# From Micro to Macro: at the root of firm heterogeneity in Italy

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**Abstract**

Large and persistent differences in firm performance are well documented, even within narrowly defined industries. A growing body of work seeks to understand the origins of this heterogeneity and its implications for firm dynamics and the propagation of shocks. Yet, it remains unclear whether heterogeneity primarily reflects conditions at entry or is shaped by shocks over the firm life cycle. Disentangling the contribution of ex-ante characteristics from ex-post shocks is therefore essential for understanding firm dynamics and for designing effective policies.

Our analysis relies on administrative microdata from the AIDA dataset, covering Italian limited liability firms over the period 2006–2021. We focus on two key performance indicators—employment and Return on Equity (ROE)—and, building on a reduced-form framework inspired by Sterk et al. (2021), we exploit their age-dependent autocovariance structure to identify the relative importance of ex-ante and ex-post heterogeneity.

We find that firms are highly heterogeneous at entry, with ex-ante factors accounting for about 95% of the cross-sectional variance in employment. However, this contribution declines rapidly over the life cycle, falling to roughly 40% by age 10 and converging to around 20% in the long run. This pattern indicates that, while initial conditions are crucial at entry, their influence weakens substantially over time, and post-entry shocks become the dominant driver of long-run dispersion. For profitability, the role of ex-ante heterogeneity is even more limited: it accounts for about 60% of dispersion at entry and quickly stabilizes at low levels, consistent with strong mean reversion and a prominent role for transitory shocks.

Sectoral analyses reveal substantial heterogeneity in the persistence of initial conditions. In capital-intensive and technologically advanced sectors, ex-ante heterogeneity remains more persistent, whereas in low-tech and less regulated sectors it dissipates rapidly, with firm dynamics largely driven by post-entry shocks.

Overall, our findings suggest that firm dynamics in Italy are less anchored in persistent initial conditions than in benchmark economies such as the United States, and are instead shaped to a greater extent by post-entry dynamics and idiosyncratic shocks. This has important implications for the transmission of shocks and for policies aimed at fostering firm growth.

**Keywords**: Firm heterogeneity, Firm growth dynamics, Ex-ante and ex-post heterogeneity, Employment growth

**JEL codes**: L25; L11; D22

# 1 Introduction

Ample evidence documents that there are enormous differences in the performance of firms, even within narrowly defined sectors. A new generation of models analyze this heterogeneity and explores the implications for the dynamics and the propagation of shocks in the economy. Yet, understanding the nature of firm heterogeneity, the exact moment when it arises, and the transiency of its effects is still limited. It is unclear what role the characteristics of the innate firms play and what role the experience of different shock sequences plays. Neither is clear which are the most relevant factors (e.g., entrepreneurial ability, business idea, technology), how they interact with shocks, and how different firms respond to idiosyncratic and common shocks. For policy design, it is paramount to understand what determines these differences and the relative importance of ex-ante and ex-post factors. In addition, it is essential to understand how differences evolve over the lifetime of the firms and how they spread among the firms. The key question is how deep to dig to explain firm heterogeneity [REF].

It is well-known that firms exhibit significant heterogeneity in performance. On one end of the spectrum, many startups fail within their first year, and the majority of those that survive experience little to no growth. On the other end, a small fraction of high-growth startups, often referred to as gazelles, make substantial and lasting contributions to aggregate job creation and productivity growth (see, e.g., Bisztray et al. 2023).

While firm dynamics have long been acknowledged as a critical determinant of macroeconomic outcomes, the underlying reasons for such stark differences in firm performance remain poorly understood. Similarly, the relationship between the nature of firm growth and its macroeconomic implications is not yet fully explored.

The existing literature has primarily focused on the age profiles of average firm exit rates, rather than investigating the fundamental autocovariance structure of firm performance by age.

We adopt a reduced-form model inspired by Sterk et al. (2021), which accounts for the possibility that differences across firms arise from both ex-ante heterogeneity in growth profiles and ex-post shocks.

Sterk et al. (2021) find that ex-ante heterogeneity in the U.S. explains a significant share of cross-sectional employment dispersion—almost 90 percent. Even after 20 years, ex-ante factors continue to account for about 40 percent of cohort employment dispersion. These findings align with empirical evidence that certain observable characteristics at the time of a firm's founding can partially predict its growth trajectory, as demonstrated by Guzman and Stern (2020).

The analysis in Sterk et al. (2021) draws on data spanning 37 years (1976–2012) and focuses on relatively young firms established between 1979 and 1993, with the oldest firms being 15 years old.

In contrast, our framework examines a shorter 15-year period (2006–2021) but incorporates a sample characterized by older firms, established between 1821 and 2012.

# 2 Background and Motivation

The present study builds on the empirical framework developed by Sterk, Sedláček, and Pugsley (2021), who analyze firm growth in the United States through a decomposition of firm-level variance into ex-ante and ex-post components. Their results show that ex-ante heterogeneity, reflecting initial conditions at entry, accounts for the majority of variance in firm outcomes over the life cycle, remaining highly persistent even in mature firms. Subsequent work has applied similar methodologies to other contexts, such as Portugal (Ferreira, Haber, Rörig, 2021), and has highlighted the importance of firm-level characteristics observed at entry, including founding strategy, capital endowment, and managerial quality, in predicting future growth (Guzman Stern, 2015; 2020; Guzman Li, 2022). These studies establish a clear benchmark for understanding the role of ex-ante conditions versus idiosyncratic shocks in shaping firm trajectories.

Our study replicates this decomposition framework using data on Italian firms, with the added dimension of sectoral heterogeneity. Italy presents a particularly interesting case for such an analysis, as prior evidence suggests a highly heterogeneous industrial structure at entry, accompanied by relatively low average growth and moderate persistence of firm outcomes (Grazzi et al., 2018; Bugamelli et al., 2012). Unlike the United States, where ex-ante heterogeneity dominates for decades, Italian firms appear to experience more pronounced effects of post-entry shocks and idiosyncratic events, which contribute to the evolution of variance over time. By leveraging the comprehensive coverage of the AIDA dataset, which includes virtually all incorporated firms in Italy, we can directly observe exit rates and growth patterns without relying on sample-based estimates, providing a precise measure of low attrition and the role of structural features in shaping firm dynamics.

In addition, extending the analysis to the sectoral level allows us to investigate whether the importance of initial conditions and post-entry shocks varies across industries with differing technological intensity, market concentration, and entry barriers. This is particularly relevant in the Italian context, where sectoral dispersion in growth, productivity, and employment is pronounced (Schivardi Schmitz, 2020). Understanding these sectoral differences also enables a more nuanced interpretation of aggregate patterns and their macroeconomic implications, including the potential role of misallocation and inefficient allocation of resources in constraining productivity growth (Hsieh Klenow, 2009; Bartelsman, Haltiwanger, Scarpetta, 2013; García-Santana, Moral-Benito, Pijoan-Mas, 2020).

Finally, our approach contributes to the broader literature on heterogeneous firms and firm-level dynamics by providing cross-country and cross-sectoral evidence that complements prior studies on the U.S. and Portugal. It underscores the significance of initial heterogeneity, the persistence of idiosyncratic shocks, and the interaction between firm characteristics and sector-specific conditions. By highlighting these dynamics, the study not only replicates the methodology of Sterk et al. (2021) but also extends it, offering insights that are directly relevant for policy design, particularly in terms of identifying stages of the firm lifecycle where interventions may be most effective and recognizing the role of sectoral structures in shaping firm growth trajectories.

# 3 Ex-Ante Heterogeneity and the Determinants of Firm Growth

A growing body of research highlights the importance of ex-ante firm heterogeneity—differences observable at or shortly after entry—in explaining the wide dispersion in firm growth outcomes. **?** show that initial differences at entry account for nearly 90 percent of cross-sectional employment dispersion in U.S. data, and that even twenty years after founding, ex-ante factors continue to explain about 40 percent of the variation in cohort employment. Their findings align with work by Jorge Guzman and Scott Stern Guzman and Stern (2015, 2020), as well as Jorge Guzman and Jinyu Li Guzman and Li (2022), who document that initial entrepreneurial signals—such as early innovation, founding characteristics, and institutional context at entry—predict long-run firm performance.

Further evidence is provided by Miguel A. Ferreira et al. Ferreira et al. (2021a), who study firm dynamics in Portugal and show that initial conditions at entry—including firm size, sector, and founding environment—have strong predictive power for subsequent survival and growth. Their results complement U.S.-based evidence by showing that ex-ante heterogeneity shapes firm trajectories even in smaller and less volatile economies, with a large share of dispersion in employment growth traceable to differences present at or near firm creation.

Recent contributions reinforce the persistence of early advantages. Eduardo Guntin and Luca Kochen Guntin and Kochen (2025) show that firms that eventually reach the top of the size distribution are already substantially larger at birth and exhibit faster growth during their first two decades. Their structural model, incorporating ex-ante heterogeneity, non-homothetic technologies, and forward-looking financial constraints, generates firm-growth dynamics consistent with empirical patterns.

Long-run empirical evidence also confirms that while firm growth contains a strong stochastic component, persistent heterogeneity remains. Using more than fifty years of U.S. manufacturing data, Giovanni Dosi et al. Dosi et al. (2019, 2020) find that although Gibrat-like randomness is pervasive, a subset of firms displays persistent growth advantages, suggesting that initial capabilities and early strategic choices play a major role over long horizons.

The theoretical foundations of these insights stem from classic dynamic models. Boyan Jovanovic Jovanovic (1982) proposes a selection model in which firms learn their productivity over time, leading the most efficient firms to grow and the least efficient to exit. Hugo Hopenhayn Hopenhayn (1992) extends this mechanism within an industry equilibrium framework with heterogeneous productivity and endogenous entry and exit. Erzo G. J. Luttmer Luttmer (2010) synthesizes these strands, showing how persistent heterogeneity, innovation, and idiosyncratic shocks jointly shape the skewed distribution of firm size and long-run growth patterns.

Other perspectives broaden the interpretation of heterogeneity. Ecological competition–colonization frameworks emphasize the differential ability of small entrants to explore new market niches and the comparative advantage of incumbents in defending established positions. Research on persistent innovators shows that sustained innovation does not necessarily translate into persistent high growth, highlighting the multidimensional nature of firm dynamics. Finally, evidence on financial heterogeneity suggests that leverage has heterogeneous effects across the firm-growth distribution, supporting growth among constrained firms while being neutral or even detrimental for high performers.

Overall, the literature converges on the idea that firms differ substantially at entry, and that these initial differences—interacting with selection mechanisms, financial frictions, and innovation processes—generate the rich variety of firm-growth trajectories observed across countries and over time.

| **Age Group** | **Frequency** | **Percent** | **Cumulative** |
|---|---|---|---|
| 0–11 | 228,444 | 23.41% | 23.41% |
| 12–32 | 488,386 | 50.04% | 73.44% |
| 33+ | 259,200 | 26.56% | 100.00% |
| **Total** | 976,030 | 100.00% | 100.00% |

Table 1: Distribution of firms by age group (unbalanced sample). Average age is 24.5 with std of 16.9.

| **Size Class** | **Frequency** | **Percent** | **Cumulative** |
|---|---|---|---|
| <= 9 | 214,139 | 16.96 | 16.96 |
| 10–49 | 474,580 | 37.59 | 54.56 |
| 50–99 | 137,596 | 10.90 | 65.45 |
| 100–249 | 96,448 | 7.64 | 73.09 |
| 250–499 | 30,748 | 2.44 | 75.53 |
| 500+ | 22,519 | 2,31 | 100.00 |
| **Total** | **976,030** | **100.00** | – |

Table 2: Distribution of firm size (unbalanced sample). Size classes follow standard EU thresholds.

| Year | Frequency | Percent | Cumulative |
|---|---|---|---|
| 2006 | 46,219 | 5.02 | 5.02 |
| 2007 | 49,023 | 5.33 | 10.35 |
| 2008 | 51,820 | 5.63 | 15.98 |
| 2009 | 49,513 | 5.38 | 21.36 |
| 2010 | 46,662 | 5.07 | 26.43 |
| 2011 | 66,108 | 7.18 | 33.61 |
| 2012 | 67,477 | 7.33 | 40.94 |
| 2013 | 67,223 | 7.30 | 48.24 |
| 2014 | 66,245 | 7.20 | 55.44 |
| 2015 | 64,659 | 7.02 | 62.46 |
| 2016 | 63,025 | 6.85 | 69.31 |
| 2017 | 61,619 | 6.69 | 76.00 |
| 2018 | 59,773 | 6.49 | 82.50 |
| 2019 | 58,483 | 6.35 | 88.85 |
| 2020 | 56,653 | 6.15 | 95.01 |
| 2021 | 45,963 | 4.99 | 100.00 |
| Total | 920,465 | 100.00 | |

Table 3: Distribution of firms surviving at least 10 years

| Year | Frequency | Percent | Cumulative |
|---|---|---|---|
| 2006 | 46,919 | 4.81 | 4.81 |
| 2007 | 50,103 | 5.13 | 9.94 |
| 2008 | 53,571 | 5.49 | 15.43 |
| 2009 | 51,530 | 5.28 | 20.71 |
| 2010 | 48,596 | 4.98 | 25.69 |
| 2011 | 69,868 | 7.16 | 32.85 |
| 2012 | 71,708 | 7.35 | 40.19 |
| 2013 | 71,570 | 7.33 | 47.53 |
| 2014 | 70,786 | 7.25 | 54.78 |
| 2015 | 69,322 | 7.10 | 61.88 |
| 2016 | 67,791 | 6.95 | 68.83 |
| 2017 | 66,504 | 6.81 | 75.64 |
| 2018 | 64,557 | 6.61 | 82.25 |
| 2019 | 63,123 | 6.47 | 88.72 |
| 2020 | 61,029 | 6.25 | 94.97 |
| 2021 | 49,053 | 5.03 | 100.00 |
| Total | 976,030 | 100.00 | – |

Table 4: Distribution of firms, whole sample

| **Sector** | **Frequency** | **Percent** | **Cumulative** |
|---|---|---|---|
| Primary & Extractive | 45,051 | 4.62 | 4.62 |
| Manufacturing | 337,236 | 34.55 | 39.17 |
| Construction | 75,494 | 7.73 | 46.90 |
| Wholesale | 269,681 | 27.63 | 74.53 |
| Services | 157,417 | 16.13 | 90.66 |
| Energy & Transport | 91,025 | 9.33 | 99.99 |
| **Total** | 976,030 | 100.00 | 100.00 |

Table 5: Sectoral distribution of firms (unbalanced sample, 6-sector classification). 126 firms with missing info on ateco.

| Sector | Firms | Share (%) | Employment | Roe | Age | n firms |
|---|---|---|---|---|---|---|
| Primary and Ext. | 45,051 | 4.62 | 86.18 | 7.14 | 24.66 | 45051 |
| Manufacturing | 337,236 | 34.55 | 7.44 | 88.97 | 27.53 | 337236 |
| Constructions | 75,494 | 7.73 | 46.00 | 6.80 | 23.19 | 75494 |
| Wholesale | 269,681 | 27.63 | 52.67 | 9.26 | 22.57 | 269681 |
| Services | 157,417 | 16.13 | 128.86 | 7.46 | 23.06 | 157417 |
| Energy and Transp. | 91,025 | 9.33 | 170.62 | 8.45 | 22.94 | 91025 |
| Total | 976,030 | 100.00 | 89.54 | 24.54 | | |

Table 6: Sectoral Distribution of Firms Characteristics (Italy, AIDA)

*Notes*: This table reports the sectoral distribution of firms and mean firm characteristics using Italian firm-level data from AIDA. Employment is measured as total employees; age is measured in years. Sector classification follows the `2-digit ISTAT sector` aggregation.

| **Sector** | **Frequency** | **Mean Employment** | **Mean ROE** |
|---|---|---|---|
| High/Medium-Tech | 113,698 | 117.17 | 9.22 |
| Low/Medium-Low-Tech | 223,538 | 74.63 | 6.71 |
| **Total** | 337,236 | 88.97 | 7.55 |

Table 7: Manufacturing sector: High- vs. Low-Tech : Frequency, Employment, and ROE

*Notes*: This table combines the frequency of firms with mean employment (EMP) and mean return on equity (ROE) in high- and low-technology manufacturing firms, based on OECD technology-intensity classification.

# 4 The autocovariance structure of employment

We start by showing the cross-sectional autocovariance function of log employment conditional on age and estimate the autocovariance structure of firm-level employment.

Let $\ln n_{i,a,j,t}$ denote the logarithm of employment for firm $i$ of age $a$ in 4-digit industry $j$ and year $t$. In our replication for Italy (spanning 10years) we follow the same specification of **?**, after purging log-employment of year-born and sector fixed effects: $\ln n_{i,a,j,t}$. This procedure eliminates variations in employment due to industry-specific technology and persistent effects from business conditions at the time of firm birth.

For each panel, we compute the cross-sectional autocovariance between residual employment at ages $a$ and $h \leq a$, using only firms observed at both ages. The estimator is defined as:

$$\widehat{\text{Cov}}\left[\ln n_{i,a,j,t}, \ln n_{i,h,j,t}\right] = \frac{1}{N_{a,h}} \sum_{i=1}^{N_{a,h}} \left(\ln n_{i,a,j,t} - \overline{\ln n_{a,j,t}}\right)\left(\ln n_{i,h,j,t} - \overline{\ln n_{h,j,t}}\right), \tag{1}$$

where $N_{a,h}$ denotes the number of firms with employment observed at both ages $a$ and $h \leq a$, and $\overline{\ln n_{a,j,t}}$ is the sample mean of the residual log employment at age $a$.

Results are presented in terms of standard deviations (left panel) and autocorrelations (right panel); see Figure 1. The sample consists of all firms observed in the period 2006-2021 with non-missing information on employment and at least one employee. [1]

The standard deviation of log employment, shown in the left panel of Figure 1, is already relatively high—above 1.4—indicating substantial size differences even at early ages. This supports the existence of ex-ante heterogeneity, as firms are not all equal at birth. Cross-sectional dispersion tends to decline slightly over time; however, even by age 10, firm heterogeneity remains considerable (around 1.2), suggesting that ex-ante conditions are highly persistent. The persistence of initial conditions is also documented for the United States and Portugal by Sterk et al. (2021) and Ferreira et al. (2021b), respectively, although in those countries cross-sectional dispersion tends to increase with age. For U.S. cohorts, as firms grow older, size differences become increasingly pronounced—particularly after 20 years—with some firms expanding substantially, while others grow more slowly, as reflected by an increase in the standard deviation from 1 to 1.3. In Portugal,

[1] Since the attrition rate in our panel is very low, we only focus on the unbalanced panel. More details provided in the Appendix)

the cross-sectional standard deviation is below 0.85 at age 0 and rises to about 0.95 by age 10 (Ferreira et al., 2021b).

A further notable feature is the substantially higher cross-sectional dispersion observed for Italian firms relative to those in the United States and Portugal. In Italy, the standard deviation of log employment at age 0 already exceeds 1.4, compared with around 1 in the United States and below 0.85 in Portugal. This indicates that Italian firms are born with much stronger ex-ante heterogeneity. The fact that dispersion declines only marginally with age suggests that these initial conditions remain largely persistent. This pattern contrasts with the U.S. and Portuguese cases, where size differences widen over time, and highlights the disproportionately important role of pre-entry factors in shaping the firm growth process in Italy.

This evidence is also consistent with well-documented structural features of the Italian economy—such as low average growth, persistent regulatory rigidities, and sluggish firm-level dynamics Bugamelli et al. (2008), Schivardi and Torrini (2008) which limit post-entry reallocation and scaling-up, thereby preventing cross-sectional dispersion from widening substantially over time.

The right-hand panel of Figure 1 displays the cross-sectional autocorrelations of log employment between firm age $a$ and an earlier age $h \leq a$, defined as $\rho_h(a) = \text{Corr}(\ell_h, \ell_a)$. Each curve corresponds to a fixed reference age $h$. The curve corresponding to $h = 0$ captures the persistence of firm size at entry, reporting the cross-sectional correlation between log employment at birth and at subsequent ages. By construction, the correlation equals 1 at age zero and then declines as firms experience idiosyncratic shocks and follow heterogeneous growth paths.

Curves associated with low values of $h$, such as $h = 0$, exhibit a steep initial decline, reflecting the high volatility of young firms: in the first few years, some firms grow rapidly while others grow slowly or fail, so the correlation between size at birth and size a few years later drops quickly. In particular, the $h = 0$ curve in our data remains slightly above 0.7 at age 5 and around 0.55 by age 10, highlighting the substantial predictive power of initial conditions over the first decade of life. In contrast, curves with higher $h$ are flatter and remain persistently high, indicating that once early-life volatility subsides, firm size becomes a strong predictor of future size. That is, after the first few years, firms that are relatively large (or small) tend to maintain their positions in the size distribution, and the relative ranking of firms stabilizes.

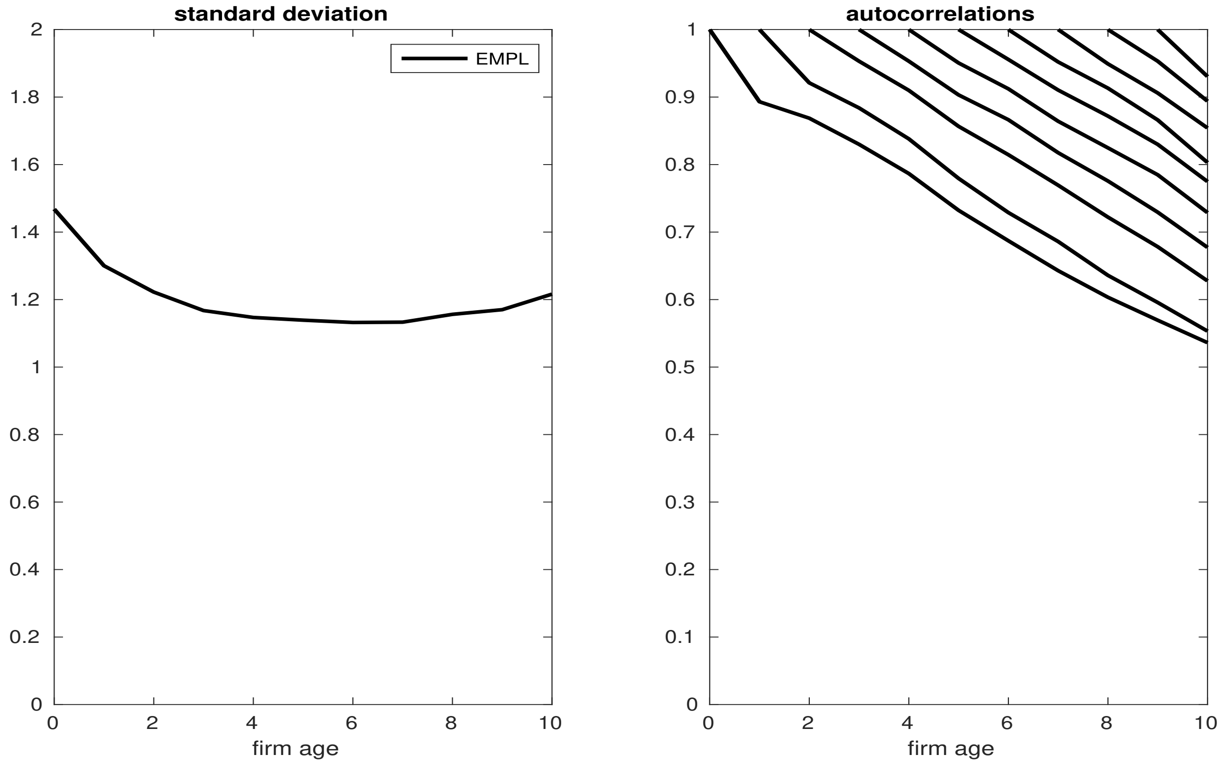
At the same time, the gradual decline in autocorrelations as firms age, conditional on a given reference age, shows that post-entry dynamics—such as transitory shocks and differential growth opportunities—also contribute to reshuffling firm size rankings. Overall, the right-hand panel indicates that firms that are large or small early in life tend to remain so, although persistence gradually weakens. Nevertheless, the relatively high ten-year correlation observed in our data suggests that initial conditions play a prominent role in shaping firm growth trajectories.

In particular, the curve corresponding to $h = 0$, which measures the persistence of firm size at birth, remains slightly above 0.7 at age 5 and around 0.55 at age 10, highlighting the substantial predictive power of initial conditions even during the first decade of life. During this ten-year period, persistence in Italy is stronger than in the United States, where Sterk et al. (2021) report that the corresponding correlation declines to roughly 0.45 by age 10 and further to approximately 0.4 by age 20. This suggests that, within the first decade of life, Italian firms retain a higher predictive link between initial size and subsequent size, reflecting the significant role of persistent ex ante heterogeneity.

At the same time, the gradual decline in autocorrelations as firms age, conditional on a given reference age, indicates that post-entry dynamics—such as transitory shocks, and differential growth opportunities—also contribute to reshuffling firm size rankings. Overall, the right panel shows that firms that are relatively large (or small) early in life tend to remain so, although this persistence weakens gradually over time. Nevertheless, the relatively high ten-year correlation observed in our data suggests that initial conditions play a prominent role in shaping firm growth trajectories, even more so than in the U.S. (Sterk et al., 2021).

This comparison is instructive. Sterk et al. (2021) interpret the stabilization of autocorrelations as evidence that ex ante heterogeneity accounts for a large share of cross-sectional variation in firm growth paths. In our case, although we do not observe a clear stabilization within the shorter observational window, the persistence implied by a ten-year correlation of 0.55 still indicates that ex ante differences across firms play a non-negligible role. Thus, despite differences in the dynamic profile of autocorrelations, both sets of findings point to the importance of persistent underlying firm characteristics, potentially alongside a more pronounced contribution of ex post shocks in our setting.

Thus 1 is a key piece of empirical evidence pointing towards the dominance of ex-ante heterogeneity rather than purely post-entry shocks. The joint analysis of panal a and b reveals that much of the dispersion in firm size is not just due to random shocks after entry (which would generate more independent fluctuations over time) but instead is due to ex-ante heterogeneity (differences present at or soon after entry). The logic:




Note: The left panel presents the standard deviation of log employment by age, after controlling for sector and year fixed effects. The right panel presents the autocorrelation of log employment between ages $a$ and $h \leq a$. Across lines, $h$ changes, while $a$ changes along the lines.

Figure 1: Standard Deviation and autocorrelations of log employment by age

# 5 Employment process

To disentangle the role of ex-ante and ex-post heterogeneity in firm growth, we follow the statistical framework proposed by Sterk et al. (2021). The model decomposes log employment into an ex-ante component—determined by initial conditions—and an ex-post component capturing shocks accumulated after entry. Formally, firm size evolves according to:

$$\ln n_{i,a} = u_{i,a} + v_{i,a} + w_{i,a} + z_{i,a},$$

where $u_{i,a}$ and $v_{i,a}$ represent the *ex-ante* component, while $w_{i,a}$ and $z_{i,a}$ constitute the *ex-post* shock structure.

The key parameters of interest are those governing ex-ante heterogeneity:

- $\rho_u$: the persistence of the permanent ex-ante component. A higher $\rho_u$ implies that initial firm-specific advantages or disadvantages decay slowly over the life cycle.
- $\sigma_\theta$: the variance of long-run firm-specific differences. This parameter captures how dispersed firms are in their innate growth potential at entry.

Together, $\rho_u$ and $\sigma_\theta$ quantify the strength and persistence of initial conditions in shaping the cross-sectional dispersion of firm size. As in Sterk et al. (2021), we adopt this model to recover the age-specific contribution of ex-ante and ex-post heterogeneity in our analysis.

## 5.1 Parameter estimates and model fit

Figure 2 illustrates the autocovariance structure observed in the data alongside the estimated model, integrating the information from both panels of Figure 1. The parameter estimates are listed in Table 8. The bottom solid line represents the autocovariance of employment at a specific age $a$ compared to employment at age 0. This pattern is convex in the lag length (as in Sterk et al. (2021)), and the relationship is also convex and increases with age given the lag length $j > 0$ **(in contrast with Sterk et al. (2021), where it is concave)**.

Figure 2 plots the cross-sectional covariance $\mathrm{Cov}(\log E_{i,h+j}, \log E_{i,h})$ as a function of base age $h$ for different lags $j$. The covariance is very high at young ages, indicating that firm size is strongly persistent early in the life cycle. For all lags, covariance declines sharply over the first years, reflecting intense selection and a rapid reduction in cross-sectional dispersion. After approximately age six, the decline flattens, consistent with the stabilization of dispersion among surviving firms. At older ages, the curves exhibit a fan pattern, with longer lags showing systematically lower covariance, capturing the accumulation of transitory shocks over time.

These patterns closely mirror those reported in Sterk et al. (2021), including the high early-life covariance levels, the steep initial decline, and the age-dependent separation across lags. The similarity suggests that the replication successfully reproduces the age–lag structure of employment persistence documented in the data.

For each lag $j$, the covariance profile exhibits a U-shaped pattern over the life cycle. Covariance declines sharply during the first years after entry, reflecting intense selection and the rapid compression of cross-sectional dispersion in firm size. After mid-life, however, the decline slows and covariance stabilizes or increases slightly. This pattern suggests that persistent firm heterogeneity becomes the dominant driver of employment differences among surviving firms. The resulting U-shape cannot be generated by a simple random walk in firm size and provides evidence for the interaction of selection, transitory growth shocks, and persistent productivity differences.

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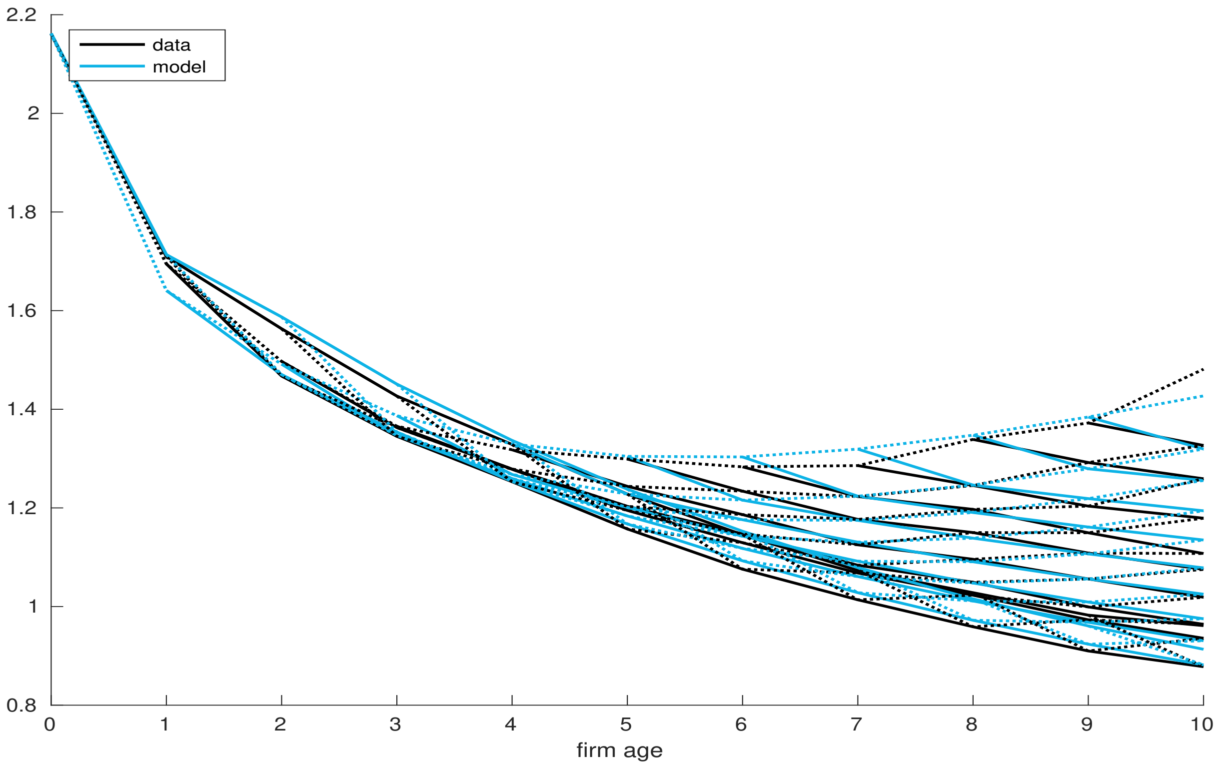
Relative to Sterk et al. (2021), the U-shaped pattern appears more pronounced in our estimates, with a clearer stabilization and mild recovery of covariance at later ages. One possible reason is that our analysis focuses on the first ten years of the firm life cycle, where selection dynamics are strongest and the transition from selection-driven dispersion to persistence-driven dynamics is more visible. The resulting U-shape cannot be generated by a simple random walk in firm size and provides evidence for the interaction of selection, transitory growth shocks, and persistent productivity differences.




Note: Cross-sectional covariance of log employment between age $a = h + j$ and $h <= a$ in the data,and in the baseline model.

Figure 2: Autocovariance Matrices: Statistical Models versus Data

Figure 3 shows a set of comparisons between the observed autocovariance structure of firm employment and what four "restricted" statistical models predict (i.e., models with certain features removed). Model I is an AR(1) process with heterogeneous intial draws, but without heterogeneity in long-run steady state, thus Model I, firms begin with different starting points, but over time they all follow the same growth pattern and settle around the same long-run level. Model II includes only ex-ante differences at entry but excludes ex-post shocks, isolating the role of initial firm characteristics. Model III is equivalent to the baseline model, including both parts of ex-ante component, removing the transitory part and re-estimating the remaining parameters.

Finally, Model IV removes the independent and identically distributed ex-post shocks, capturing only persistent heterogeneity without random shocks over time. Together, these restricted models allow for a clear examination of how different sources of variation—initial firm characteristics and subsequent stochastic shocks—contribute to the overall autocovariance structure of firm employment.

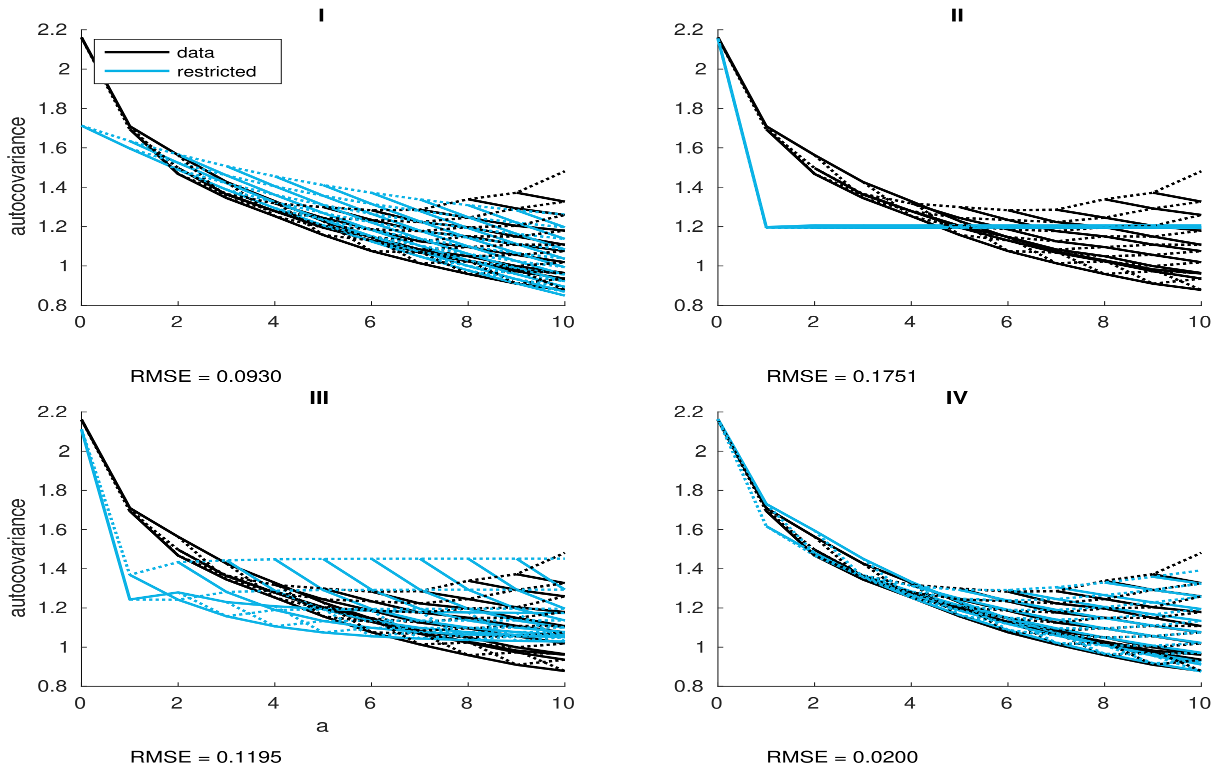



Figure 3: Autocovariance Matrices: Restricted Models

Cross-sectional covariance of log employment between age $a = h + j$ and age $h \leq a$ is shown for the baseline model and the four restricted models.

In Model I, $\rho_w$, $\sigma_\varepsilon$, and $\tilde{\sigma}_v$ are estimated, while imposing $\rho_u = \rho_v = \rho_w$ and $\sigma_\theta = \tilde{\sigma}_u = \sigma_z = 0$.

In Model II, $\rho_u$, $\sigma_\theta$, and $\tilde{\sigma}_u$ are estimated, while imposing $\rho_w = \rho_v = \sigma_\varepsilon = \tilde{\sigma}_v = \sigma_z = 0$.

Model III corresponds to the baseline with the restriction $\rho_v = \tilde{\sigma}_v = 0$.

Model IV corresponds to the baseline with the restriction $\sigma_z = 0$.

The figure also reports RMSE values for each of the restricted models; for the baseline model, RMSE = 0,016

| MODEL | $\rho_u$ | $\rho_v$ | $\rho_w$ | $\sigma_{th}$ | $\sigma_u$ | $\sigma_v$ | $\sigma_{eps}$ | $\sigma_z$ | RMSE |
|---|---|---|---|---|---|---|---|---|---|
| $AR1_{GEN}$ | -0.121 | 0.861 | 0.986 | 0.786 | 3.038 | 1.314 | 0.294 | 0.206 | 0.016 |

Table 8: Parameter estimates from Reduced-Form Model-Employment

LR ex ante component of the dispersion of employment = $theta/(1 - rho_u)$ good fit

# 6 Mapping model component to the data

## 6.1 Ex-ante and ex-post heterogeneity

Figure 4 plots the fraction of total cross-sectional variance in firm size accounted for by the ex-ante component. At entry (age 0), ex-ante heterogeneity explains approximately 95% of overall dispersion, with only about 5% attributable to ex-post shocks realized during the first year. However, this contribution declines rapidly as firms age: by age 10—based on 24,694 firms in our sample—the ex-ante component accounts for roughly 40% of total variance, and as age approaches infinity, it stabilizes at around 20%. This pattern indicates that while initial heterogeneity is decisive at entry, its importance diminishes quickly over the firm life cycle, with idiosyncratic shocks and post-entry dynamics playing an increasingly central role in shaping long-run dispersion. This evidence contrasts with the findings for the United States reported by Sterk et al. (2021), where the contribution of ex-ante heterogeneity remains substantial throughout the firm's life and never falls below 40%. Compared to the benchmark results in Sterk et al. (2021), our findings point to a broadly similar qualitative pattern but a markedly different degree of persistence in ex-ante heterogeneity. Consistent with their evidence, we find that initial conditions play a dominant role at entry, accounting for approximately 95% of the cross-sectional dispersion in firm size. However, unlike the US evidence, where the contribution of ex-ante heterogeneity remains persistently high and never falls below roughly 40%, we document a substantially faster decline over the firm life cycle in the Italian economy. The ex-ante component decreases rapidly during the first decade of a firm's life, reaching about 40% by age 10 and converging to around 20% in the long run. This sharper decay suggests that post-entry dynamics and idiosyncratic shocks play a considerably more important role in shaping long-run dispersion than in the US context. Overall, these results are consistent with an environment characterized by weaker persistence of initial advantages and stronger reallocation through life-cycle shocks, implying that firm-level heterogeneity in Italy is less anchored in pre-determined characteristics and more driven by realized performance over time.

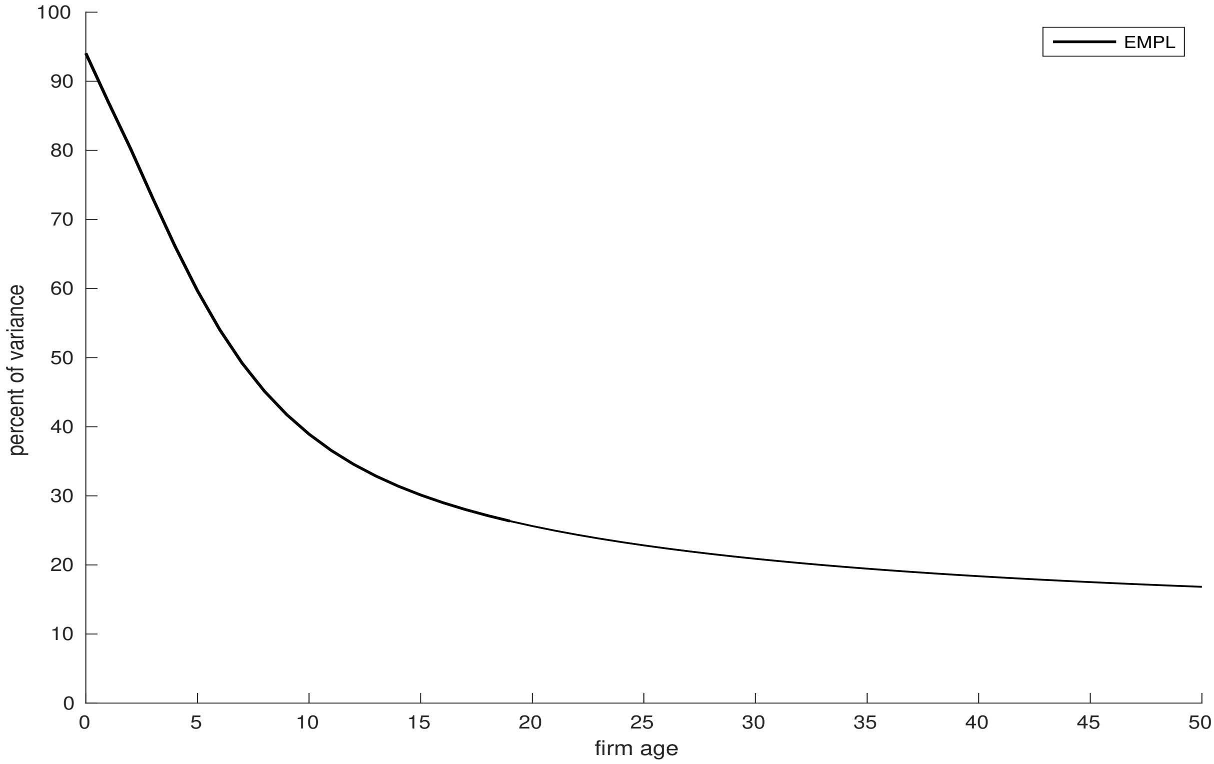



Figure 4: Contribution of Ex Ante Heterogeneity to Cross-Sectional Dispersion in Employment

# 7 An analysis by sector

In this section, we extend our previous analysis, which introduced sector fixed effects to account for industry-specific variations in firm growth at the economy-wide level. While this earlier approach provided valuable insights into the overall patterns of firm dynamics across different sectors, we now take a deeper dive into sector-specific analysis. The goal is to better understand how ex-ante factors, such as initial firm characteristics, contribute to employment variance within each sector and whether these factors differ across industries.

Figure 5 compares the ex-ante contribution to the total variance in employment across the six selected sectors: Manufacturing, Services, Wholesales, Construction, Energy and Transports, and Primary and Extractive Industries, using the Ateco 2-digit classification. These sectors were specifically chosen for their substantial market share and economic relevance in the Italian economy. The manufacturing sector alone accounts for over one-third of the firms in the sample, followed by Wholesale, Services, and Energy Transports, as shown in Table 5.

This sectoral breakdown allows us to refine our understanding of how ex-ante heterogeneity—the factors that influence firm growth before a firm enters the market—impacts employment growth within each specific sector. By re-estimating the employment process for each sector, we isolate the contribution of these initial conditions to the cross-sectional variance in employment. In doing so, we aim to assess whether the results observed at the economy-wide level hold at the sector level, or if different sectors exhibit unique dynamics driven by their industry-specific characteristics.

The choice of these six sectors is motivated by their economic significance and heterogeneity in terms of growth drivers. For example, the manufacturing sector is typically more capital-intensive and driven by technological innovation, whereas the service sector may depend more on human capital and organizational factors. Meanwhile, sectors such as Energy & Transport and Construction are often influenced by regulatory policies, infrastructure, and market competition. By isolating the variance in employment within these industries, we can better understand how ex-ante factors—such as firm size, resources, and market positioning at the time of entry—shape long-term growth prospects in each specific context.

This deeper sectoral analysis contributes to the broader understanding of firm dynamics in the Italian economy, shedding light on sector-specific growth patterns and helping identify policy levers that may be more or less effective depending on the challenges each sector faces. Furthermore, this approach builds upon the existing literature on firm dynamics, extending the analysis to provide a more granular, industry-specific perspective on the role of initial conditions in shaping firm growth trajectories.

It turns out that the specified employment process fits the data well also at the sectoral level, with the Root Mean Squared Error (RMSE) varying between 0.023 (e.g., construction) and 0.051 (e.g., services), see 9. For comparison, the RMSE for the economy-wide analysis is 0.016 (see Table 8.) Table 9 reports RMSE values for the reduced-form model across sectors, indicating an overall satisfactory fit. Manufacturing and Wholesales exhibit the lowest prediction errors, suggesting particularly strong model performance in these sectors, while Constructions displays the highest RMSE, pointing to relatively weaker explanatory power. Together with the pronounced cross-sectoral differences in persistence and volatility parameters, these results underscore meaningful sectoral heterogeneity and support the use of a disaggregated, sector-level specification rather than a pooled approach.

Across all macro sectors, ex-ante heterogeneity accounts for the vast majority of employment dispersion at entry, ranging between 90 and 96 percent. This finding indicates strong initial sorting in firm size at birth, reflecting substantial heterogeneity in initial scale, technology, and organizational capacity. However, despite this common starting point, the persistence of ex-ante heterogeneity varies markedly across sectors.

In Construction, wholesale and Services, the contribution of ex-ante heterogeneity declines rapidly over the firm life cycle. In Construction, the ex-ante component falls from approximately 90 percent at entry to about 13 percent by age ten and becomes negligible in the long run, dropping below 2 percent after twenty years. Wholesale firms exhibit a similar but slightly more persistent pattern: ex-ante heterogeneity declines from roughly 95 percent at entry to around 35 percent at age ten and to less than 3 percent at long horizons. In Services, the ex-ante share falls from about 92 percent at entry to roughly 17 percent by age ten and stabilizes at approximately 5 percent in the long run. These sectors are characterized by relatively low entry barriers, limited scalability, and strong exposure to demand fluctuations, which amplify the role of post-entry shocks in shaping firm growth paths.

Manufacturing displays a more intermediate pattern. At entry, ex-ante heterogeneity explains about 96 percent of employment dispersion. This share declines more gradually than in non-tradable sectors, falling to roughly 50 percent by age ten and stabilizing at approximately 20 percent in the long run. This results is supported by the work of Melitz and Redding (2014) showing that manufacturing displays a more intermediate pattern in terms of employment dispersion. Their research highlights significant ex-ante heterogeneity in productivity, size, and other characteristics among firms within manufacturing industries, which explains a substantial share of employment dispersion at entry. Furthermore, they emphasize that trade liberalization drives within-industry resource reallocations, leading to a gradual decline in heterogeneity as less productive firms exit and more productive firms expand. The slower erosion of initial conditions in manufacturing is consistent with higher capital intensity, greater scope for technological differentiation, and exposure to international competition, which allow some firms to sustain scale advantages for longer periods.

Energy and Transport stand out as a clear exception. In this sector, ex-ante heterogeneity remains highly persistent over the firm life cycle. The contribution of initial heterogeneity declines from about 93 percent at entry to roughly 50 percent by age ten and remains close to 45 percent even after fifty years. This level of persistence suggests that strong entry barriers, regulation, and scale economies substantially limit reallocation and preserve initial differences in firm size over time.This level of persistence suggests that strong entry barriers, regulation, and scale economies substantially limit reallocation and preserve initial differences in firm size over time, a pattern consistent with empirical evidence showing that firm-level heterogeneity in performance and size persists longer in capital-intensive and regulated sectors due to slower adjustment, reallocation constraints, and the enduring influence of initial conditions (Foster, Haltiwanger  Syverson, 2008; Bartelsman, Haltiwanger  Scarpetta, 2009).

Taken together, the sectoral evidence reveals substantial heterogeneity in the persistence of firm growth potential across the Italian economy. While initial firm characteristics are decisive at entry in all sectors, their long-run importance is highly sector-specific. Outside of regulated and capital-intensive sectors, long-run employment dispersion is overwhelmingly driven by post-entry dynamics rather than by persistent differences in initial firm characteristics.

These findings stand in sharp contrast to the evidence for the United States documented by Sterk et al. (2021). In their analysis, ex-ante heterogeneity remains quantitatively important throughout the firm life cycle, never accounting for less than 40 percent of employment dispersion even at long horizons. By comparison, the Italian economy-wide contribution of ex-ante heterogeneity falls to around 20 percent in the long run, and to near zero in several major sectors such as Construction, Wholesale, and Services. The only Italian sectors exhibiting persistence comparable to the US benchmark are Energy and Transport and, to a lesser extent, Manufacturing.

This contrast suggests that the Italian economy is characterized by a much weaker persistence of firm-level growth potential. While firms are strongly sorted at entry, post-entry shocks, institutional frictions, and slow reallocation play a dominant role in reshaping the firm size distribution over time. As a result, long-run firm size in Italy reflects accumulated post-entry dynamics to a much greater extent than in the United States, where initial firm characteristics remain a key determinant of growth trajectories.

Figure 5 illustrates the evolution of the contribution of ex-ante heterogeneity to firm-level employment dispersion across macro sectors, replicating the framework of Sterk et al. (2021). While all sectors exhibit a very high ex-ante component at entry, the persistence of initial heterogeneity over the firm life cycle differs substantially across sectors.

Construction firms start with an ex-ante share of approximately 90 percent at entry, but this contribution declines rapidly, falling below 15 percent by age 10 and becoming negligible—below 2 percent—after twenty years. A similarly rapid erosion of initial heterogeneity is observed in Wholesale, where the ex-ante component drops from roughly 95 percent at entry to around 35 percent by age 10 and to less than 3 percent at long horizons. Service firms also display a fast decline: the ex-ante share decreases from about 92 percent at entry to roughly 17 percent by age 10 and stabilizes at around 5 percent in the long run.

Manufacturing exhibits a more gradual pattern. The contribution of ex-ante heterogeneity is very high at entry, close to 96 percent, and remains quantitatively important during the first decade of a firm's life. However, it declines steadily thereafter, reaching approximately 50 percent by age 10 and stabilizing at around 20 percent at longer horizons. This intermediate degree of persistence suggests that initial differences in scale and productive capacity matter for longer in manufacturing than in non-tradable sectors, but are eventually eroded by cumulative shocks and competitive forces. Autor et al. (2020) document persistent productivity and scale advantages of "superstar" firms, especially in manufacturing and tradable sectors. This directly supports the idea that initial conditions decay more slowly where scale and technology matter.

Energy and Transport stand out as an exception. In this sector, the ex-ante component declines much more slowly, falling from about 93 percent at entry to roughly 50 percent by age 10 and remaining close to 45 percent even after fifty years. Primary and Extractive activities display a similarly persistent pattern, with the ex-ante share remaining above 40 percent at long horizons. These sectors are characterized by high capital intensity, strong entry barriers, and regulation, which limit reallocation and preserve initial differences in firm size. Calligaris et al. (2024) document that capital-intensive and regulated sectors exhibit lower dynamism and more persistent firm-level dispersion, especially in network and extractive industries.

Taken together, these results indicate that the scope for firm-level shocks to shape long-run employment outcomes is highly sector-specific. In Construction, Wholesale, and Services, long-run dispersion is overwhelmingly driven by post-entry dynamics, whereas in Energy, Transport, and Primary sectors, initial firm characteristics continue to play a major role throughout the firm life cycle.

| MODEL | $\rho_u$ | $\rho_v$ | $\rho_w$ | $\sigma_{th}$ | $\sigma_u$ | $\sigma_v$ | $\sigma_{eps}$ | $\sigma_z$ | RMSE |
|---|---|---|---|---|---|---|---|---|---|
| Manufacturing | -0.181 | 0.906 | 1.007 | 0.742 | 1.903 | 1.143 | 0.206 | 0.165 | 0.022 |
| Energy & Transports | -0.027 | 0.805 | 0.905 | 0.946 | 0.126 | 1.596 | 0.432 | 0.141 | 0.067 |
| Primary and Extractive | -0.084 | 0.792 | 1.082 | 0.907 | 0.150 | 1.154 | 0.168 | 0.372 | 0.066 |
| Services | 0.989 | 0.816 | 0.950 | 0.000 | 0.550 | 1.826 | 0.437 | 0.126 | 0.049 |
| Wholesales | -0.454 | 0.944 | 1.033 | 0.432 | 0.676 | 1.255 | 0.247 | 0.191 | 0.023 |
| Constructions | -0.208 | 0.820 | 1.065 | 0.561 | 0.000 | 1.552 | 0.251 | 0.402 | 0.082 |

Table 9: Parameter estimates from Reduced-Form Model across Sectors

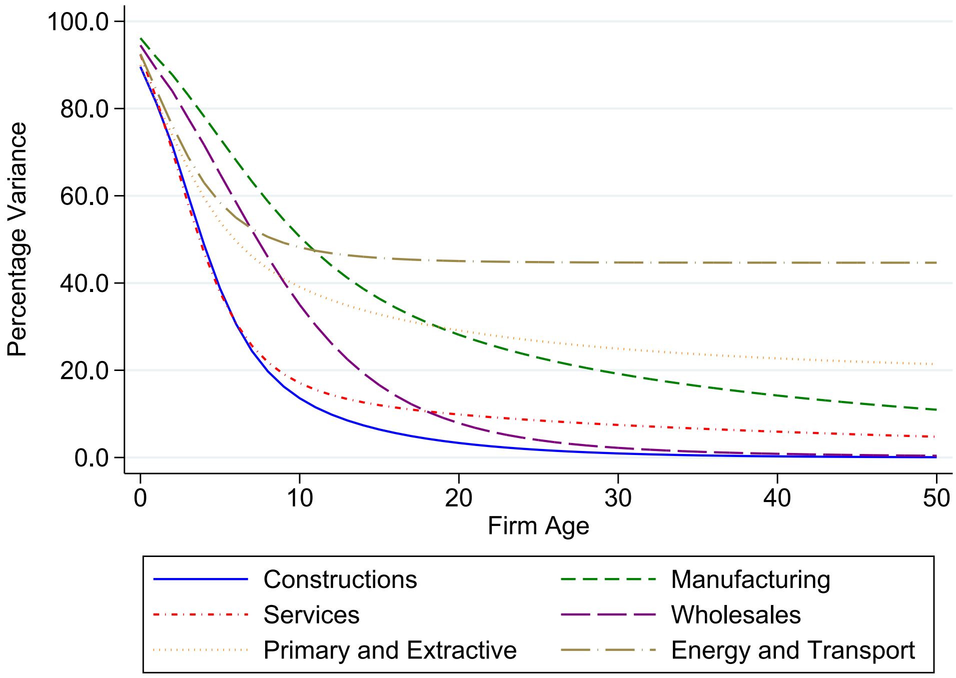



Figure 5: Variance by firm age and sector

# 8 Manufacturing sector: high and low tech

The comparison between high-tech and low-tech manufacturing reveals a clear and economically meaningful divergence in the persistence of ex-ante heterogeneity over the firm life cycle.

High-tech industries display extremely persistent ex-ante heterogeneity. At birth, the ex-ante component accounts for almost 100% of total dispersion. It declines only gradually, remaining around 75% at age 10, and stabilizing at roughly 45–50% thereafter. This pattern indicates that initial firm-specific characteristics—such as managerial ability, innovation potential, or technology-embedded productivity—continue to play a dominant role even decades after entry. High-tech firms therefore retain a strong imprint of their initial conditions, which is consistent with sectors where innovation, quality upgrading, and intangible assets generate persistent performance differentials.

Low-tech manufacturing shows the opposite pattern. Although ex-ante heterogeneity is very high at entry (approximately 98%), it dissipates rapidly. By age 10 the ex-ante share falls to about 40%, and it continues to decline steadily, reaching 20% around age 30 and stabilizing near 15% for older firms. This implies that ex-post shocks—such as market conditions, input cost volatility, or operational adjustments—quickly dominate firm dynamics. In these industries, initial firm advantages decay rapidly, and subsequent performance is largely driven by idiosyncratic shocks rather than persistent intrinsic traits.

Taken together, these results align strongly with our overarching hypothesis. High-tech industries, where the ex-ante component remains large and persistent, should exhibit stronger amplification of shocks in the regression analysis. In other words, we expect larger and more persistent coefficients on lagged size and age, reflecting the fact that initial firm characteristics continue to shape growth trajectories. Conversely, in low-tech manufacturing—where ex-ante heterogeneity fades quickly—we expect more muted responses: smaller coefficients, lower persistence, and growth patterns more strongly influenced by transitory shocks.

This contrast provides a clean within-manufacturing validation of the mechanism identified in our structural model: sectors with slowly decaying ex-ante heterogeneity should display steeper age–growth and size–growth gradients, while sectors with rapid dissipation of ex-ante heterogeneity should display flatter profiles.

To formalize these differences, we estimate regressions of net employment growth on lagged firm size and age, allowing for heterogeneous effects across sectors through interactions with sector dummies, as described in Section 9. In addition, we explicitly exploit the within-manufacturing variation

| MODEL | $\rho_u$ | $\rho_v$ | $\rho_w$ | $\sigma_{th}$ | $\sigma_u$ | $\sigma_v$ | $\sigma_{eps}$ | $\sigma_z$ | RMSE |
|---|---|---|---|---|---|---|---|---|---|
| High Tech | -0.155 | 0.895 | 0.967 | 0.756 | 2.827 | 1.295 | 0.208 | 0.000 | 0.021 |
| Low Tech | -0.191 | 0.915 | 1.030 | 0.724 | 1.506 | 1.024 | 0.197 | 0.213 | 0.033 |

Table 10: Parameter estimates from Reduced-Form Model in the Manufacturing Sector

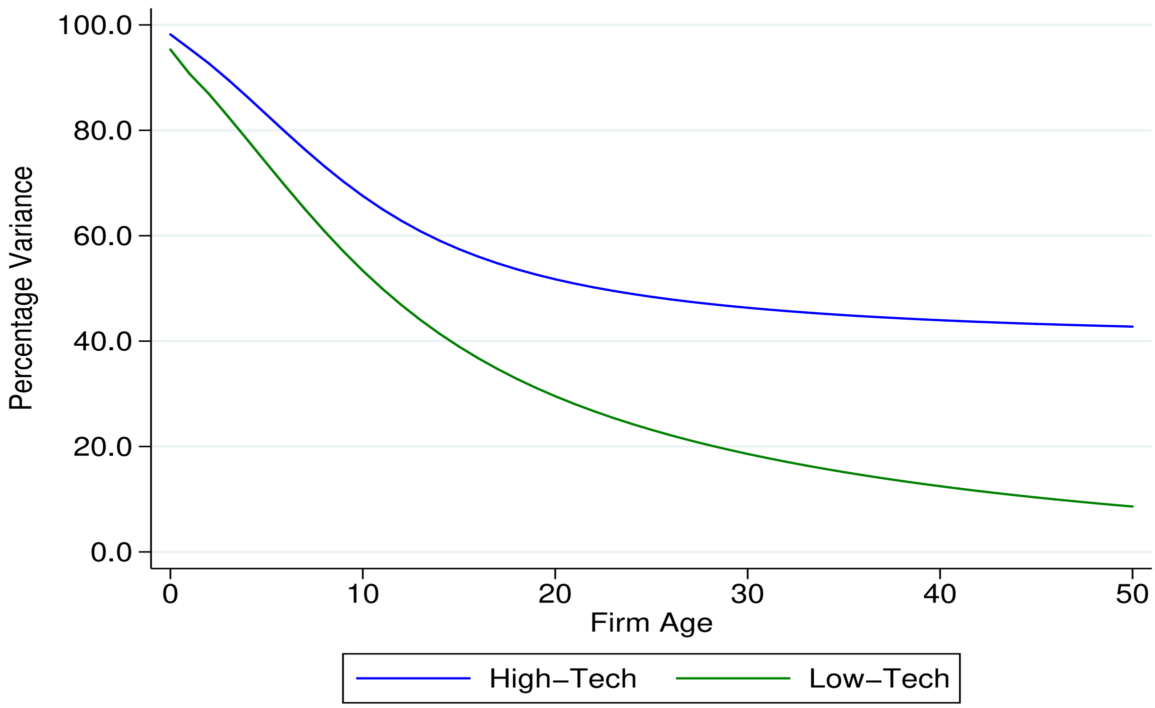



Figure 6: High and low tech manufacturing sector

by distinguishing between high-tech and low-tech industries, which display markedly different degrees of persistence in ex-ante heterogeneity.

Our results suggest that sectors characterized by a more persistent ex-ante component—such as Energy and Transport and Primary and Extractive industries—should exhibit stronger amplification of initial conditions, reflected in larger and more persistent coefficients on both size and age. Conversely, sectors in which ex-ante heterogeneity dissipates rapidly—such as Construction, Wholesale, and Services—are expected to display more muted and short-lived responses to initial firm characteristics.

The manufacturing evidence provides a further refinement of this mechanism. In particular, high-tech manufacturing—where ex-ante heterogeneity remains highly persistent over the firm life cycle—is expected to exhibit stronger and more persistent effects of initial size and age on growth dynamics. By contrast, low-tech manufacturing, where initial heterogeneity decays rapidly and post-entry shocks dominate, should display weaker and less persistent coefficients.

Overall, this approach links the decomposition of firm-level heterogeneity into ex-ante and ex-post components to observable differences in growth dynamics across sectors, highlighting the central role of sectoral structure—and in particular technological intensity within manufacturing—in shaping the persistence of firm-level dynamics and the transmission of shocks over the life cycle.

# 9 From Macro to Micro: a regression based approach

While our study does not rely on a calibrated theoretical model, it provides relevant insights by demonstrating how firm-level heterogeneity influences the transmission of shocks across the economy. Following the empirical strategy of Scoccianti and Sette (2024), we consider firm-level growth rates (e.g., employment growth or ROE, following Davis et al. (1998)) as dependent variables and regress them on firm characteristics such as size and age, along with sectoral indicators. This allows us to test whether firms with a high ex-ante component exhibit systematically different responses to shocks compared to those with a lower ex-ante component. In particular, we hypothesize that the magnitude of the regression coefficients will differ significantly across groups, reflecting that firms with higher initial heterogeneity may amplify or dampen the effects of shocks more than firms with lower ex-ante variation. By identifying such differences, our analysis sheds light on how structural firm heterogeneity shapes the propagation of shocks and sectoral dynamics in the Italian economy, providing empirical guidance for policymakers even in the absence of a full theoretical calibration. Moreover, this approach allows us to directly link our findings to the ex-ante versus ex-post decomposition of Sterk et al. (2021), highlighting the role of initial firm characteristics in amplifying or mitigating growth differentials across sectors.

Scoccianti and Sette (2024) document how firm dynamics differ for firms located in the South versus the Center-North of Italy, using the universe of private sector firms with at least one employee over the last three decades. Controlling for industry fixed effects, they find that in both regions, firms' age and size negatively correlate with their growth, with this negative correlation being much stronger in the South. Building on this framework, we analyze firm dynamics across sectors, allowing us to explore sectoral heterogeneity in growth patterns.

We replicate equation (1) of Scoccianti and Sette (2024), adapted to our setting. In the baseline specification, the dependent variable is the Davis–Haltiwanger net employment growth rate (Davis et al., 1998), which accounts for both entry and exit from the market:

$$\text{net\_growth}_{i,t} = \frac{L_{i,t} - L_{i,t-1}}{\frac{1}{2}\left(L_{i,t} + L_{i,t-1}\right)}, \qquad L_{i,t} = \text{employment of firm } i \text{ at time } t.$$

This measure is particularly suitable because it captures net employment changes on both the extensive and intensive margins, with support $[-2, 2]$, taking value $-2$ when a firm exits and 2 when it enters. Averaging size over two periods in the denominator also mitigates potential regression-to-the-mean biases.

The estimated model is:

$$\begin{aligned} \text{net\_growth}_{i,t} = \alpha_0 + \alpha_1 \,\text{emp}_{i,t-1} + \alpha_2 \,\text{age}_{i,t} + \eta_{c(i)} \\ + \sum_{s \neq 6} \gamma_s \, D_{i,s} + \sum_{s \neq 6} \delta_s \left( D_{i,s} \cdot X_{i,t} \right) + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

Firm *size* is defined as (log) employment, while firm *age* is defined as the logarithm of firm age. The dependent variable is firm net employment growth, measured as the standard symmetric growth rate of employment.

In the baseline specification, we include cohort fixed effects, defined by the year of firm entry, to control for systematic differences across entry cohorts in initial conditions and macroeconomic environments. In addition, we control for a rich set of 6-digit ATECO industry fixed effects in the first two specifications, in order to absorb persistent industry-level heterogeneity. Standard errors are clustered at the firm level to account for within-firm serial correlation in the error terms over time.

In subsequent specifications, we move from detailed industry controls to a more aggregated sectoral structure by introducing sector dummies. The dummy $D_{i,s}$ equals 1 if firm $i$ belongs to sector $s$, and 0 otherwise. We first consider a 6-sector classification (Table 5) and then further refine the analysis within manufacturing by distinguishing between high- and low-tech industries using dedicated indicator variables (Table 7).

In the final specifications, we allow for heterogeneous effects by interacting sector dummies with either lagged firm size or firm age $X_{i,t}$, depending on the specification. These interactions are designed to capture sector-specific differences in both the size–growth and age–growth relationships, thereby allowing for heterogeneous life-cycle dynamics and differential persistence of initial conditions across industries.

Finally, we replicate the same exercises by replacing the dependent variable with return on equity (ROE). By linking these empirical patterns to the ex-ante component emphasized in Sterk et al. (2021), we interpret sectoral growth differences as partially driven by initial firm heterogeneity, providing a bridge between micro-level dynamics and aggregate amplification mechanisms. .

Higher ex-ante heterogeneity increases the sensitivity of firm growth to initial conditions, because persistent productivity differences interact with shocks, leading to stronger amplification effects. As a result, size and age should display larger estimated coefficients in high ex-ante sectors.

# 10 Regression Results

**Table 12 – Baseline Regressions** Column (1) reports the regression of net employment growth on lagged firm size (log of employees), controlling for sector and year fixed effects. The coefficient on $\log(\text{emp}_{t-1})$ is -0.0343

and highly significant, indicating that smaller firms grow faster, consistent with standard firm growth literature [ADD REF]. The relationship between size and growth remains significant when adding firm's age as additional regressor (see Column (2)). This result is in line with Scoccianti and Sette (2024) and represents a violation of Gibrat's law according to which the growth performance of firms should be independent of their size. We observe instead that conditional on survival, smaller firms tend to grow faster than larger ones to reach a minimum efficient scale of production (see also Lotti et al. (2009)) The coefficient on log(age) is -0.0657, also highly significant and negative, thus younger firms grow faster.

These results provide a clear baseline: size and age exert a negative effect on employment growth across all firms, once years and sectors fixed effects are accounted for, confirming the general negative relationship between firm maturity and growth.

**Table 13 – Sectoral Regressions with Interactions** Columns (1)–(3) extend the baseline by including first sector dummies and then interactions with size and age, allowing us to assess heterogeneity across sectors.

The sector dummies capture mean differences in net employment growth relative to the omitted sector (Energy & Transports). Constructions has a strongly negative coefficient (-0.0619), indicating overall slower growth relative to the baseline, firms in this sector grow on average 6.2 percentage points slower than those in Energy  Transport. Services (-0.0298, p¡0.01) and Wholesale (-0.0294, p¡0.01) also grow more slowly, by approximately 3 percentage points, while Primary  Extractive (-0.0106, p¡0.01) and Manufacturing (-0.0066, p¡0.01) show only slight reductions relative to the baseline. These results highlight that Energy  Transport is the fastest-growing sector on average and that there is substantial heterogeneity in growth rates across sectors even after controlling for firm size.

When combined with the ex-ante variance of employment growth (Table **??**), a clear pattern emerges: sectors with more negative baseline growth coefficients, such as Constructions, Services, and Wholesale, tend to exhibit a sharp decline in ex-ante variance over the firm lifecycle, indicating that growth becomes more predictable as firms age. In contrast, sectors closer to the baseline, like Manufacturing and Primary  Extractive, retain higher ex-ante variance, reflecting greater heterogeneity in growth trajectories across firms. This alignment between baseline growth and variance dynamics underscores the importance of a disaggregated sectoral perspective in modeling employment growth.

Interactions between sector dummies and lagged employment reveal how the effect of firm size varies across sectors. Positive coefficients in constructions (0.0028), manufacturing (0.0097), wholesale (0.0058), and services (0.0064) indicate that the negative effect of size is partially mitigated in sectors with high or persistent ex-ante heterogeneity.

- For sectors where ex-ante declines rapidly (wholesale and low ex-ante manufacturing), the interactions are smaller, consistent with the idea that when initial heterogeneity dissipates quickly, firm size has less differential impact on growth. CHECK - Primary sector have near-zero interactions, reflecting moderate to slowly declining ex-ante shares, in line with the earlier ex-ante decomposition.

Age interactions show how the growth penalty associated with age varies by sector. Constructions (0.0096) and manufacturing (0.0063) have positive coefficients, suggesting that older firms in these high-ex-ante sectors retain some growth potential relative to others, consistent with a persistence effect from initial conditions. Services have a negative interaction (-0.0152), indicating that older firms in this sector slow down more than in high-ex-ante sectors, reflecting the lower persistence of ex-ante in services (stabilizing at 45%). - Primary and energy sectors show coefficients close to zero, again consistent with the ex-ante patterns where either the component dissipates gradually or initially is less relevant.

**Linking Regressions to Sectoral Ex-Ante Shares** The regression results closely mirror the ex-ante dynamics observed in the sectoral decomposition graph: Across sectors, we observe substantial heterogeneity in both the level and persistence of ex-ante heterogeneity, as well as in its interaction with growth dynamics. In construction and high-ex-ante manufacturing, the role of initial conditions is particularly strong: ex-ante heterogeneity starts at very high levels (around 97%) and declines only gradually over time. In these sectors, positive interaction coefficients suggest that initial firm characteristics tend to amplify subsequent growth dynamics, implying that firms with stronger initial positions benefit more persistently from their early advantages.

A different pattern emerges in wholesale and low-ex-ante manufacturing, where ex-ante heterogeneity declines rapidly and becomes negligible by mid-life. Consistently, interaction effects with size and age are small or statistically insignificant, indicating that initial conditions play a limited role in shaping long-run growth trajectories in these sectors.

The service sector lies between these two extremes. Ex-ante heterogeneity begins at relatively high levels (around 85%) but stabilizes at a non-negligible long-run value of approximately 45%. This suggests a partial persistence of initial conditions. The associated interaction effects are moderate, while the negative interaction with age points to a gradual erosion of growth potential over the firm life cycle.

In energy and transport, ex-ante heterogeneity remains high and declines only slowly over time. Although interaction effects are generally modest, they remain positive, indicating that initial conditions continue to exert a meaningful—albeit less pronounced—influence on growth patterns.

Finally, in primary and extractive sectors, ex-ante heterogeneity steadily declines toward zero, and interaction effects are small. This pattern suggests that in these industries, initial firm characteristics are less important in explaining growth dynamics, with outcomes being driven more by post-entry developments.

In summary, the interaction coefficients in Table 13 confirm that the impact of firm size and age on employment growth is strongly modulated by the sectoral ex-ante composition. Sectors with high and persistent ex-ante shares exhibit amplified growth effects of firm characteristics, whereas sectors with low or rapidly decaying ex-ante show limited amplification. This evidence supports the hypothesis that ex-ante heterogeneity acts as a mechanism of differential shock transmission across sectors, consistent with the theoretical reasoning outlined earlier.

# 11 Tables

Table 11: Sectoral Ex-Ante Heterogeneity at Entry, Age 10, and Age 50, Baseline Growth, and Regression Interactions

| **Sector** | **Entry** | **10** | **50** | **Baseline Growth $\beta$** | **Emp$\times$ Sector** | **Age $\times$ Sector** |
|---|---|---|---|---|---|---|
| Construction | 89.59 | 16.25 | 0.0855 | -0.0619*** | 0.0028*** | 0.0096*** |
| Energy & Trans. | 92.51 | 49.20 | 44.6595 | 0.0000 | 0.0000 | 0.0000 |
| Manufact. | 96.15 | 54.49 | 11.23 | -0.0066*** | 0.0097*** | 0.0063*** |
| Primary & Extract. | 89.93 | 40.98 | 21.51 | -0.0106*** | -0.0067*** | -0.0056* |
| Services | 92.41 | 19.09 | 4.86 | -0.0298*** | 0.0064*** | -0.0152*** |
| Wholesale | 94.51 | 40.25 | 0.424 | -0.0294*** | 0.0058*** | -0.0001 |

*Notes*: The table shows the ex-ante share of employment variance at entry, age 10, and age 50, combined with baseline sector coefficients and interaction terms.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: EMPLOYMENT GROWTH-SECTOR-baseline regressions

| | (1)<br>emp_growth | (2)<br>emp_growth |
|---|---|---|
| $\log(\text{emp})_{t-1}$ | -0.0343*** | -0.0337*** |
| | (0.000) | (0.000) |
| log(age) | | -0.0657*** |
| | | (0.001) |
| sector fe | yes | yes |
| year fe | yes | yes |
| R-squared | 0.0310 | 0.0353 |
| Observations | 862,000 | 862,000 |

Robust standard errors in parentheses (clustered at the firm level)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13 replicates estimates of Table 12 adding sector dummies (column 1) and interactions between employment and sectors.

Table 13: EMPLOYMENT GROWTH – Sector regressions with interactions

| | (1) emp_growth | (2) emp_growth | (3) emp_growth |
|---|---|---|---|
| $\log(\text{emp}_{t-1})$ | -0.0248*** | -0.0300*** | -0.0248*** |
| | (0.000) | (0.001) | (0.000) |
| log(age) | -0.0652*** | -0.0651*** | -0.0649*** |
| | (0.001) | (0.001) | (0.002) |
| Primary | -0.0106*** | 0.0074 | 0.0057 |
| | (0.002) | (0.007) | (0.010) |
| Manufacturing | -0.0066*** | -0.0427*** | -0.0265*** |
| | (0.001) | (0.005) | (0.007) |
| Constructions | -0.0619*** | -0.0743*** | -0.0902*** |
| | (0.002) | (0.006) | (0.010) |
| Wholesale | -0.0294*** | -0.0505*** | -0.0290*** |
| | (0.001) | (0.005) | (0.007) |
| Services | -0.0298*** | -0.0528*** | 0.0139* |
| | (0.002) | (0.005) | (0.008) |
| Primary × $\log(\text{emp}_{t-1})$ | | -0.0067*** | |
| | | (0.002) | |
| Manufacturing × $\log(\text{emp}_{t-1})$ | | 0.0097*** | |
| | | (0.001) | |
| Constructions × $\log(\text{emp}_{t-1})$ | | 0.0028* | |
| | | (0.002) | |
| Wholesale × $\log(\text{emp}_{t-1})$ | | 0.0058*** | |
| | | (0.001) | |
| Services × $\log(\text{emp}_{t-1})$ | | 0.0064*** | |
| | | (0.001) | |
| Primary × log(age) | | | -0.0056* |
| | | | (0.003) |
| Manufacturing × log(age) | | | 0.0063*** |
| | | | (0.002) |
| Constructions × log(age) | | | 0.0096*** |
| | | | (0.003) |
| Wholesale × log(age) | | | -0.0001 |
| | | | (0.002) |
| Services × log(age) | | | -0.0152*** |
| | | | (0.002) |
| year fe | yes | yes | yes |
| R-squared | 0.0239 | 0.0242 | 0.0243 |
| Observations | 862,000 | 862,000 | 862,000 |

Robust standard errors in parentheses (clustered at the firm level)

Omitted sector: Energy & Transports.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

## 11.1 Manufacturing: high versus low tech

Table 14: EMPLOYMENT GROWTH – Manufacturing sector

| | (1) emp_growth | (2) emp_growth | (3) emp_growth | (4) emp_growth |
|---|---|---|---|---|
| $\log(\text{emp}_{t-1})$ | -0.0207*** | -0.0204*** | -0.0211*** | -0.0212*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| log(age) | | -0.0372*** | -0.0370*** | -0.0370*** |
| | | (0.002) | (0.002) | (0.002) |
| Low-Tech | | | -0.0145*** | -0.0152*** |
| LT$\times$ $\log(\text{emp}_{t-1})$ | | | | 0.0002*** |
| Constant | 0.0875*** | 0.2034*** | 0.2146*** | 0.2150*** |
| R-squared | 0.0167 | 0.0188 | 0.0197 | 0.0197 |
| Observations | 303,000 | 303,000 | 303,000 | 303,000 |

Robust standard errors in parentheses (clustered at the firm level)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# 12 ROE regressions

Turning to profitability dynamics, the regression results for ROE display patterns that are markedly different from those observed for employment growth, and these differences closely align with the ex-ante decomposition shown in Figure 7. In the baseline specification (Table 15), firm size has a weak and only marginally significant negative effect on ROE growth, while firm age enters with a positive and highly significant coefficient. This already suggests that, unlike employment, profitability dynamics are not characterized by a strong "catch-up" mechanism of small and young firms; rather, more mature firms tend to exhibit higher and more stable returns. Once we control for lagged profitability, the explanatory power of the regression increases substantially, and the coefficient on $\text{ROE}_{t-1}$ is negative and significant, indicating mean reversion in profitability. This result is consistent with the graphical evidence: the ex-ante contribution to ROE dispersion declines rapidly over the firm life cycle, implying that initial heterogeneity is quickly eroded and that idiosyncratic shocks dominate the evolution of profits.

The sectoral regressions with interactions further reinforce this interpretation. Compared to employment, interaction effects with size and age are generally weaker and less systematically aligned with the ex-ante ranking of sectors. While some sectors—such as construction and services—display positive size interactions, these effects are not consistently related to persistent ex-ante heterogeneity. In fact, sectors characterized by a rapid decline in ex-ante ROE dispersion (as in Figure 7) tend to exhibit limited or unstable interaction effects, suggesting that initial conditions play a smaller role in shaping profitability dynamics. Similarly, the interaction with age is often negative, indicating that the positive baseline effect of age on ROE diminishes in several sectors, consistent with the idea that profitability converges over time.

Overall, the evidence points to a weaker role of ex-ante heterogeneity in driving ROE dynamics compared to employment. While employment growth reflects persistent differences across firms that amplify the impact of initial conditions, profitability appears to be largely governed by mean reversion and transitory shocks. This contrast highlights an important dimension of firm heterogeneity: ex-ante components are central for quantities such as employment, but much less so for financial performance measures like ROE, where dispersion is increasingly driven by ex-post realizations rather than initial firm characteristics.

This interpretation is further supported by the graphical evidence in Figure 7, where the ex-ante component of ROE dispersion drops sharply already in the early years of the firm life cycle—from levels close to 90% at entry to well below 50% within the first decade—and stabilizes at relatively low levels thereafter. This rapid convergence indicates that initial differences in profitability are quickly dominated by idiosyncratic shocks, in contrast with the more persistent patterns observed for employment. Consistently, the reduced-form estimates reported in Table 19 show a very low RMSE (0.001), alongside moderate persistence parameters (e.g., $\rho_u = 0.440$, $\rho_v = 0.783$, $\rho_w = 0.698$), suggesting that the model captures well the short-run dynamics of ROE despite the limited role of persistent heterogeneity. Overall, these results confirm that profitability fluctuations are largely driven by transitory components rather than by long-lasting ex-ante differences across firms.

Table 15: ROE GROWTH - baseline

| | (1)<br>ROE_growth | (2)<br>ROE_growth | (3)<br>ROE_growth |
|---|---|---|---|
| $\log(\text{emp}_{t-1})$ | -0.0005 | -0.0012$^{*}$ | -0.0030$^{***}$ |
| | (0.001) | (0.001) | (0.001) |
| log(age) | | 0.0742$^{***}$ | 0.0311$^{***}$ |
| | | (0.003) | (0.004) |
| $\text{ROE}_{t-1}$ | | | -0.0157$^{***}$ |
| | | | (0.000) |
| sector fe | yes | yes | |
| year fe | yes | yes | |
| R-squared | 0.0005 | 0.0009 | 0.1066 |
| Observations | 794,000 | 794,000 | 794,000 |

Robust standard errors clustered at firm level.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 16: ROE GROWTH – Sector regressions with interactions

| | (1) ROE_growth | (2) ROE_growth | (3) ROE_growth |
|---|---|---|---|
| $\log(\text{emp}_{t-1})$ | -0.0008 | -0.0047** | -0.0009 |
| | (0.001) | (0.002) | (0.001) |
| log(age) | 0.0741*** | 0.0742*** | 0.0819*** |
| | (0.003) | (0.003) | (0.005) |
| Primary | 0.0359*** | -0.0008 | 0.0591*** |
| | (0.004) | (0.012) | (0.020) |
| Manufacturing | 0.0375*** | 0.0440*** | 0.0782*** |
| | (0.003) | (0.009) | (0.014) |
| Constructions | -0.0216*** | -0.0531*** | -0.0136 |
| | (0.004) | (0.012) | (0.019) |
| Wholesale | 0.0158*** | -0.0025 | 0.0163 |
| | (0.003) | (0.008) | (0.013) |
| Services | 0.0053 | -0.0174* | 0.0592*** |
| | (0.003) | (0.009) | (0.015) |
| Primary × $\log(\text{emp}_{t-1})$ | | 0.0109*** | |
| | | (0.003) | |
| Manufacturing × $\log(\text{emp}_{t-1})$ | | -0.0018 | |
| | | (0.002) | |
| Constructions × $\log(\text{emp}_{t-1})$ | | 0.0097*** | |
| | | (0.003) | |
| Wholesale × $\log(\text{emp}_{t-1})$ | | 0.0053** | |
| | | (0.002) | |
| Services × $\log(\text{emp}_{t-1})$ | | 0.0066*** | |
| | | (0.002) | |
| Energy × $\log(\text{emp}_{t-1})$ | | 0.0000 | |
| | | (.) | |
| Primary × log(age) | | | -0.0079 |
| | | | (0.006) |
| Manufacturing × log(age) | | | -0.0135*** |
| | | | (0.004) |
| Constructions × log(age) | | | -0.0028 |
| | | | (0.006) |
| Wholesale × log(age) | | | -0.0002 |
| | | | (0.004) |
| Services × log(age) | | | -0.0185*** |
| | | | (0.005) |
| Constant | -0.2813*** | -0.2672*** | -0.3039*** |
| | (0.011) | (0.013) | (0.015) |
| Observations | 794,471 | 794,471 | 794,471 |

Year fixed effects are also included Robust standard errors in parentheses (clustered at the firm level).
Omitted sector: Energy & Transports.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: ROE GROWTH – Sector regressions (extended specification)

| | (1)<br>ROE_growth | (2)<br>ROE_growth | (3)<br>ROE_growth |
|---|---|---|---|
| $ROE_{t-1}$ | -0.0156*** | -0.0157*** | -0.0156*** |
| | (0.000) | (0.000) | (0.000) |
| $\log(emp_{t-1})$ | -0.0009 | -0.0161*** | -0.0008 |
| | (0.001) | (0.002) | (0.001) |
| log(age) | 0.0306*** | 0.0318*** | 0.0334*** |
| | (0.004) | (0.004) | (0.006) |
| Primary | 0.0128** | -0.0556*** | 0.0278 |
| | (0.006) | (0.015) | (0.024) |
| Manufacturing | 0.0316*** | 0.0327*** | -0.0209 |
| | (0.004) | (0.012) | (0.017) |
| Constructions | -0.0396*** | -0.1918*** | 0.0107 |
| | (0.006) | (0.015) | (0.022) |
| Wholesale | 0.0232*** | -0.0047 | 0.0591*** |
| | (0.004) | (0.011) | (0.017) |
| Services | -0.0106** | -0.1303*** | 0.0322* |
| | (0.005) | (0.012) | (0.019) |
| Primary $\times \log(emp_{t-1})$ | | 0.0188*** | |
| | | (0.004) | |
| Manufacturing $\times \log(emp_{t-1})$ | | -0.0004 | |
| | | (0.003) | |
| Constructions $\times \log(emp_{t-1})$ | | 0.0477*** | |
| | | (0.004) | |
| Wholesale $\times \log(emp_{t-1})$ | | 0.0049* | |
| | | (0.003) | |
| Services $\times \log(emp_{t-1})$ | | 0.0357*** | |
| | | (0.003) | |
| Primary × log(age) | | | -0.0051 |
| | | | (0.008) |
| Manufacturing × log(age) | | | 0.0165*** |
| | | | (0.005) |
| Constructions × log(age) | | | -0.0169** |
| | | | (0.007) |
| Wholesale × log(age) | | | -0.0123** |
| | | | (0.005) |
| Services × log(age) | | | -0.0147** |
| | | | (0.006) |
| Constant | -0.0079 | 0.0459*** | -0.0165 |
| | (0.012) | (0.015) | (0.018) |
| Observations | 794,471 | 794,471 | 794,471 |

Year fixed effects are also included. Robust standard errors in parentheses (clustered at the firm level). Omitted sector: Energy & Transports.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: ROE GROWTH – Manufacturing sector

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | ROE_growth | ROE_growth | ROE_growth | ROE_growth | ROE_growth |
| $\log(\text{emp})_{t-1}$ | -0.0058*** | -0.0063*** | -0.0185*** | -0.0210*** | -0.0252*** |
| log(age) | | 0.0063*** | 0.0074*** | 0.0074*** | 0.0074*** |
| $\text{ROE}_{t-1}$ | | | -0.0168*** | -0.0169*** | -0.0169*** |
| Low-Tech | | | | -0.0537*** | -0.0791*** |
| L-T $\times$ $\log(\text{emp})_{t-1}$ | | | | | 0.0067* |
| Constant | -0.0002 | -0.1765*** | -0.0266** | 0.0172 | 0.0331** |
| R-squared | 0.0003 | 0.0008 | 0.1029 | 0.1034 | 0.1034 |
| Observations | 287,000 | 287,000 | 287,000 | 287,000 | 287,000 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

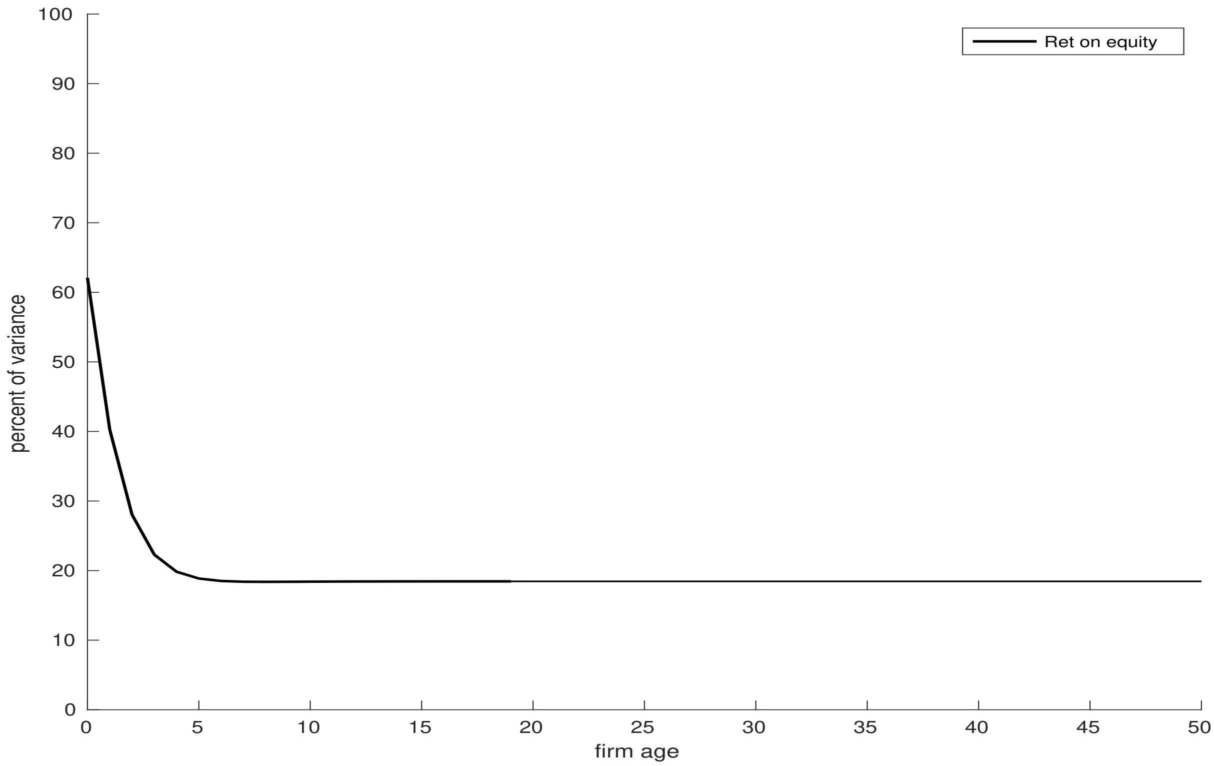



Figure 7: Contribution of Ex Ante Heterogeneity to Cross-Sectional Dispersion

| MODEL | $rho_u$ | $rho_v$ | $rho_w$ | $sig_th$ | $sig_u$ | $sig_v$ | $sig_eps$ | $sig_z$ | RMSE |
|---|---|---|---|---|---|---|---|---|---|
| $AR1_{GEN}$ | 0.440 | 0.783 | 0.698 | 0.023 | 0.089 | 0.085 | 0.063 | 0.044 | 0.001 |

Table 19: Parameter estimates from Reduced-Form Model-ROE

# 13 Conclusion

This paper has examined the origins and persistence of firm-level heterogeneity in the Italian economy, distinguishing between ex-ante characteristics and ex-post idiosyncratic shocks. Using administrative balance-sheet data from the AIDA dataset over the period 2006–2021, and a reduced-form framework inspired by Sterk et al. (2021), we exploit the age-dependent autocovariance structure of firm outcomes to decompose cross-sectional dispersion into its underlying components. The analysis focuses on two key dimensions of firm performance: employment and Return on Equity (ROE).

Our findings show that firms are highly heterogeneous at entry, with ex-ante characteristics accounting for the vast majority of employment dispersion. However, this dominance declines rapidly over the life cycle: the contribution of initial conditions falls substantially with age and converges to relatively low levels in the long run. This indicates that, while initial differences are crucial at entry, post-entry dynamics and idiosyncratic shocks play a central role in shaping long-run outcomes. The contrast is even more pronounced for profitability. For ROE, the role of ex-ante heterogeneity is more limited and short-lived, with strong mean reversion and a dominant contribution of transitory shocks.

Sectoral heterogeneity further refines this picture. In capital-intensive and technologically advanced sectors, ex-ante characteristics remain more persistent and continue to influence firm performance over longer horizons. By contrast, in low-technology and less regulated sectors, the influence of initial conditions dissipates quickly, and firm dynamics are largely driven by post-entry shocks and accumulated experience.

Overall, our results point to an economic environment in which firm dynamics are less anchored in persistent initial conditions than in benchmark economies such as the United States, and more strongly shaped by post-entry adjustments and shocks. This has important implications for both policy and macroeconomic dynamics. On the one hand, policies solely targeting firm creation or initial conditions may have limited long-run effects in many sectors. On the other hand, interventions that facilitate post-entry growth, reallocation, and efficient scaling are likely to be more effective in shaping long-term firm performance. More broadly, the transmission of shocks in the Italian economy is likely to operate primarily through dynamic firm responses rather than through persistent cross-sectional heterogeneity.

# References


Autor, D., Dorn, D., Katz, L. F., Patterson, C., and Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *Quarterly Journal of Economics*, 135(2):645–709.

Bisztray, M., de Nicola, F., and Muraközy, B. (2023). High-growth firms' contribution to aggregate productivity growth. *Small Business Economics*, 60:771–811.

Bugamelli, M., Schivardi, F., and Zizza, R. (2008). The euro and firm restructuring. Working Paper 14454, National Bureau of Economic Research (NBER).

Calligaris, S., Criscuolo, C., and Marcolin, L. (2024). Mark-ups in the digital era. LSE Research Online Documents on Economics 126813, London School of Economics and Political Science, LSE Library.

Davis, S. J., Haltiwanger, J. C., and Schuh, S. (1998). *Job Creation and Destruction*. MIT Press, Cambridge, MA.

Dosi, G. et al. (2019). The evolution of firms and industries. *Industrial and Corporate Change*.

Dosi, G. et al. (2020). Long-run firm dynamics and growth heterogeneity. *Structural Change and Economic Dynamics*.

Ferreira, M. A. et al. (2021a). Firm dynamics and entry conditions: Evidence from portugal. *Journal of Business Economics / or relevant empirical IO journal*.

Ferreira, M. H., Haber, T., and Rörig, C. (2021b). Financial factors, firm size and firm potential. Technical Report 2176, Cambridge Working Papers in Economics.

Guntin, E. and Kochen, L. (2025). Firm growth, size distribution, and ex-ante heterogeneity. *Working Paper*.

Guzman, J. and Li, J. (2022). The signals of success: Firm formation and performance. *Journal of Finance (or working paper version)*.

Guzman, J. and Stern, S. (2015). Nowcasting the startup ecosystem. Technical Report w21003, National Bureau of Economic Research.

Guzman, J. and Stern, S. (2020). *The State of American Entrepreneurship*. MIT Press.

Hopenhayn, H. A. (1992). Entry, exit, and firm dynamics in long run equilibrium. *Econometrica*.

Jovanovic, B. (1982). Selection and the evolution of industry. *Econometrica*.

Lotti, F., Santarelli, E., and Vivarelli, M. (2009). Defending gibrat's law as a long-run regularity. *Small Business Economics*, 32(1):31–44.

Luttmer, E. G. J. (2010). Models of growth and firm heterogeneity. *Quarterly Journal of Economics*.

Melitz, M. J. and Redding, S. J. (2014). Heterogeneous firms and trade. In Gopinath, G., Helpman, E., and Rogoff, K., editors, *Handbook of International Economics*, volume 4, pages 1–54. Elsevier, Amsterdam.

Schivardi, F. and Torrini, R. (2008). Firm size distribution and employment protection legislation in italy. *Labour Economics*, 15(3):482–511.

Scoccianti, F. and Sette, E. (2024). Regional heterogeneity in firm dynamics: The case of italy. *Italian Economic Journal*, 10(3):977–992.

Sterk, V., Sedláček, P., and Pugsley, B. (2021). The nature of firm growth. *American Economic Review*, 111(2):547–579.