panel

	Obs.	Mean	St. Dev.	p10	p25	p50	p75	p90
			A. 1999–2014					
Value Added	3,597,015	1267.33	25335.86	48.43	105.61	257.59	663.35	1759.31
Employees	3,597,015	22.38	287.54	1	2.75	6.17	14.17	34.92
Capital Stock	3,597,015	1344.78	36252.45	13.13	37.26	116.62	423.25	1484.65
TFP	3,597,015	33.34	72.90	11.72	18.03	26.46	38.15	55.96
			B. 2000					
Value Added	156,340	1446.81	19569.59	58.90	130.18	325.09	846.65	2201.01
Employees	156,340	24.84	188.86	1.08	3	7.17	17.33	41.83
Capital Stock	156,340	1282.33	27590.41	12.32	35.06	113.36	459.49	1622.62
TFP	156,340	37.16	155.01	13.96	20.29	29.07	41.92	61.37
			C. 2005					
Value Added	212,965	1307.73	20859.78	49.39	108.71	268.31	693.52	1845.26
Employees	212,965	22.95	237.47	1	2.67	6.25	14.50	36.42
Capital Stock	212,965	1360.94	30714.00	14.80	40.42	122.66	438.47	1548.73
TFP	212,965	33.42	50.43	12.22	18.57	26.89	38.28	55.58
			D. 2010					
Value Added	270,649	1185.80	30347.97	46.00	98.00	235.00	592.00	1557.00
Employees	270,649	21	365.44	1	2.50	5.92	13	31.33
Capital Stock	270,649	1341.20	37601.52	12.36	36.00	113.78	403.03	1410.86
TFP	270,649	32.47	48.11	11.30	17.52	25.72	36.90	54.25
			E. 2014					
Value Added	252,342	1255.55	30781.23	46.79	99.59	238.36	613.33	1651.38
Employees	252,342	22.40	369.16	1.17	3	6	13.50	32.50
Capital Stock	252,342	1406.36	46482.24	14.27	39.11	120.80	417.02	1422.56
TFP	252,342	30.74	38.41	10.69	16.77	24.90	35.83	52.35

Notes: Value Added and Capital Stock at constant 2010 prices (thousand euros). TFP: thousand euros of value added generated per employee and per thousand euros of capital stock (constant 2010 prices). Employees: average number of workers employed across the year according to INPS. *Sources:* Cerved-INPS.

Table A.5: Comparison with the Invind Dataset

	Observations	Correlation
Sales	37,095	0.9941
Employment	37,095	0.8914
Investment	33,746	0.9082

Notes: The table reports correlations between the values in the Cerved-INPS sample and those reported in the Invind dataset regarding sales, employment and investment. *Sources:* Cerved-INPS and Invind.

B Construction of the Capital Stock

Firm-level real capital stocks, K_{it}, are recovered by means of a Perpetual Inventory Method (PIM)

$$K_{it} = (1 - d_{st})K_{i,t-1} + I_{it}$$

where investment in year t, I_{it}, is deflated by a sector specific investment deflator, recovered from national accounts, and the sector-specific depreciation rate, d_{st}, is computed from aggregate data coming from national accounts as well.[25]

The starting value, K_{i0}, is the first observation on firm i's book value, corrected for the (imputed) average age of firm i's capital stock, T_i (in practice, the initial book value is deflated using the sectoral investment deflator from T_i years before). This latter is computed as suggested by Bond et al. (1997)

$$T_i = \begin{cases} T^s_{max}\frac{\text{DEPR}_{i0}}{\text{GKAP}_{i0}} - 4 & \text{if } T^s_{max}\frac{\text{DEPR}_{i0}}{\text{GKAP}_{i0}} > 8 \\ \frac{T^s_{max}}{2}\frac{\text{DEPR}_{i0}}{\text{GKAP}_{i0}} & \text{if } T^s_{max}\frac{\text{DEPR}_{i0}}{\text{GKAP}_{i0}} \leq 8 \end{cases} \tag{12}$$

where DEPR_{i0} is the book value of firm i total cumulated depreciation allowances, and GKAP_{i0} is the book value of firm i gross capital stock. T^s_{max} is a sector-specific measure of the useful life of capital goods, obtained from Istat aggregate data as

$$T^s_{max} = \frac{1}{T}\sum_{t=0}^{T}\left(\frac{\text{NKAP}_{st}}{\text{DEPR}_{st}}\right)$$

where NKAP_{st} is sector s' aggregate net capital stock, and DEPR_{st} is sector s' aggregate depreciations.

Lastly, initial book values and investment are corrected for revaluation of assets.[26]

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[25] Available at `dati.istat.it/`.

[26] In 2008, the Italian Government allowed firms to revalue their fixed capital at market values, inducing an increase in book values of capital and investment. In order to correct for the distortion in measured investment and capital, we find in the balance sheet the stock of revaluations in a given year. Then, we correct the capital stock by subtracting the value of revaluation reserves, and investment by subtracting the change in revaluation reserves (Bond et al., 2015).

C Production Functions Estimation

C.1 Theory

The methodology by Ackerberg et al. (2015) falls, together with the methodologies by Olley and Pakes (1996) (OP) and Levinsohn and Petrin (2003) (LP), in the so-called "control function" approach to tackle the issue of the simultaneity between shocks observed by a firm and input usage.

More formally, consider the following Value-Added Based Cobb-Douglas production function (in logs)[27]

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it} \tag{13}$$

where y_{it} is (log) firm i's real value added at time t, l_{it} the (log) number of employees, k_{it} the log of firm i's real capital stock at time t, β_l and β_k are labour and capital elasticities, and ω_{it} is observed or predictable by firms when making their input decisions, while ϵ_{it} are unobservable i.i.d. shocks.

A well-known issue in estimating (13) by OLS is that a firm having prior knowledge about its productivity, would respond to positive expected shocks by increasing input usage; that is, firm input choices will likely depend on ω_{it} (which is unobservable by the econometrician and gathered into the error term), so OLS estimates of β_k and β_l will be inconsistent.

C.1.1 Olley and Pakes (1996) and Levinsohn and Petrin (2003)

The basic idea at the core of OP and LP is to use an observable x_{it} (investment, i_{it}, in OP, intermediate inputs, m_{it}, in LP) to proxy for unobserved productivity ω_{it}. More formally, the observable, x_{it}, is assumed to be a function of the state variables k_{it} and ω_{it}

$$x_{it} = f_t\left(k_{it}, \omega_{it}\right) \tag{14}$$

where k_{it} is a state variable in that it is assumed to evolve depending on its value and investment decisions at $t-1$

$$k_{it} = \kappa\left(k_{i,t-1}, i_{i,t-1}\right), \tag{15}$$

and productivity is assumed to evolve according to a first order Markov process, e.g. we can consider an AR(1) process for simplicity

$$\omega_{it} = \rho \cdot \omega_{i,t-1} + \xi_{it} \tag{16}$$

where ξ_{it} is an uncorrelated, zero-mean shock (White noise); this implies that firm i's expectations about its future productivity are based solely on its current productivity. Lastly, OP and LP assume labor to be non-dynamic (i.e. freely adjustable after observing ω_{it}) and thus left out from (14).

Most crucially, x_{it} is assumed to be strictly increasing in ω_{it}, and thus invertible to obtain

$$\omega_{it} = f_t^{-1}\left(k_{it}, x_{it}\right) \tag{17}$$

Plugging it into (13) we get

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + f_t^{-1}\left(k_{it}, x_{it}\right) + \epsilon_{it} = \beta_l l_{it} + \phi_t\left(k_{it}, x_{it}\right) + \epsilon_{it} \tag{18}$$

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[27] The following considerations can be easily extended to the Gross Output Based case, where one would like to estimate $q_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_k k_{it} + \alpha_m m_{it} + \omega_{it} + \epsilon_{it}$.

where ϕ_t is approximated, non-parametrically, either by a kernel density or a higher order polynomial.

Given these assumptions, estimation proceeds in two stages. The first stage generates GMM estimates $\hat{\beta}_l$ and $\hat{\phi}_t(k_{it}, x_{it})$, and is based on the following moment condition

$$E[\epsilon_{it}|I_{it}] = E[y_{it} - \beta_l l_{it} - \phi_t(k_{it}, x_{it})|I_{it}] = 0 \tag{19}$$

where firm i's information set at time t, I_{it}, includes current and past productivity shocks, but not future ones.

The estimates $\hat{\beta}_l$ and $\hat{\phi}_t(k_{it}, x_{it})$ are then plugged in the second stage equation, which is derived as follows.

First, we can estimate the productivity residual at time $t-1$ in terms of observables

$$\hat{\omega}_{i,t-1} = \hat{\phi}_{t-1}(k_{i,t-1}, x_{i,t-1}) - \beta_0 - \beta_k k_{i,t-1} \tag{20}$$

Second, given the AR(1) process for productivity in (16) and the first stage estimates, we can write

$$\hat{\omega}_{it} = \rho \cdot \hat{\omega}_{i,t-1} + \xi_{it} = \rho \cdot \left(\hat{\phi}_{t-1}(k_{i,t-1}, x_{i,t-1}) - \beta_0 - \beta_k k_{i,t-1}\right) + \xi_{it} \tag{21}$$

Then, the second stage equation is given as follows

$$\begin{aligned} y_{it} - \hat{\beta}_l l_{it} &= \beta_0 + \beta_k k_{it} + \hat{\omega}_{it} + \epsilon_{it} = \\ &= \beta_0 + \beta_k k_{it} + \rho \cdot \left(\hat{\phi}_{t-1}(k_{i,t-1}, x_{i,t-1}) - \beta_0 - \beta_k k_{i,t-1}\right) + \xi_{it} + \epsilon_{it} \end{aligned} \tag{22}$$

where the moment condition

$$\begin{aligned} &E[\xi_{it} + \epsilon_{it}|I_{i,t-1}] = \\ &\quad = E[y_{it} - \beta_0 - \beta_l l_{it} - \beta_k k_{it} - \rho \cdot (\phi_{t-1}(k_{i,t-1}, x_{i,t-1}) - \beta_0 - \beta_k k_{i,t-1})|I_{i,t-1}] = 0 \end{aligned} \tag{23}$$

allows to recover $\hat{\beta}_k$.

C.1.2 Functional Dependence Problems (Ackerberg et al., 2006)

Ackerberg et al. (2006) suggest a potential problem with the Olley and Pakes (1996) and Levinsohn and Petrin (2003) methodologies, as far as the identification of the coefficient on the labor input in the first stage is concerned. The problem is one of collinearity in the first stage where, in order to identify the coefficient β_l, l_{it} must vary independently of $\phi_t(k_{it}, x_{it})$.

However, one can assume that l_{it} and x_{it} are both function of the same state variables (productivity and capital). This implies that there is collinearity between l_{it} and $\phi_t(k_{it}, x_{it})$, as they both depend on the same variables. Therefore, β_l cannot be identified in the first stage: intuitively, in equation (18), the contribution of labor to output cannot be separately identified from $\phi_t(k_{it}, x_{it})$.

C.1.3 Wooldridge (2009) one-step procedure

Wooldridge (2009) proposes to implement the two steps of the Olley and Pakes (1996) and Levinsohn and Petrin (2003) methodologies into a unique step, within a GMM framework, resulting in more efficient estimates and allowing one to directly obtain standard errors without relying on bootstrapping methods.

In practice, Wooldridge (2009) proposes to estimate

$$\begin{aligned} y_{it} &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it} = \\ &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \rho \cdot \left(\phi_{t-1}\left(k_{i,t-1}, x_{i,t-1}\right) - \beta_0 - \beta_k k_{i,t-1}\right) + \xi_{it} + \epsilon_{it} \end{aligned} \tag{24}$$

by minimizing the two moment conditions

$$E\left[\epsilon_{it} | I_{it}\right] = 0 \tag{25}$$

and

$$E\left[\xi_{it} + \epsilon_{it} | I_{i,t-1}\right] = 0 \tag{26}$$

simultaneously. To proceed with GMM estimation, as instrument, in addition to the exogenous state variable, one can use the first lag of labor. One could also use lags of more than one period, but this would mean losing more initial time periods.

C.1.4 The Alternative Procedure by Ackerberg et al. (2015)

To overcome the functional dependence problems highlighted above, Ackerberg et al. (2015) (ACF) explicitly assume firms' intermediate input demand to be given by

$$m_{it} = \tilde{f}_t\left(k_{it}, l_{it}, \omega_{it}\right) \tag{27}$$

which generalizes (14) in the LP case by conditioning on l_{it}, and where $\tilde{f}_t\left(k_{it}, l_{it}, \omega_{it}\right)$ is assumed to be strictly increasing in ω_{it}, thus invertible to give $\omega_{it} = \tilde{f}_t^{-1}\left(k_{it}, l_{it}, m_{it}\right)$.

The first stage equation then becomes

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \tilde{f}_t^{-1}\left(k_{it}, l_{it}, m_{it}\right) + \epsilon_{it} = \tilde{\phi}_t\left(k_{it}, l_{it}, m_{it}\right) + \epsilon_{it} \tag{28}$$

and the first stage moment condition

$$E\left[\epsilon_{it} | I_{it}\right] = E\left[y_{it} - \tilde{\phi}_t\left(k_{it}, l_{it}, m_{it}\right) \Big| I_{it}\right] = 0 \tag{29}$$

Therefore, differently from the Levinsohn and Petrin (2003) case, we cannot identify β_l in the first stage. Ackerberg et al. (2015) then propose estimating β_l along with β_k in the second stage

$$\begin{aligned} y_{it} &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \hat{\omega}_{it} + \epsilon_{it} = \\ &= \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \rho \cdot \left(\hat{\tilde{\phi}}_{t-1}\left(k_{i,t-1}, l_{i,t-1}, m_{i,t-1}\right) - \beta_0 - \beta_l l_{i,t-1} - \beta_k k_{i,t-1}\right) + \xi_{it} + \epsilon_{it} \end{aligned} \tag{30}$$

using the moment condition

$$E\left[\xi_{it} + \epsilon_{it} | I_{i,t-1}\right] = 0 \tag{31}$$

which in this case allows to recover both $\hat{\beta}_l$ and $\hat{\beta}_k$.

This moment condition is less restrictive than (26). Specifically, in (26) we have a restricted version of (31) where $\tilde{\phi}_t\left(k_{it}, l_{it}, m_{it}\right)$ is linear in l_{it}; concretely, imposing such a less restrictive assumption allows, for instance, to have labour to be chosen dynamically with adjustment costs.

C.2 Summary of the Results

Table C.1 reports average estimated elasticities from value added based production function specifications, while Table C.2 those estimated from gross output based production function specifications.

Table C.1: AVERAGE ESTIMATED ELASTICITIES
(VALUE ADDED BASED PRODUCTION FUNCTION)

	OLS		FE		WLP		ACF	
	β_l	β_k	β_l	β_k	β_l	β_k	β_l	β_k
A. Whole Economy								
Sectors	76	76	76	76	76	76	76	76
Mean	0.7518	0.1988	0.6250	0.1408	0.6238	0.2011	0.6825	0.2415
St.Dev.	0.1045	0.0598	0.1097	0.0388	0.1123	0.0693	0.1088	0.0712
Min.	0.3912	0.0450	0.3141	0.0691	0.3157	0.0723	0.3835	0.1045
Max.	1.0009	0.4032	0.8066	0.2883	0.8285	0.5262	0.9184	0.4292
B. Manufacturing								
Sectors	23	23	23	23	23	23	23	23
Mean	0.8255	0.1756	0.7159	0.1209	0.6426	0.1795	0.7536	0.2129
St.Dev.	0.0513	0.0440	0.0602	0.0138	0.0494	0.0315	0.0545	0.0447
Min.	0.7276	0.0450	0.5435	0.0755	0.5395	0.1424	0.6715	0.1045
Max.	1.0009	0.2592	0.8066	0.1411	0.7432	0.2772	0.9184	0.3199
C. Whole Economy Excluding Manufacturing								
Sectors	53	53	53	53	53	53	53	53
Mean	0.7198	0.2088	0.5855	0.1494	0.6156	0.2104	0.6517	0.2538
St.Dev.	0.1057	0.0633	0.1028	0.0429	0.1301	0.0788	0.1123	0.0772
Min.	0.3912	0.0871	0.3141	0.0691	0.3157	0.0723	0.3835	0.1204
Max.	0.8599	0.4032	0.7449	0.2883	0.8285	0.5262	0.8424	0.4292

Notes: The table reports average estimated elasticities from value added based production functions specifications. Elasticities are allowed to vary across 2-digit ATECO sectors, and sectors with estimates which are not significant at least at 5% level are excluded (i.e. those with too few data points). Our preferred methodology is Ackerberg et al. (2015) (ACF), but we report also results from OLS, FE and Wooldridge (2009) (WLP) estimation. *Sources:* Cerved-INPS.

Table C.2: Average Estimated Elasticities
(Gross Output Based Production Function)

	OLS			ACF		
	α_l	α_k	α_m	α_l	α_k	α_m
A. Whole Economy						
Sectors	76	76	76	76	76	76
Mean	0.2386	0.0310	0.7387	0.2484	0.0423	0.7155
St.Dev.	0.0865	0.0217	0.0875	0.0850	0.0266	0.0914
Min.	0.0770	0.0007	0.4958	0.1135	0.0043	0.4570
Max.	0.4802	0.0830	0.8894	0.4863	0.1113	0.8702
B. Manufacturing						
Sectors	23	23	23	23	23	23
Mean	0.2095	0.0152	0.7819	0.2185	0.0228	0.7659
St.Dev.	0.0533	0.0106	0.0570	0.0469	0.0114	0.0508
Min.	0.1287	0.0007	0.6583	0.1378	0.0043	0.6638
Max.	0.3447	0.0519	0.8707	0.3299	0.0547	0.8528
A. Whole Economy Excluding Manufacturing						
Sectors	53	53	53	53	53	53
Mean	0.2512	0.0379	0.7199	0.2613	0.0508	0.6936
St.Dev.	0.0952	0.0217	0.0921	0.0945	0.0269	0.0966
Min.	0.0770	0.0014	0.4958	0.1135	0.0066	0.4570
Max.	0.4802	0.0830	0.8894	0.4863	0.1113	0.8702

Notes: The table reports average estimated elasticities from gross output based production functions specifications. Elasticities are allowed to vary across 2-digit ATECO sectors. Our preferred methodology is Ackerberg et al. (2015) (ACF), but we report also results from OLS estimation. *Sources:* Cerved-INPS.

D Markups Estimation

The approach proposed by De Loecker and Warzynski (2012) to compute time-varying firm-level markups relies on the basic assumption that firms minimize costs. Under this assumption and considering a fully flexible input, X, the price-cost margin (i.e. the markup μ_{it}) is equal to the ratio between the elasticity of output with respect to the flexible input, θ_{it}^{X}, and the expenditure share of input X in output, $\alpha_{it}^{X} = \frac{P_{it}^{X} X_{it}}{P_{it} Q_{it}}$, that is

$$\mu_{it} = \frac{\theta_{it}^{X}}{\alpha_{it}^{X}} \tag{32}$$

where the expenditure share of the variable input is corrected from unanticipated shocks: that is, we want to retain only the anticipated output, assuming that firms do not observe unanticipated shocks to production when making their optimal input decisions. In practice, the (actually observed) gross output $Q_{it} \cdot \exp(\epsilon_{it})$ is regressed on a rich polynomial expression of observable inputs, in order to get rid of unanticipated shocks ϵ_{it} and retain Q_{it} as the anticipated output. The expenditure share is then estimated as

$$\hat{\alpha}_{it}^{X} = \frac{P_{it}^{X} X_{it}}{P_{it} \frac{Q_{it} \exp(\epsilon_{it})}{\exp(\hat{\epsilon}_{it})}}$$

The assumption on the flexibility of the input adopted to compute markups is a crucial one. Indeed, if the input upon which markups are computed has dynamic implications, μ_{it} would not include just the price-cost margin, but also wedges originating from the dynamic optimization problem of that input. Given the presence of several rigidities in the Italian labor market, we compute markups from both the labor input and intermediate inputs.

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