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# Employee Age and Experience as Determinants of New Firm Survival: Evidence from Turkish Matched Employer–Employee Data

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# Employee Age and Experience as Determinants of New Firm Survival:

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**Abstract**

This paper investigates the relationship between workforce age composition, prior experience, and firm survival using matched employer–employee data from Turkey spanning 2007 to 2023. Using the universe of Turkish firms from the Entrepreneur Information System (EIS), we estimate discrete-time hazard models on manufacturing corporations and document three main findings. First, the relationship between average employee age and exit risk is non-linear but not smoothly quadratic: exit hazards are significantly elevated only for firms with very young (15–20) or older (45+) workforces, while the 25–40 age range shows no meaningful differences. This challenges the standard inverted-U specification commonly adopted in the literature. Second, this age effect is entirely confined to micro-firms (1–10 employees); for larger firms, capital intensity, export status, and supply-chain linkages dominate survival prospects. Third, prior employment experience of the workforce—measured through sector-specific experience, former employer characteristics, and employment network concentration—significantly predicts survival, especially for smaller firms. The influence of both age and experience variables fades as firms age, consistent with the gradual replacement of entry conditions by accumulated organizational capital. Our results highlight the size-dependent nature of human capital's role in firm survival and carry implications for policies aimed at supporting new-firm longevity in developing economies.

**JEL Classification:** L11, L26, L60, M13

**Keywords:** Firm survival, startups, employee experience, employee age, human capital, matched employer-employee data

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# 1 Introduction

Establishing new firms is essential for job creation, sectoral renewal, and economywide dynamism. Yet most newly established firms exit the market within a few years. Understanding which factors contribute most to the survival of new firms is therefore a first-order question for researchers and policymakers alike. Once these factors are well understood, it becomes possible to design policies that help a larger share of entering firms survive and contribute to employment and output over time.

A large body of research has investigated the determinants of new firm survival, with particular emphasis on founder characteristics, firm size, industry conditions, and financial constraints (see, e.g., Cefis et al., 2022; Josefy et al., 2017; Manjón-Antolín and Arauzo-Carod, 2008, for surveys). In recent years, the availability of matched employer-employee datasets has opened a new avenue: studying how the characteristics and prior experience of a startup's *entire* initial workforce—not just its founder—shape survival prospects. Several studies have documented that founder age, experience, and human capital are significant predictors of survival (Azoulay et al., 2020; Brüderl et al., 1992; Cooper et al., 1994; Hagen et al., 2025), while others have examined how the age composition and diversity of the workforce relate to firm performance (Grund and Westergård-Nielsen, 2008; Backman and Karlsson, 2020; Maliranta and Nurmi, 2019).

This paper contributes to this literature by exploiting the Entrepreneur Information System (EIS)—a comprehensive matched employer–employee database covering the universe of Turkish firms from 2007 to 2023. The EIS does not contain information on the entrepreneur's personal characteristics. To circumvent this limitation, we exploit detailed information on all employees. We argue that this approach is well-suited to the Turkish context, where the vast majority of entering firms employ fewer than five people, so that the average employee's characteristics closely approximate those of the owner-operator. The linked employer-employee structure of the data also allows us to trace each employee's prior employment history, enabling us to construct a rich set of variables capturing sector-specific experience, the characteristics of former employers, and the degree of employment network concentration.

Our paper makes three contributions to the existing literature. First, by using linked employer-employee data, we are able to control for a large number of prior experience aspects of the initial workforce that are typically unobserved. These include the share of employees with same-sector experience, the size and age of former employers, the concentration of prior employment networks (measured by a Herfindahl index), and whether the startup has upstream or downstream supply-chain links to former employers (spin-off status). This rich set of experience variables goes well beyond what is typically available in studies relying on firm-level or founder-level data alone.

Second, we focus on entry conditions and their persistence. We use only entry-year characteristics as determinants of survival, which has two advantages: it avoids endogeneity arising from time-varying covariates that are themselves determined by the firm's survival trajectory, and it directly addresses the question of how much initial endowments matter for long-run outcomes. By estimating separate models for different firm-age groups, we document the gradual fading of the effects of initial conditions as firms accumulate capital and organizational routines.

Third, we systematically study differences between entry-size categories. Nearly all prior studies estimate pooled models across firm sizes and report the resulting coefficients as if they apply uniformly. We show that this approach is misleading: the effects of workforce age and experience on survival are confined almost entirely to micro-firms with fewer than ten employees. For firms with ten or more employees, entirely different factors—capital intensity, export status, and supply-chain linkages—dominate survival prospects. This finding has important implications for both empirical methodology and policy design.

A key methodological contribution concerns our treatment of employee age. The standard approach in the literature is to include average employee age and its square as regressors, yielding an inverted U-shaped relationship with survival (Grund and Westergård-Nielsen, 2008; Maliranta and Nurmi, 2019; Backman and Karlsson, 2020). We show that this specification is misleading. When we replace the continuous age terms with age-group dummies, a sharper picture emerges: exit hazards are significantly elevated only for firms whose average employee age falls below 20 or above 45, while the entire 25–40 range shows no meaningful differences relative to the 35–40 base group. The apparent "inverted U" in continuous specifications is thus an artifact of the extreme tails, not a smooth quadratic relationship across the age distribution. This finding has parallels with recent evidence from Sweden showing that the relationship between founder age and firm performance is more complex than a simple inverted U (Hagen et al., 2025).

Our main empirical findings can be summarized as follows. Using discrete-time hazard models estimated on the full population of manufacturing corporations entering between 2007 and 2020, we find that the employee-age effect is statistically and economically significant only for micro-firms (1–10 employees). When we estimate separate models by firm age (using the 2007–2009 entry cohort tracked over 15 years), we find that the age effect is strongest in the first two years and largely vanishes after five years, consistent with the fading of initial conditions. Among the experience variables, sector-specific experience, the age of former employers, and the concentration of prior employment networks are the most robust predictors of survival, with effects that are largely stable across R&D-intensive and high-growth sectors.

The remainder of the paper is organized as follows. Section 2 reviews the literature on workforce demographics, prior experience, and firm survival. Section 3 describes the data and provides descriptive statistics on firm entry, exit, and workforce characteristics.

Section 4 introduces the econometric specification. Section 5 reports the regression results and discusses them in detail. Section 6 concludes.

# 2 Literature Review

The relationship between employee age and firm survival has been studied across several disciplines, drawing on human capital theory, organizational ecology, labor economics, and team-composition research. This section reviews the key theoretical perspectives and empirical findings.

## 2.1 Theoretical Perspectives

Human capital theory provides the foundational argument that older, more experienced employees possess greater knowledge, skills, and professional networks, all of which can enhance organizational performance and resilience (Becker, 1964). An experienced workforce may solve problems more efficiently, avoid costly errors, and improve decision-making, thereby reducing the hazard of firm failure. These arguments extend to entrepreneurs: older owner-managers bring accumulated industry knowledge and business acumen that can steer firms away from failure (Cooper et al., 1994; Brüderl et al., 1992).

However, theoretical counterpoints suggest potential downsides to an aging workforce. While Stinchcombe (1965) emphasized the "liability of newness"—the fragility of young organizations that lack established routines—subsequent organizational ecology research has identified a countervailing "liability of senescence," whereby older organizations and workforces become rigid and resistant to change. Older employees may adhere to established routines and be less inclined to adopt new technologies, which can hinder innovation and responsiveness in dynamic environments (Backman and Karlsson, 2020). Esteve-Pérez et al. (2018) show that the survival advantage of firm age and accumulated productivity varies over the industry life cycle: in mature industries, older firms may face higher exit hazards than in growing ones, suggesting that the benefits of experience are context-dependent. Career concerns models formalize this intuition: Holmström (1999) shows that younger workers have stronger incentives to exert effort because the future salary gains from building a reputation are large in present-value terms, whereas effort incentives decline as workers approach retirement. In signaling models (Spence, 1973), effort serves as a signal of underlying ability, and younger workers—who have not yet established their reputations—invest more heavily in this signal. Recent evidence on job crafting behavior confirms that younger workers engage more proactively in shaping their jobs, consistent with a longer time horizon over which to reap returns (Schepp and Boehm, 2025).

These opposing forces suggest a non-linear relationship between workforce age and firm outcomes. Several scholars have posited an inverted U-shape, where moderate age and experience optimize performance while workforces that are too young or too old underperform (Grund and Westergård-Nielsen, 2008). Management theory on team composition reinforces this view: diverse age cohorts can yield knowledge complementarities, whereas homogeneity—whether all young or all old—sacrifices either fresh ideas or deep experience. The organizational demography approach (Pfeffer, 1983) argues that social similarity is important for interaction, communication, and cohesion, suggesting potential costs to age diversity as well.

A parallel theoretical tradition, rooted in models of firm dynamics, provides a useful lens for understanding when initial conditions matter most. Jovanovic (1982) models firm survival as a process of passive learning: entering firms are uncertain about their own productivity and learn over time, with less productive firms exiting. Geroski et al. (2010) provide the foundational empirical evidence that founding conditions strongly predict survival in early years but that their influence diminishes over time as post-entry factors take over. In this framework, initial endowments—including human capital—have their greatest impact in the early stages, when firms have not yet accumulated information or tangible assets. As Dahl and Klepper (2015) argue, the early hiring decisions of new firms importantly influence their performance and are difficult to emulate or change when a firm is older, so that the quality of the labor force assembled when a firm is young may serve as the basis for an enduring firm capability.

In developing countries, the age–entrepreneurship relationship is further complicated by the prevalence of subsistence entrepreneurship (Schoar, 2010). Bernstein et al. (2022) show that in Brazil, responsive entrepreneurs—those who create firms in response to local opportunities—tend to be younger and more skilled, whereas necessity or subsistence entrepreneurs are driven by different motivations. Young individuals may have greater tolerance for risk and flexibility in their personal circumstances, while older entrepreneurs may benefit from accumulated wealth and social capital but face greater responsibilities and risk aversion (de Kok et al., 2010; Evans and Jovanovic, 1989).

## 2.2 Empirical Evidence on Founder and Manager Age

Given the outsized influence of founders on firm direction, a substantial strand of literature examines the relationship between founder or manager age and firm outcomes. Cooper et al. (1994) found that initial human capital—industry know-how and managerial experience—is a strong predictor of new venture survival and performance. Brüderl et al. (1992) showed that an entrepreneur's industry experience markedly increased survival time for German startups. Colombo and Grilli (2005) found that among Italian high-tech startups, founder-specific human capital positively affected growth and early survival, whereas general work experience had weaker effects.

Azoulay et al. (2020) provided influential evidence that the most successful high-growth entrepreneurs are predominantly middle-aged: the mean age at founding for the 1-in-1,000 fastest growing new ventures is 45. Prior experience in the specific industry predicts much greater rates of entrepreneurial success, strongly rejecting common hypotheses that emphasize youth as a key trait of successful entrepreneurs. Backman and Karlsson (2020) found that the age of the operational manager is more important for new firms than for incumbents; however, their results on employee age are more complex, with the share of older employees positively associated with survival in some specifications but not others. Their finding that the relationship between manager age and firm exit changes functional shape across firm-size categories foreshadows one of our key results.

Most recently, Hagen et al. (2025) analyze Swedish administrative data and document a more nuanced pattern than a simple inverted U. While the relationship between founder age and survival is broadly inverse-U-shaped, they find significant disruptions between ages 60 and 70, with firm survival temporarily improving at the conventional retirement age of 65. They attribute this to the different selection of entrepreneurs at pension age—individuals with greater financial security, industry experience, and education. Hashai and Zahra (2022) show that founder team prior work experience can be either an asset or a liability depending on the growth stage: deep experience in related industries improves early growth, but experience in unrelated industries or in very large firms can constrain later strategic flexibility. These findings reinforce our argument that the age–survival relationship is more complex than a smooth quadratic and may exhibit discrete shifts at particular age thresholds.

## 2.3 Workforce Composition, Experience, and Survival

Beyond leadership, a firm's overall workforce characteristics shape its survival prospects. Grund and Westergård-Nielsen (2008) use Danish linked employer-employee data and find that both mean age and dispersion of age are inversely U-shaped related to firm performance, with productivity maximized at intermediate values. However, Børing (2021) finds no clear evidence of an age-related productivity–wage gap using Norwegian data, cautioning against simple narratives. Danley and Eriksson (2022), using Swedish matched employer-employee data, provide direct evidence that co-worker complementarities matter: new firms whose employees bring complementary skills and experience from different backgrounds survive longer.

Several studies have emphasized the importance of prior experience. Dahl and Reichstein (2007), using Danish labor market data covering all startups with at least one employee, find that spin-offs from surviving parents and industry-specific experience positively affect the likelihood of survival, while spin-offs from parents that exit are less likely to survive. The spinoff literature has grown substantially: Dahl and Sorenson (2014) provide a framework for understanding the who, why, and how of spinoffs, while Eriksson and Kuhn (2006) document patterns of spinoff entry and exit in Denmark, and Fackler et al. (2016) show for Germany that parent-firm characteristics—particularly size and survival—strongly predict spinoff performance. Gifford et al. (2021) show that founders with prior same-industry experience are more likely to survive, while very high-growth firms have founders who previously worked in universities or started firms. Combining different types of founder experience has a consistently positive relationship with performance. Hashai and Zahra (2022) add an important nuance: prior work experience in related industries is an asset for early growth, but experience in unrelated industries or in very large firms can become a liability as the startup matures.

The role of prior employment networks has received growing attention. Sarada and Tocoian (2019) use Brazilian data and find that new firms with previously connected founding employees experience higher survival odds but slower early growth. They interpret this as evidence that working with former co-workers confers benefits such as resolved informational asymmetries and resource sharing. However, high growth may benefit from a more varied resource set, facilitated by drawing on individuals from multiple employment backgrounds. Our FormerHHI variable directly captures this cohesion–diversity trade-off.

Maliranta and Nurmi (2019) examine Finnish data and find an inverted-U relationship between entrepreneur and employee age and survival, while employees' prior employment in high-productivity firms strongly predicts new-firm survival. Cressy (1996) demonstrates for UK startups that human capital is the "true" determinant of survival and that the correlation between financial capital and survival is largely spurious, with provision of finance being demand-driven.

On firm-level characteristics, the literature consistently finds that larger firms, exporters, and firms with supply-chain linkages survive longer (Mata et al., 1995; Esteve-Pérez and Mañez-Castillejo, 2008). Bernard et al. (2019) demonstrate that production network position—having upstream suppliers and downstream customers—is a powerful determinant of firm performance. Bagley (2019) confirms that network embeddedness strongly predicts survival, particularly for young firms. The role of financial constraints has been debated: Evans and Jovanovic (1989) show that liquidity constraints bind and that a would-be entrepreneur must bear most of the risk, while Cressy (1996) argues that the apparent finance gap may reflect unmeasured human capital differences. Legal form also matters: new firms started as incorporations generally show much higher economic resilience than partnerships (Wennberg and Lindqvist, 2010).

## 2.4 Age Diversity and Innovation

The complementarity between young and old workers within a firm is a recurring theme. Grund and Westergård-Nielsen (2008) argue that young employees bring new ideas and skills on new technologies, whereas older employees have knowledge about intra-firm structures and relevant markets and networks. They find an inverted-U relationship between both the mean and the standard deviation of employee age and labor productivity. Backman and Kohlhase (2020) extend this analysis to workforce diversity more broadly, finding that labor force diversity—including age diversity—is positively associated with firm survival in Swedish data, particularly for knowledge-intensive firms. Danley and Eriksson (2022) provide complementary evidence that it is not diversity per se but the complementarity of co-workers' prior experience that drives the survival benefit.

Innovation is a critical driver of firm survival, and employee age plays a significant role in shaping a firm's innovative capacity. Azoulay et al. (2020) note that despite potential advantages, young entrepreneurs may face substantial disadvantages in terms of human capital, social capital, and financial capital. Audretsch (1991) shows that firm survival varies systematically with the technological regime: in industries where innovation is driven by new entrants, young and small firms may have an advantage, while in routinized regimes, experience and scale dominate. Agarwal (1998) further demonstrates that small-firm survival is closely linked to technological activity, with firms in high-technology industries facing both greater opportunities and greater risks. The tension between youthful creativity and experienced judgment is unlikely to be resolved by a simple monotone or quadratic relationship—a point our empirical results strongly confirm.

# 3 Data and Descriptive Statistics

We utilize firm-level data from the Entrepreneur Information System (EIS) database of the Turkish Ministry of Industry and Technology.[1] The dataset covers all private firms in the Turkish manufacturing and services sectors from 2006 to 2023, excluding the public sector, agriculture, and non-profit organizations.[2]

[1]Earlier firm-level studies on Turkish manufacturing used pre-2001 census data or survey-based datasets covering shorter periods. See, for example, Taymaz (2005) on firm size and productivity, Özler and Taymaz (2007) on foreign ownership, competition, and survival dynamics, and Taymaz and Yilmaz (2014) on foreign ownership, survival, and growth dynamics using both pre-2001 census data and 2003–2009 survey data. The present study is the first to exploit the comprehensive administrative EIS database, which covers the universe of firms from 2006 onward.

[2]We define "entry" as the first quarter the firm employs at least one employee and "exit" as the last quarter of employment. The exit status of those firms in the last quarter of the dataset (2023:Q4) is missing. We exclude firms that are observed only one quarter or intermittently in the dataset. Our sample covers entrants from 2007 to 2020, and we follow the life cycle of all entrants until the end of 2023.

At the firm level, detailed annual balance sheets and income statements are available for corporations since 2006. Using the quarterly Social Security Administration (SSA) database (available from 2012 onward), we can track the firms at which individuals work over time, enabling us to construct employee-level variables including prior work experience and wages in previous jobs.

Throughout the analysis, we distinguish between manufacturing and service-sector firms and between *corporations* (incorporated or limited-liability firms and first class traders, which have balance sheet information) and *partnerships* (individual-owned firms, which generally do not). Our regression analysis focuses primarily on manufacturing corporations, which allows us to construct key variables such as capital intensity, financial debt ratios, and R&D indicators. We present cross-sector comparisons (including services and partnerships) in the Appendix.

## 3.1 Firm Entry, Exit, and Young-Firm Dynamics

Turkish firms display very high turnover. Over the 2007–2022 period covered by the EIS, the total number of active firms grew from approximately 2.6 million to over 4 million, driven by consistently high entry rates. After excluding mergers and acquisitions, manufacturing corporations alone recorded over more than 25,000 new entrants annually during 2007–2020, while exit rates fluctuated between 3% and 5% depending on macroeconomic conditions.

Figure 1 illustrates the share of firms at ages 0, 1, and 3 in the total number of firms, separately for four groups: manufacturing corporate, manufacturing partnership, services corporate, and services partnership. In all four groups, the share of age-0 firms (new entrants) substantially exceeds the share of age-1 and age-3 firms, reflecting the well-known "liability of newness"—the high exit rate in the first years.

Figure 2 reinforces this observation by showing the employment share of firms at the same three ages. The three lines are even closer together in employment terms than in firm-count terms, indicating that surviving firms grow only as much as the employment share vacated by exiting firms. This pattern is especially pronounced in manufacturing corporations, where age-0, age-1, and age-3 firms each account for roughly 2–5% of total employment.

## 3.2 Survival Patterns

Figure 3 presents Kaplan–Meier survival curves for all four sector–legal-form groups. Manufacturing corporations exhibit the highest survival rates: approximately 50% survive to age 5, and 32% survive to age 15. Services corporations come next, followed by manufacturing and services partnerships with much steeper survival curves. The clear

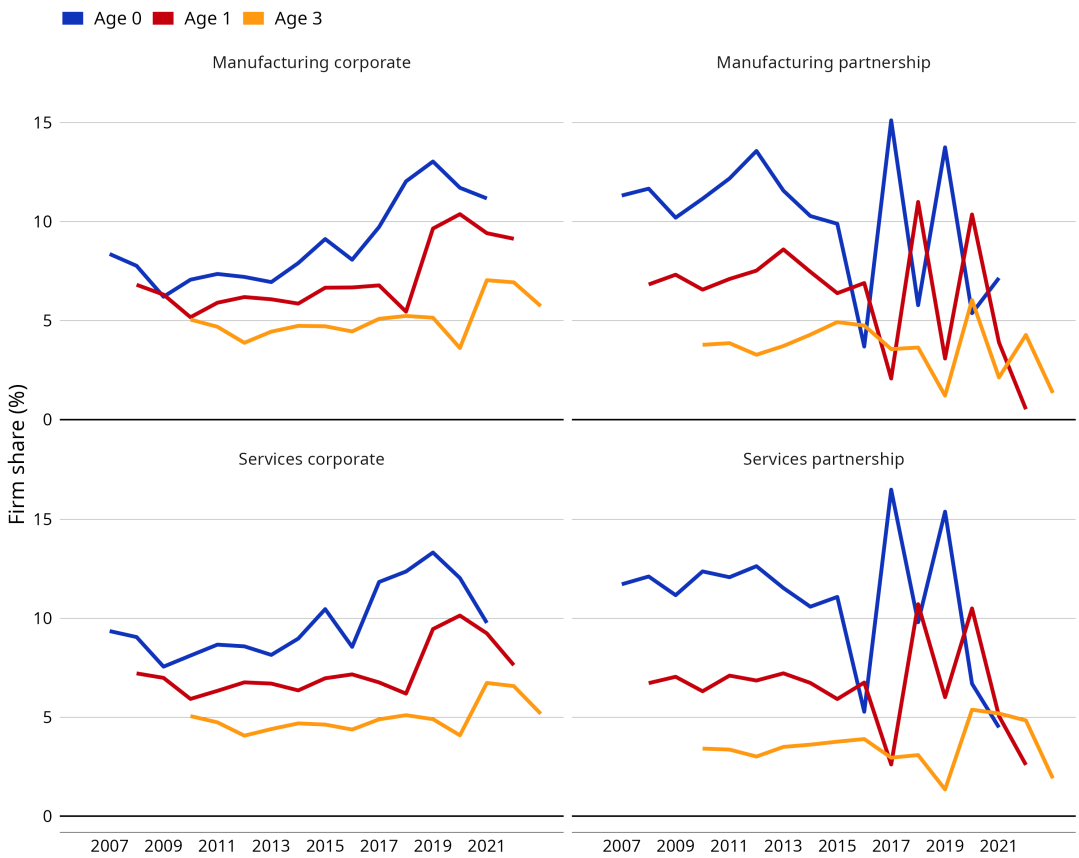


Figure 1: Share of firms at age 0, 1, and 3 in total number of firms (%)

dominance of manufacturing corporations in terms of survival motivates our decision to focus the main regression analysis on this group.

Figure 4 decomposes the survival experience of manufacturing corporations by firm size at establishment. The relationship between entry size and survival is monotonically positive and quantitatively large. Micro-firms (1–10 employees) exhibit the steepest decline, with less than 30% surviving to age 15, while firms entering with 100+ employees achieve 15-year survival rates of approximately 75%.

Figure 5 presents the survival curves for manufacturing corporate micro-firms (1–10 employees), disaggregated by average employee age group at entry. This figure is central to the paper's argument. Three features stand out. First, firms with very young workforces (average age 15–20) exhibit dramatically lower survival rates. Second, firms with workforces aged 45+ also show markedly lower survival. Third—and most importantly—the survival curves for the 25–30, 30–35, and 35–40 age groups are virtually indistinguishable from one another. This visual pattern foreshadows our regression finding that only the extreme age groups show significantly different survival prospects.

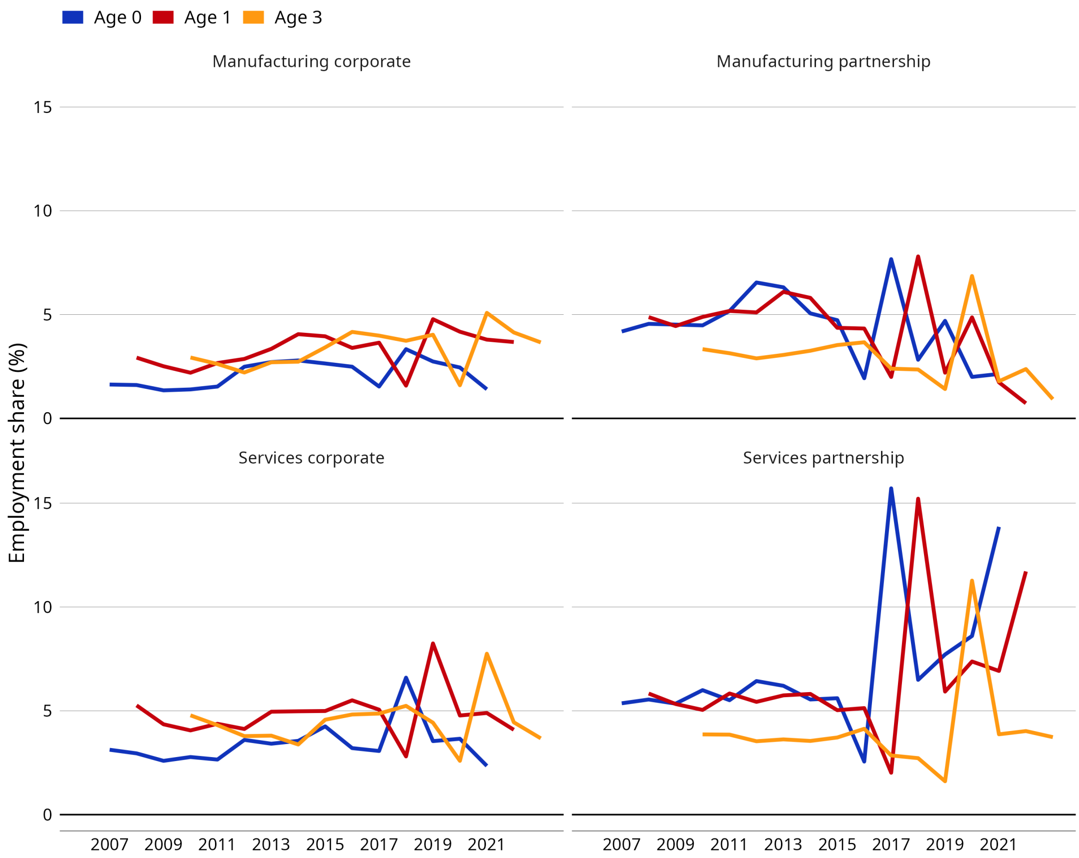


Figure 2: Employment share of firms at age 0, 1, and 3 (% of total employment)

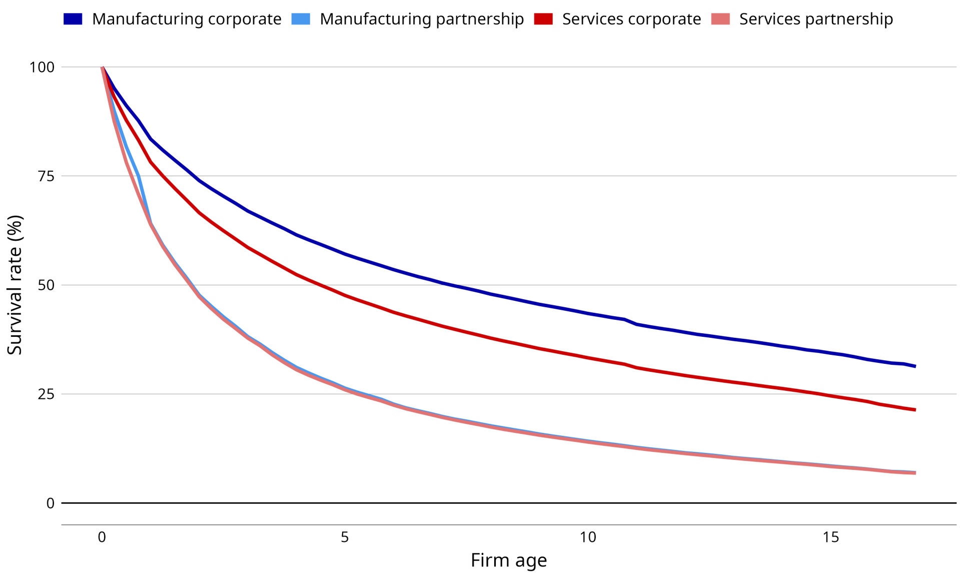


Figure 3: Survival rates by legal form and sector

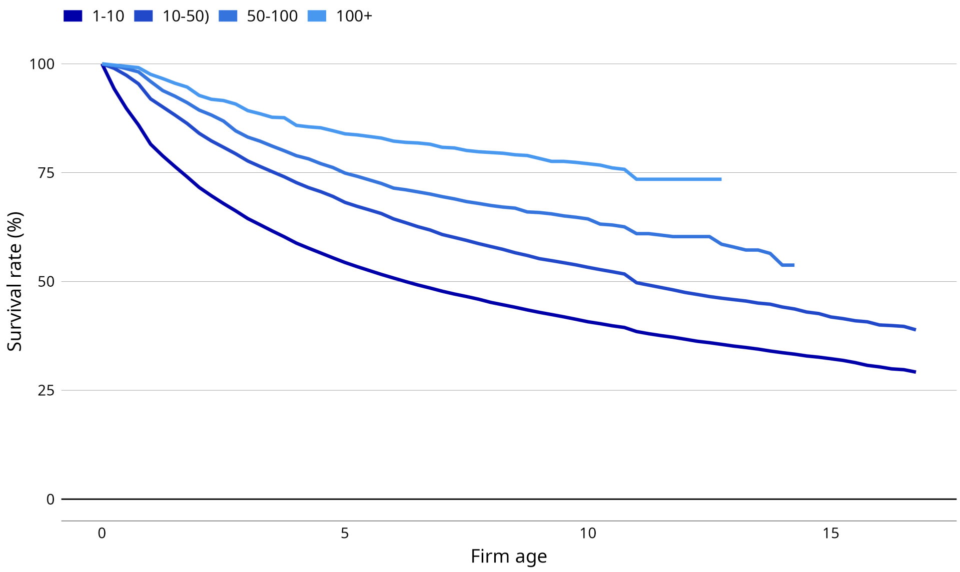


Figure 4: Survival rates by firm size at establishment — Manufacturing corporations

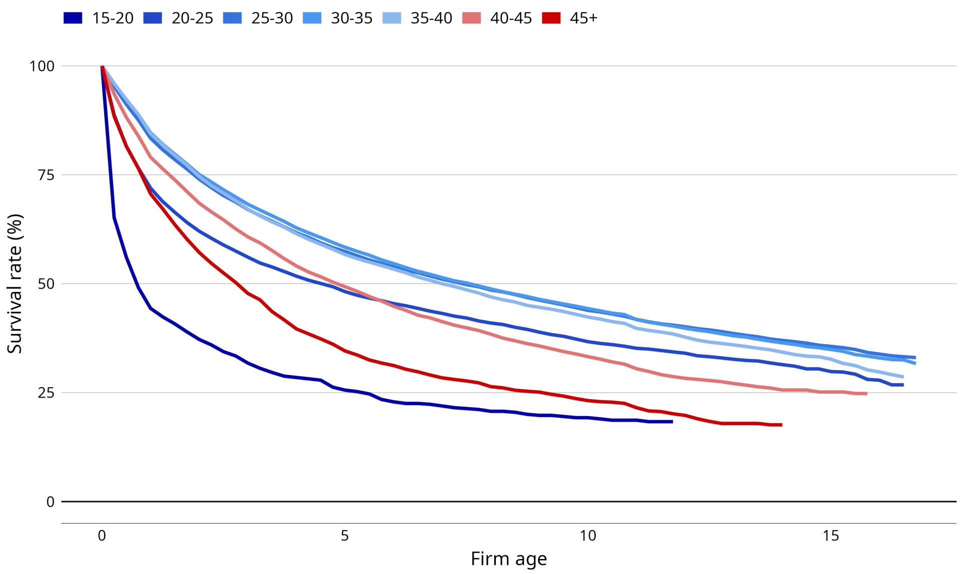


Figure 5: Survival rates by average employee age group — Manufacturing corporations, micro-firms (1–10 employees)

### 3.3 Variable Definitions and Descriptive Statistics

Table 1 presents the definitions and descriptive statistics for the variables used in the regression analysis. The sample covers manufacturing corporations, with firm-level variables available for the full 2007–2020 period (228,759 firm-year observations) and experience variables available only from 2013 onward (1,576,439 observations), since the SSA employee-tracking data begin in 2012.[3]

[3]The underlying data extend through 2023. However, firms entering after 2020 are excluded from the analysis for two reasons: they would have too few years of post-entry observation to contribute meaningfully to the survival estimates, and the COVID-19 pandemic created exceptional entry and exit conditions in 2020–2021 that would confound the analysis of normal survival dynamics. Including or

We organize the variables into three groups. The first group comprises *experience variables* that capture the prior employment backgrounds of the startup's initial workforce. These are calculated for employees employed in the first four quarters of a startup. They include the average employee age (entered as age-group dummies), whether all employees are labor market entrants with no prior employment history (Fullnew), the share of employees with same-sector experience (SameSector), and a set of variables describing the characteristics of former employers: their average size (FormerSize), average age (FormerFage), average wage (FormerWage), and the Herfindahl index of employment concentration across former employers (FormerHHI).[4] We also include the share of employees coming from firms that had exited (FormerExit) and dummy variables for upstream and downstream spin-offs: UpSpinoff equals one if the startup buys inputs from a firm where one of its employees previously worked, and DownSpinoff equals one if the startup sells output to such a firm.

The second group consists of *workforce control variables*: the share of female employees, within-firm age dispersion, and wage dispersion. The third group contains *firm-level variables*: firm size, average wage, multi-plant status, supply-chain linkages, export status, capital intensity, R&D status, and the financial debt ratio. Table A.1 in the Appendix provides descriptive statistics broken down by firm size.

# 4 Empirical Model

We estimate discrete-time hazard models using a complementary log-log (cloglog) specification. The dependent variable is a binary indicator equal to one if firm $i$ exits in quarter $t$ and zero otherwise. The complementary log-log model is the discrete-time counterpart of the continuous-time Cox proportional hazard model and preserves the proportional hazards property while accommodating the grouped (quarterly) nature of our data (Manjón-Antolín and Arauzo-Carod, 2008).

The model takes the form:

$$\log\left[-\log(1-h_{it})\right] = \alpha(t) + \mathbf{x}_i'\boldsymbol{\beta}, \tag{1}$$

where $h_{it} = \Pr(T_i = t \mid T_i \geq t)$ is the discrete-time hazard—the conditional probability that firm $i$ exits in quarter $t$, given survival to that point—$\alpha(t)$ captures the baseline hazard (absorbed into the quarter-age fixed effects), and $\mathbf{x}_i$ is the vector of entry-year covariates. The coefficients $\boldsymbol{\beta}$ have a proportional hazard interpretation: $\exp(\beta_k)$ gives

excluding the 2021–2023 entrants does not affect the results for the earlier cohorts.

[4]The HHI is defined as $\text{HHI} = \sum_j N_j(N_j-1)/[N(N-1)]$ for $N \geq 2$, where $N$ is the total number of employees in the new firm and $N_j$ is the number who were previously employed at firm $j$. A value of 1 indicates that all employees came from the same firm; lower values indicate more diverse employment backgrounds and higher values could be a proxy for "team experience."

Table 1: Variable Definitions and Descriptive Statistics — Manufacturing Corporations

| Label | Description | Mean | St. dev. |
|---|---|---|---|
| *Variables for the 2007–2020 period (n = 228,759)* | | | |
| EmpAge | Average employee age | 32.981 | 5.683 |
| EmpAgeSdev | Std. dev. of employee age (normalized) | 0.196 | 0.109 |
| FirmSize | Firm size (log employees) | 1.506 | 1.137 |
| Wage | Daily wage rate (log) | 3.846 | 0.637 |
| WageSdev | Std. dev. of log wage rate | 0.074 | 0.138 |
| Female | Share of female employees | 0.222 | 0.271 |
| MultiPlant | Multi-plant dummy | 0.126 | 0.331 |
| NoUplink | No upstream link | 0.083 | 0.276 |
| NoDownlink | No downstream link | 0.158 | 0.365 |
| Exporter | Exporter dummy | 0.214 | 0.410 |
| Kint | Capital intensity (log) | 0.923 | 5.427 |
| R&D | R&D performer dummy | 0.020 | 0.139 |
| FinDebt | Financial debt to assets ratio | 0.386 | 0.487 |
| *Variables for the 2013–2020 period (n = 1,576,439)* | | | |
| Fullnew | All-new-employee dummy | 0.173 | 0.379 |
| SameSector | Share of employees from same sector | 0.143 | 0.240 |
| FormerSize | Former firm size (log) | 2.455 | 1.801 |
| FormerFage | Former firm age (log) | 2.067 | 1.273 |
| FormerWage | Former wage rate (log) | 0.140 | 0.256 |
| FormerHHI | HHI index of former employment | 0.379 | 0.328 |
| FormerExit | Share of employees from exited firms | 0.167 | 0.260 |
| UpSpinoff | Buys inputs from former employer (dummy) | 0.170 | 0.375 |
| DownSpinoff | Sells output to former employer (dummy) | 0.071 | 0.256 |

*Notes:* Experience variables (Fullnew through DownSpinoff) are calculated for employees employed in the first four quarters of a startup. FormerHHI is defined as $\text{HHI} = \sum N_j(N_j - 1)/[N(N-1)]$ for $N \geq 2$, where $N$ is total employees in the new firm and $N_j$ is the number of employees previously employed at firm $j$.

the hazard ratio for a one-unit change in covariate $x_k$.

A distinctive feature of our approach is that we use only entry-year characteristics as regressors. This focus on initial conditions avoids the endogeneity that arises when time-varying covariates are themselves shaped by the firm's survival trajectory and directly addresses the question of how much the initial workforce endowment matters for long-run survival prospects.

All models include fixed effects for calendar quarter, two-digit NACE sector, and province. The key explanatory variables are the employee age-group dummies. In the standard specification, average employee age and its square are entered as continuous regressors, yielding an inverted-U relationship. We depart from this convention by using six age-group dummies (15–20, 20–25, 25–30, 30–35, 40–45, and 45+), with the 35–40 group as the reference category. This flexible specification allows the data to reveal the true shape of the age–survival relationship without imposing a smooth quadratic form.

# 5 Results

## 5.1 Baseline Results for Manufacturing Corporations

Table 2 reports the baseline estimates for manufacturing corporations entering between 2007 and 2020, building up the specification across four models.

**Employee age.** Model 1 uses the conventional specification with continuous average employee age and its square, along with log firm size. Both age terms are highly significant ($-0.0839$ and 0.0012, respectively), yielding the familiar inverted-U pattern documented in earlier studies using Danish, Finnish, and Swedish data (Grund and Westergård-Nielsen, 2008; Maliranta and Nurmi, 2019; Backman and Karlsson, 2020). The implied exit-hazard minimum is at an average employee age of approximately 35, broadly consistent with the descriptive evidence in Figure 5.

Model 2 replaces the continuous age terms with age-group dummies and reveals a strikingly different picture. Relative to the 35–40 base group, only two groups exhibit significantly higher exit hazards: the 15–20 group (coefficient 0.615, significant at 1%) and the 45+ group (0.297, significant at 0.1%). The intermediate groups—20–25, 25–30, and 30–35—are all statistically indistinguishable from the base. The 40–45 group is significant but with a much smaller coefficient (0.088). This pattern demonstrates that the apparent inverted U is not a smooth quadratic relationship across the age distribution but rather a plateau over the broad 25–40 range with sharply elevated exit hazards only at the tails. The BIC is virtually identical between Models 1 and 2, confirming that the age-group specification fits the data equally well while revealing information that the quadratic form conceals.

The elevated exit hazard for very young workforces (15–20) is consistent with career-concerns models (Holmström, 1999): while younger workers may exert high effort, they lack the tacit knowledge and professional networks that protect firms against adverse shocks. In the Turkish context, firms with average employee ages below 20 are likely to be staffed almost entirely by recent school-leavers with no prior work experience. At the other extreme, the elevated hazard for the 45+ group aligns with the organizational-ecology argument that older workforces may be less adaptable (Stinchcombe, 1965; Backman et al., 2016). However, our finding that the 25–40 range is essentially flat challenges the smooth trade-off between adaptability and experience posited by much of the literature; instead, it suggests that within this broad middle range, other factors dominate the survival calculus. This resonates with Hagen et al. (2025), who find that the founder-age–performance relationship in Sweden exhibits discrete jumps rather than a smooth quadratic.

Table 2: Determinants of Exit, 2013–2020 Entrants — Manufacturing Corporations

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | |
|---|---|---|---|---|---|---|---|---|
| EmpAge | −0.0839*** | (0.0196) | | | | | | |
| $\text{EmpAge}^2$ | 0.0012*** | (0.0002) | | | | | | |
| *Employee age (base: 35–40)* | | | | | | | | |
| 15–20 | | | 0.6148** | (0.1885) | 0.5727** | (0.1841) | 0.5042*** | (0.1457) |
| 20–25 | | | 0.1251$^{\cdot}$ | (0.0695) | 0.1022 | (0.0690) | 0.0959 | (0.0616) |
| 25–30 | | | 0.0228 | (0.0197) | 0.0168 | (0.0210) | 0.0295 | (0.0202) |
| 30–35 | | | 0.0200 | (0.0215) | 0.0231 | (0.0226) | 0.0293 | (0.0198) |
| 40–45 | | | 0.0875*** | (0.0215) | 0.0795*** | (0.0218) | 0.0480* | (0.0225) |
| 45+ | | | 0.2969*** | (0.0344) | 0.2902*** | (0.0378) | 0.2125*** | (0.0418) |
| FirmSize | −0.3802*** | (0.0744) | −0.3810*** | (0.0739) | −0.3631*** | (0.0832) | −0.2381*** | (0.0513) |
| Wage | | | | | −0.4311* | (0.1836) | −0.4933** | (0.1769) |
| WageSdev | | | | | 0.1873 | (0.2640) | 0.3643 | (0.2246) |
| EmpAgeSdev | | | | | −0.2489*** | (0.0752) | −0.1652$^{\cdot}$ | (0.0928) |
| Female | | | | | 0.8269*** | (0.0773) | 0.8711*** | (0.0795) |
| Wage × Female | | | | | −0.1654*** | (0.0201) | −0.1873*** | (0.0226) |
| MultiPlant | | | | | | | −0.2010*** | (0.0287) |
| NoUplink | | | | | | | 0.6025*** | (0.0625) |
| NoDownlink | | | | | | | 0.3015*** | (0.0815) |
| Exporter | | | | | | | −0.2703*** | (0.0344) |
| Kint | | | | | | | 0.0325* | (0.0149) |
| R&D | | | | | | | −0.0361 | (0.0474) |
| FinDebt | | | | | | | −0.3715*** | (0.0594) |
| Observations | 2,286,965 | | 2,286,965 | | 2,286,645 | | 2,286,471 | |
| Sq. Cor. | 0.0303 | | 0.0306 | | 0.0313 | | 0.0469 | |
| Pseudo $R^2$ | 0.0672 | | 0.0672 | | 0.0682 | | 0.0847 | |
| BIC | 497,370.7 | | 497,398.7 | | 496,301.5 | | 487,642.7 | |

*Notes:* All models include time (quarterly), sector (NACE 2-digit), and province fixed effects. Standard errors in parentheses. ***, **, *, and $^{\cdot}$ denote statistical significance at 0.1%, 1%, 5%, and 10%, respectively.

**Workforce controls.** Model 3 adds workforce-level controls. Higher average wages are associated with significantly lower exit hazards ($-0.431$, at 5%), consistent with wages proxying for workforce quality (Dahl and Klepper, 2015). The share of female employees enters with a positive coefficient (0.827, highly significant), but its interaction with wages is strongly negative ($-0.165$). This implies that the female-share effect is concentrated among low-wage firms, likely reflecting the composition of female-intensive manufacturing subsectors (garments, food processing) with lower barriers to entry and higher turnover, rather than a causal gender effect. Maliranta and Nurmi (2019) find a positive association between female share and survival in Finland, while Grund and Westergård-Nielsen (2008) report a negative effect on productivity in Denmark; our interaction specification suggests both findings may be reconciled once wage levels are accounted for. Within-firm employee-age diversity (EmpAgeSdev) reduces exit hazards ($-0.249$, at 0.1%), consistent with the complementarity argument that mixed-age workforces simultaneously supply both adaptive capacity and experiential knowledge (Grund and Westergård-Nielsen, 2008), though this effect weakens to marginal significance once firm-level controls are added in Model 4.

**Firm-level controls.** Model 4 is the preferred specification. Firm size remains strongly negative ($-0.238$). The most powerful firm-level predictors are the supply-chain linkage variables: firms that fail to establish an upstream connection in their first year (NoUplink: 0.603) face an 83% higher exit hazard ($\exp(0.603) \approx 1.83$), while missing downstream linkages (NoDownlink: 0.302) raise exit hazards by 35%. These large effects underscore the critical importance of network embeddedness for new-firm survival (Bernard et al., 2019; Bagley, 2019).

Export status reduces exit hazards by approximately 24% ($\exp(-0.270) \approx 0.76$), consistent with revenue diversification and competitive signaling (Freixanet and Renart, 2020). Financial debt access (FinDebt: $-0.372$) is strongly protective, consistent with the theoretical importance of financial constraints for new-firm survival (Evans and Jovanovic, 1989), though as Cressy (1996) cautions, the relationship may partly reflect reverse causality. R&D status is not significant, likely reflecting its very low incidence among manufacturing startups in our sample (2%).

Finally, capital intensity enters with a small positive coefficient (0.033), suggesting that higher capital intensity at entry is associated with a slightly greater hazard of exit. This may appear counterintuitive, since one might expect capital-intensive firms — with their larger sunk costs — to be more resilient. However, two considerations help reconcile this finding. First, the variable captures capital intensity at the time of entry, not at the current period. Second, since the vast majority of entrants in our sample are small, the estimated coefficient predominantly reflects the experience of micro- and small firms, where high capital intensity may signal suboptimal scale due to indivisibilities in fixed assets. Consistent with this interpretation, when we allow the effect to vary by firm size, capital intensity is associated with improved survival for large entrants (50 or more employees).

**Model fit.** The Pseudo $R^2$ increases from 0.067 in Model 1 to 0.085 in Model 4, with the largest improvement when firm-level controls are added, confirming that while workforce demographics matter, firm-level characteristics—particularly supply-chain linkages and financial access—account for a larger share of exit-hazard variation.

## 5.2 Results by Firm Size at Entry

Tables 3 and 4 present the paper's central decomposition: separate estimates by entry-size group. Table 3 covers the full 2007–2020 entry cohort with the base controls; Table 4 restricts to the 2013–2020 cohort and adds experience variables. This decomposition tests whether the age–survival relationship attenuates with firm size—as the human capital complementarity literature suggests it should, since larger, more capital-intensive firms have alternative buffers against the risks of a suboptimal workforce mix (Iranzo et al., 2008)—and reveals that results obtained from pooled samples are driven almost entirely by micro-firms.

**Employee age by size group (Table 3).** For micro-firms (1–10 employees), the age-group pattern from the pooled model is preserved: the 15–20 group has a coefficient of 0.424 (at 0.1%), implying a 53% higher exit hazard than the 35–40 reference group, and the 45+ group is also significant (0.173). The 25–30 and 30–35 groups remain insignificant, confirming the flat plateau across the 25–40 range.

For small firms (10–50 employees), a qualitatively different pattern emerges. The extreme age groups are no longer significant. Instead, the 25–30 and 30–35 groups show *negative* and significant coefficients (−0.107 and −0.088), suggesting that somewhat younger workforces may confer a modest survival advantage in this size class. This reversal is consistent with Backman and Karlsson (2020), who find that the functional shape of the age–exit relationship changes across firm-size categories in Sweden. For medium and large firms (50+), no age group is significant—a clean null result confirming that once firms reach a sufficient scale, workforce age composition simply does not matter for survival, consistent with the view that physical capital and organizational depth substitute for optimal workforce composition (Mata et al., 1995).

**Other controls across size groups.** Several variables exhibit interesting size-dependent patterns. Firm size within the micro category has a large effect (−0.387) but is insignificant for small firms, suggesting that even small increments in employment within the micro class substantially improve survival. The supply-chain variables are universally important: NoUplink is significant across all sizes, with the largest coefficient for 50+ firms (0.711). NoDownlink, however, reverses sign for 50+ firms (−0.736), suggesting that for large firms, not having an initial downstream link may reflect a deliberate capacity-

Table 3: Determinants of Exit by Entry Size, 2007–2020 Entrants — Manufacturing Corporations

| | All firms | | 1–10 emp. | | 10–50 emp. | | 50+ emp. | |
|---|---|---|---|---|---|---|---|---|
| *Employee age (base: 35–40)* | | | | | | | | |
| 15–20 | 0.5042*** | (0.1457) | 0.4243*** | (0.1195) | | | | |
| 20–25 | 0.0959 | (0.0616) | 0.0751 | (0.0598) | −0.0338 | (0.1051) | −0.7493* | (0.3252) |
| 25–30 | 0.0295 | (0.0202) | 0.0039 | (0.0204) | −0.1073* | (0.0449) | −0.1045 | (0.1809) |
| 30–35 | 0.0293 | (0.0198) | 0.0188 | (0.0182) | −0.0878** | (0.0337) | −0.1697 | (0.1363) |
| 40–45 | 0.0480* | (0.0225) | 0.0472* | (0.0211) | 0.0165 | (0.0845) | −0.7306 | (0.5457) |
| 45+ | 0.2125*** | (0.0418) | 0.1727*** | (0.0369) | 0.1797 | (0.3135) | | |
| FirmSize | −0.2381*** | (0.0513) | −0.3869*** | (0.0635) | −0.0365 | (0.0385) | −0.2662** | (0.0917) |
| Wage | −0.4933** | (0.1769) | −0.5021** | (0.1694) | −0.7139*** | (0.1762) | −0.4894· | (0.2921) |
| WageSdev | 0.3643 | (0.2246) | 0.4795* | (0.1932) | 0.4208* | (0.2035) | −1.121· | (0.5971) |
| EmpAgeSdev | −0.1652· | (0.0928) | 0.1274 | (0.1312) | 1.652*** | (0.2890) | 3.539** | (1.117) |
| Female | 0.8711*** | (0.0795) | 0.7384*** | (0.0908) | 1.110** | (0.4036) | −0.3078 | (1.559) |
| Wage × Female | −0.1873*** | (0.0226) | −0.1658*** | (0.0231) | −0.1728 | (0.1088) | 0.1272 | (0.4159) |
| MultiPlant | −0.2010*** | (0.0287) | −0.1450*** | (0.0387) | −0.3175*** | (0.0452) | −0.2030* | (0.1022) |
| NoUplink | 0.6025*** | (0.0625) | 0.5767*** | (0.0500) | 0.6212*** | (0.1361) | 0.7107** | (0.2387) |
| NoDownlink | 0.3015*** | (0.0815) | 0.3234*** | (0.0772) | 0.1062 | (0.1177) | −0.7360** | (0.2684) |
| Exporter | −0.2703*** | (0.0344) | −0.2576*** | (0.0369) | −0.3282*** | (0.0448) | −0.3262* | (0.1417) |
| Kint | 0.0325* | (0.0149) | 0.0379* | (0.0159) | 0.0063 | (0.0044) | −0.0150** | (0.0049) |
| R&D | −0.0361 | (0.0474) | −0.0135 | (0.0595) | −0.1052 | (0.1001) | 0.2354 | (0.2093) |
| FinDebt | −0.3715*** | (0.0594) | −0.3505*** | (0.0612) | −0.4194*** | (0.0738) | −0.9141*** | (0.1180) |
| Observations | 2,286,471 | | 1,785,185 | | 427,983 | | 70,066 | |
| Sq. Cor. | 0.0469 | | 0.0537 | | 0.0219 | | 0.0344 | |
| Pseudo $R^2$ | 0.0847 | | 0.0889 | | 0.0671 | | 0.1442 | |
| BIC | 487,642.7 | | 408,963.5 | | 72,126.5 | | 9,566.1 | |

*Notes:* All models include time (quarterly), sector (NACE 2-digit), and province fixed effects. Standard errors in parentheses. ***, **, *, and · denote statistical significance at 0.1%, 1%, 5%, and 10%, respectively.

building strategy. FinDebt increases in magnitude with firm size (−0.351 for micro, −0.914 for 50+), reflecting the greater capital requirements of larger-scale operations.

**Experience variables (Table 4).** The experience variables reveal the paper's richest set of findings. SameSector—the share of employees with same-sector experience—is the most consistently powerful predictor, with negative coefficients that increase in magnitude with firm size (−0.428 for micro, −0.777 for small, −0.836 for 50+). This is consistent with Dahl and Reichstein (2007) and Gifford et al. (2021): industry-specific knowledge is a transferable asset whose value increases with organizational scale, where sector know-how is harder to substitute through learning-by-doing.

FormerFage (the age of previous employers) is negative and significant across all groups (−0.067 for micro to −0.259 for 50+): employees from older, more established firms bring institutional knowledge that enhances survival, echoing Dahl and Klepper (2015)'s argument about enduring firm capabilities. FormerHHI is negative and significant (−0.167 for micro to −0.963 for 50+), indicating that higher employment concentration—employees coming from the same former employer—benefits survival. This is consistent with Sarada and Tocoian (2019), who find that prior work connections improve survival in Brazil: shared organizational experience facilitates coordination, reduces informational asymmetries, and enables resource sharing within the new firm.

FormerSize enters positively for micro and small firms (0.037 and 0.063): employees from larger previous employers are associated with higher exit hazards in smaller startups, consistent with the "jack of all trades" argument (Lazear, 2005) that small-firm experience transfers more directly to the startup environment. FormerExit is insignificant for micro-firms but becomes negative and significant for small (−0.472) and 50+ (−0.569) firms, suggesting that employees from failed firms may bring valuable "lessons from failure" to larger startups.

UpSpinoff (buying inputs from a firm where an employee previously worked) is negative for all size groups but significant only for micro-firms (−0.175), where having a secure supplier relationship is a lifeline (Dahl and Sorenson, 2014; Fackler et al., 2016). In contrast, DownSpinoff is positive across size groups, but significant only for micro-firms (0.171), indicating that dependence on a former employer as a customer creates vulnerability.

## 5.3 Results by Firm Age

Table 5 tests whether the influence of initial workforce characteristics on survival diminishes as firms age—as Jovanovic (1982)'s learning framework predicts and Geroski et al. (2010) have documented empirically, since initial endowments should matter most when uncertainty about firm quality is highest and should wane as firms accumulate capital and organizational routines. We restrict the sample to manufacturing micro-corporations

Table 4: Determinants of Exit by Entry Size, 2013–2020 Entrants — Manufacturing Corporations

| | All firms | | 1–10 emp. | | 10–50 emp. | | 50+ emp. | |
|---|---|---|---|---|---|---|---|---|
| *Employee Age (base: 35–40)* | | | | | | | | |
| 15–20 | 0.4005*** | (0.0987) | 0.3622*** | (0.0839) | | | | |
| 20–25 | 0.0979 | (0.0632) | 0.0923 | (0.0636) | −0.1979 | (0.1877) | −0.7175 | (0.5483) |
| 25–30 | 0.0062 | (0.0203) | 0.0023 | (0.0221) | −0.1802** | (0.0642) | −0.1341 | (0.1989) |
| 30–35 | 0.0120 | (0.0191) | −0.0035 | (0.0208) | −0.0633 | (0.0400) | −0.1597 | (0.1699) |
| 40–45 | 0.0480· | (0.0275) | 0.0502· | (0.0264) | 0.1294 | (0.0892) | −0.6092 | (0.7108) |
| 45+ | 0.1476*** | (0.0399) | 0.1355*** | (0.0365) | 0.2759 | (0.3532) | | |
| FirmSize | −0.2650*** | (0.0419) | −0.3703*** | (0.0409) | −0.0749 | (0.0565) | −0.3186* | (0.1318) |
| Wage | −0.6971** | (0.2377) | −0.6684** | (0.2195) | −1.228** | (0.4242) | 0.3579 | (0.5967) |
| WageSdev | 0.4461* | (0.2269) | 0.4993** | (0.1894) | 0.8134* | (0.3267) | −0.4204 | (0.9630) |
| EmpAgeSdev | 0.1562 | (0.1547) | 0.2545 | (0.1572) | 1.571*** | (0.4012) | 3.936* | (1.624) |
| Female | 0.5086* | (0.2120) | 0.3406 | (0.2140) | 1.154 | (0.8387) | 1.788 | (2.581) |
| Wage × Female | −0.1188* | (0.0494) | −0.0863· | (0.0485) | −0.2416 | (0.2032) | −0.3798 | (0.6148) |
| MultiPlant | −0.1857*** | (0.0368) | −0.1281* | (0.0506) | −0.3152*** | (0.0653) | −0.2622· | (0.1428) |
| NoUplink | 0.6095*** | (0.0651) | 0.5882*** | (0.0566) | 0.7519*** | (0.1651) | 1.123*** | (0.2826) |
| NoDownlink | 0.3633*** | (0.0883) | 0.3772*** | (0.0838) | 0.1822 | (0.1464) | −1.095** | (0.4077) |
| Exporter | −0.3729*** | (0.0453) | −0.3429*** | (0.0484) | −0.4723*** | (0.0737) | −0.2726 | (0.1807) |
| Kint | 0.0383* | (0.0184) | 0.0447* | (0.0198) | 0.0033 | (0.0061) | 0.0010 | (0.0082) |
| R&D | 0.0240 | (0.0618) | 0.0607 | (0.0778) | 0.0154 | (0.1550) | −0.3681 | (0.3411) |
| FinDebt | −0.4648*** | (0.0662) | −0.4314*** | (0.0676) | −0.5769*** | (0.0954) | −1.026*** | (0.2196) |
| *Employee Experience* | | | | | | | | |
| Fullnew | 0.1007· | (0.0526) | 0.0813· | (0.0454) | −0.0009 | (0.2016) | | |
| SameSector | −0.4619*** | (0.1267) | −0.4283** | (0.1319) | −0.7767*** | (0.1732) | −0.8359* | (0.3636) |
| FormerSize | 0.0437*** | (0.0054) | 0.0365*** | (0.0048) | 0.0625** | (0.0195) | −0.0811 | (0.0832) |
| FormerFage | −0.0824*** | (0.0084) | −0.0672*** | (0.0073) | −0.2019*** | (0.0351) | −0.2594** | (0.0869) |
| FormerWage | 0.1257 | (0.0775) | 0.1422* | (0.0700) | 0.0126 | (0.2998) | −1.025· | (0.5412) |
| FormerHHI | −0.2465** | (0.0846) | −0.1667* | (0.0796) | −0.4630** | (0.1750) | −0.9629* | (0.3957) |
| FormerExit | −0.0332 | (0.0772) | 0.0208 | (0.0615) | −0.4724*** | (0.0840) | −0.5689* | (0.2796) |
| UpSpinoff | −0.1264** | (0.0409) | −0.1750*** | (0.0461) | −0.0389 | (0.0392) | −0.1032 | (0.1196) |
| DownSpinoff | 0.1957*** | (0.0376) | 0.1710*** | (0.0371) | 0.0956· | (0.0512) | 0.0609 | (0.1285) |
| Obs; Sq. Cor. | 1,301,864; 0.066 | | 1,025,596; 0.070 | | 224,650; 0.042 | | 46,899; 0.044 | |
| Pseudo $R^2$; BIC | 0.107; 297,034 | | 0.106; 257,021 | | 0.101; 36,764 | | 0.171; 6,065 | |

*Notes:* See notes to Table 3. Experience variables are calculated for employees employed in the first four quarters of a startup and are available only from 2013 onward.

Table 5: Determinants of Exit by Firm Age, 2007–2009 Entrants — Manufacturing Micro Corporations

| | 0–2 years | | 3–5 years | | 6–8 years | | 9–11 years | | 12+ years | |
|---|---|---|---|---|---|---|---|---|---|---|
| *Employee age (base: 35–40)* | | | | | | | | | | |
| 15–20 | 0.5283$^{**}$ | (0.1614) | 0.2000 | (0.3372) | 0.1417 | (0.2893) | −0.9693 | (0.6532) | 0.4399 | (0.4484) |
| 20–25 | 0.1453$^{\cdot}$ | (0.0807) | −0.0783 | (0.1160) | −0.1508 | (0.1414) | 0.0003 | (0.1687) | −0.1375 | (0.1437) |
| 25–30 | 0.0668 | (0.0555) | −0.0641 | (0.0440) | −0.2553$^{*}$ | (0.0999) | 0.0293 | (0.1531) | −0.2407$^{\cdot}$ | (0.1230) |
| 30–35 | 0.0732$^{*}$ | (0.0373) | 0.0413 | (0.0511) | −0.0269 | (0.1253) | −0.0511 | (0.1118) | −0.1752$^{\cdot}$ | (0.1004) |
| 40–45 | 0.1234$^{\cdot}$ | (0.0739) | 0.2731$^{**}$ | (0.0938) | 0.0713 | (0.1463) | 0.2598 | (0.2020) | −0.6396$^{*}$ | (0.2708) |
| 45+ | 0.1272$^{*}$ | (0.0620) | 0.7881$^{***}$ | (0.2083) | 0.2088 | (0.2638) | −0.0535 | (0.2926) | −0.5828 | (0.4266) |
| FirmSize | −0.4903$^{***}$ | (0.0865) | −0.0633$^{\cdot}$ | (0.0366) | −0.0220 | (0.0784) | −0.1177$^{*}$ | (0.0566) | −0.1319 | (0.1125) |
| Wage | −0.1835 | (0.1787) | 0.1263 | (0.1263) | −0.3787$^{*}$ | (0.1867) | 0.0044 | (0.2790) | −0.3866 | (0.3057) |
| WageSdev | 0.1473 | (0.2449) | −0.1019 | (0.2378) | 0.5927 | (0.3848) | 0.0198 | (0.5401) | 0.0050 | (0.6386) |
| EmpAgeSdev | 0.6286$^{*}$ | (0.2910) | −0.1175 | (0.1806) | −0.3205 | (0.3856) | 0.3614 | (0.2294) | −0.0985 | (0.4833) |
| Female | −0.3698 | (0.7699) | 0.2848 | (0.7317) | −1.1930 | (1.3010) | −2.483$^{*}$ | (1.2390) | −2.3600 | (2.1530) |
| Wage × Female | 0.1846 | (0.2360) | 0.0045 | (0.2383) | 0.5186 | (0.4118) | 0.8441$^{*}$ | (0.4081) | 0.8443 | (0.6992) |
| MultiPlant | −0.2456$^{**}$ | (0.0751) | −0.2400$^{*}$ | (0.0997) | 0.0907 | (0.1480) | −0.1681 | (0.1522) | −0.0096 | (0.1053) |
| NoUplink | 0.6361$^{***}$ | (0.0909) | 0.3736$^{***}$ | (0.0788) | 0.2454$^{**}$ | (0.0809) | 0.2181 | (0.1478) | 0.1224 | (0.1186) |
| NoDownlink | 0.2871$^{**}$ | (0.0982) | 0.1013 | (0.0759) | 0.1324$^{*}$ | (0.0515) | 0.1205 | (0.1185) | 0.1218 | (0.0931) |
| Exporter | −0.0749$^{\cdot}$ | (0.0410) | −0.1033 | (0.0636) | −0.0631 | (0.0722) | −0.0414 | (0.1276) | −0.0684 | (0.1111) |
| Kint | 0.0767$^{*}$ | (0.0354) | −0.0009 | (0.0055) | 0.0046 | (0.0043) | 0.0008 | (0.0065) | −0.0057 | (0.0064) |
| R&D | −0.1872 | (0.1878) | −0.4991$^{**}$ | (0.1562) | −0.1163 | (0.2077) | 0.1931 | (0.2706) | −0.2164 | (0.3856) |
| FinDebt | −0.4340$^{***}$ | (0.0834) | −0.0930$^{\cdot}$ | (0.0525) | 0.0009 | (0.0816) | −0.0414 | (0.0935) | 0.0094 | (0.0714) |
| Observations | 118,745 | | 85,614 | | 69,381 | | 58,765 | | 59,376 | |
| Sq. Cor. | 0.0531 | | 0.0091 | | 0.0075 | | 0.0086 | | 0.0088 | |
| Pseudo $R^2$ | 0.0826 | | 0.0340 | | 0.0380 | | 0.0416 | | 0.0557 | |
| BIC | 36,866.2 | | 17,868.1 | | 11,213.5 | | 8,801.9 | | 8,412.4 | |

*Notes:* All models include time (quarterly), sector (NACE 2-digit), and province fixed effects. Standard errors in parentheses. $^{***}$, $^{**}$, $^{*}$, and $^{\cdot}$ denote statistical significance at 0.1%, 1%, 5%, and 10%, respectively.

entering between 2007 and 2009—a cohort tracked for up to 15 years—and estimate separate models for five firm-age windows: 0–2, 3–5, 6–8, 9–11, and 12+ years. By focusing on micro-firms, we examine the group for which entry conditions matter most (Tables 3 and 4), providing the strongest possible test of whether these effects eventually fade.

**Employee age across firm-age windows.** In years 0–2, the age pattern mirrors the cross-sectional findings: the 15–20 group has a large and significant coefficient (0.528), and the 45+ group is also significant (0.127). The pattern shifts notably in years 3–5: the 15–20 coefficient drops to 0.200 and loses significance, suggesting that the disadvantage of a very young workforce is concentrated in the first two years. By contrast, the 45+ coefficient surges to 0.788 (at 0.1%) and 40–45 also becomes significant (0.273). This delayed emergence of the older-workforce penalty is intriguing: the disadvantages of an aging workforce—rigidity, reluctance to adapt—may manifest not at entry but once the firm must respond to evolving market conditions, consistent with the organizational-ecology literature on the "liability of aging" (Stinchcombe, 1965). By years 6–8 and beyond, virtually no age-group dummy is significant.

**Fading of other entry conditions.** The same fading is evident across the full set of controls. Firm size, the single most important predictor in years 0–2 (−0.490), loses significance by years 6–8, consistent with the Jovanovic (1982) learning model. The NoUplink variable declines monotonically from 0.636 (years 0–2) to 0.245 (years 6–8) and becomes insignificant thereafter, suggesting that surviving firms eventually develop alternative linkages. FinDebt is strongly significant in years 0–2 (−0.434) but entirely insignificant thereafter, consistent with financial constraints being most binding in the startup phase (Evans and Jovanovic, 1989).

Two variables partially defy the fading pattern. Multi-plant status retains significance through years 3–5, suggesting durable benefits from organizational complexity. R&D status, insignificant at entry, becomes significant at 3–5 years (−0.499), consistent with innovation investments taking time to bear fruit.

**Model fit.** The Pseudo $R^2$ drops sharply from 0.083 in years 0–2 to 0.034 in years 3–5 and remains low thereafter. Entry conditions collectively explain a meaningful share of exit variation in the first two years but become progressively less relevant, consistent with the gradual replacement of initial endowments by accumulated organizational capital (Jovanovic, 1982) and suggesting that policy interventions should be concentrated in the first few years when the leverage of entry conditions is greatest.

## 5.4 Results by Sector Type

Tables 6 and 7 examine whether survival determinants differ across manufacturing subsectors. We compare the full sample with two subgroups: R&D-intensive sectors (R&D/sales

$\geq 0.5\%$ in 2022) and growth sectors (employment $\times 2.5$ from 2007 to 2020). Table 6 covers the 2007–2020 cohort with base controls; Table 7 restricts to 2013–2020 and adds experience variables.

**Employee age across sectors (Table 6).** The age-group pattern from the pooled model is broadly preserved, with one notable exception. In R&D-intensive sectors, the 40–45 age group becomes highly significant (0.158, at 0.1%), in contrast to its marginal significance in the full sample (0.048). This suggests that in technology-oriented sectors, even moderately older workforces face elevated exit risks, consistent with the view that rapid technological change raises the premium on younger, more adaptable employees (Backman et al., 2016; Agarwal, 1998). In growth sectors, by contrast, the age effects are attenuated: the 15–20 coefficient is smaller (0.357 vs. 0.504) and the 45+ coefficient is only marginally significant, suggesting that favorable demand conditions reduce the importance of workforce composition.

**Other controls (Table 6).** The export effect is notably stronger in R&D-intensive (−0.348) and growth (−0.480) sectors than in the full sample (−0.270), consistent with the greater importance of international competitiveness in dynamic sectors. The female-share effect, large and significant in the full sample, becomes insignificant in both subsector groups, confirming that this association is driven by traditional manufacturing. The supply-chain and financial-debt variables remain universally significant with magnitudes comparable to the full sample.

**Experience variables (Table 7).** The most distinctive finding is the behavior of Fullnew (all employees new to the labor market). While only marginally significant in the full sample (0.101), it becomes clearly significant in R&D-intensive (0.171) and growth (0.230) sectors: having no experienced employees is particularly damaging in dynamic environments. SameSector remains significant in R&D-intensive sectors (−0.307, marginal) but loses significance in growth sectors, where generic entrepreneurial ability may matter more than sector-specific knowledge. FormerHHI is especially strong in growth sectors (−0.343, at 0.1%), indicating that concentrated prior employment networks—teams with shared organizational experience—are particularly valuable when the industry is expanding and coordination demands are high. The DownSpinoff variable loses significance in both subsector groups, suggesting that downstream supply-chain dependence is specific to traditional manufacturing.

## 5.5 Cross-Sector and Legal-Form Comparisons

Appendix Table A.2 extends the analysis to all four sector–legal-form groups: manufacturing corporate, manufacturing partnership, services corporate, and services partnership. This table, which includes the experience variables for the 2013–2020 cohort, serves primarily as a robustness check, and we highlight only the most noteworthy patterns.

Table 6: Determinants of Exit by Sector Type, 2007–2020 Entrants — Manufacturing Corporations

| | All sectors | | R&D-intensive | | Growth | |
|---|---|---|---|---|---|---|
| *Employee age (base: 35–40)* | | | | | | |
| 15–20 | 0.5042*** | (0.1457) | 0.4753*** | (0.1103) | 0.3569* | (0.1730) |
| 20–25 | 0.0959 | (0.0616) | 0.1086 | (0.0810) | 0.0266 | (0.0638) |
| 25–30 | 0.0295 | (0.0202) | −0.0218 | (0.0485) | −0.0165 | (0.0562) |
| 30–35 | 0.0293 | (0.0198) | 0.0122 | (0.0419) | −0.0724 | (0.0566) |
| 40–45 | 0.0480* | (0.0225) | 0.1577*** | (0.0455) | 0.0209 | (0.0690) |
| 45+ | 0.2125*** | (0.0418) | 0.2055** | (0.0698) | 0.1597* | (0.0794) |
| FirmSize | −0.2381*** | (0.0513) | −0.3075*** | (0.0774) | −0.3169*** | (0.0711) |
| Wage | −0.4933** | (0.1769) | −0.3010* | (0.1210) | −0.3938** | (0.1351) |
| WageSdev | 0.3643 | (0.2246) | −0.0281 | (0.2166) | 0.2592 | (0.2774) |
| EmpAgeSdev | −0.1652· | (0.0928) | 0.0546 | (0.2597) | −0.0417 | (0.2130) |
| Female | 0.8711*** | (0.0795) | 0.0476 | (0.2091) | 0.5559· | (0.3018) |
| Wage × Female | −0.1873*** | (0.0226) | −0.0154 | (0.0521) | −0.1430· | (0.0743) |
| MultiPlant | −0.2010*** | (0.0287) | −0.0834 | (0.0580) | −0.0406 | (0.0714) |
| NoUplink | 0.6025*** | (0.0625) | 0.5374*** | (0.0657) | 0.5541*** | (0.0511) |
| NoDownlink | 0.3015*** | (0.0815) | 0.3677*** | (0.0799) | 0.4057*** | (0.0613) |
| Exporter | −0.2703*** | (0.0344) | −0.3482*** | (0.0496) | −0.4800*** | (0.0621) |
| Kint | 0.0325* | (0.0149) | 0.0281* | (0.0138) | 0.0214· | (0.0117) |
| R&D | −0.0361 | (0.0474) | 0.0235 | (0.0980) | 0.1180 | (0.1282) |
| FinDebt | −0.3715*** | (0.0594) | −0.3648*** | (0.0688) | −0.3875*** | (0.0765) |
| Observations | 2,286,471 | | 274,137 | | 140,406 | |
| Sq. Cor. | 0.0469 | | 0.0499 | | 0.0595 | |
| Pseudo $R^2$ | 0.0847 | | 0.0990 | | 0.1074 | |
| BIC | 487,642.7 | | 56,467.5 | | 33,317.3 | |

*Notes:* All models include time (quarterly), sector (NACE 2-digit), and province fixed effects. R&D-intensive are defined as sectors with R&D/sales ratio $\geq$ 0.5% in 2022. Growth are defined as sectors where employment increased at least 2.5 times from 2007 to 2020. Standard errors in parentheses. ***, **, *, and · denote statistical significance at 0.1%, 1%, 5%, and 10%, respectively.

The 45+ age effect is positive and significant across all four groups in both time periods, confirming that the survival penalty for older workforces is not sector- or legal-form-specific. The 15–20 effect, however, is significant only for corporations, not for partnerships—an asymmetry that may reflect the different nature of very young workers in partnerships (often family members or the owner-operator) versus corporations.

The most striking cross-group difference concerns firm size: its coefficient is negative for corporations but *positive* for both manufacturing and services partnerships. This reversal likely reflects fundamentally different growth dynamics: for owner-operated partnerships, increasing registered employment may signal overexpansion beyond the owner's managerial capacity, whereas for corporations, size reflects organizational depth (Mata et al., 1995). An additional factor is informality: in partnerships, the owner and family members often work without formal registration, and informal workers may go unrecorded in the data. The true size of a partnership may therefore be larger than what the registered employment figures suggest, and an increase in formal employment may reflect

Table 7: Determinants of Exit by Sector Type, 2013–2020 Entrants — Manufacturing Corporations

| | All sectors | | R&D-intensive | | Growth | |
|---|---|---|---|---|---|---|
| *Employee age (base: 35–40)* | | | | | | |
| 15–20 | 0.4005*** | (0.0987) | 0.4398*** | (0.1003) | 0.1890 | (0.1441) |
| 20–25 | 0.0979 | (0.0632) | 0.1691· | (0.0990) | −0.0021 | (0.0694) |
| 25–30 | 0.0062 | (0.0203) | 0.0157 | (0.0609) | −0.0871 | (0.0617) |
| 30–35 | 0.0120 | (0.0191) | 0.0335 | (0.0552) | −0.1129· | (0.0614) |
| 40–45 | 0.0480· | (0.0275) | 0.2507*** | (0.0697) | 0.0194 | (0.0733) |
| 45+ | 0.1476*** | (0.0399) | 0.1557* | (0.0780) | 0.0795 | (0.0943) |
| FirmSize | −0.2650*** | (0.0419) | −0.3617*** | (0.0651) | −0.3565*** | (0.0511) |
| Wage | −0.6971** | (0.2377) | −0.4330** | (0.1609) | −0.3546· | (0.1999) |
| WageSdev | 0.4461* | (0.2269) | −0.1233 | (0.2616) | 0.2821 | (0.2960) |
| EmpAgeSdev | 0.1562 | (0.1547) | 0.4454 | (0.3695) | 0.3357 | (0.2455) |
| Female | 0.5086* | (0.2120) | −0.6049 | (0.4041) | 0.3520 | (0.4581) |
| Wage × Female | −0.1188* | (0.0494) | 0.1162 | (0.0928) | −0.1058 | (0.1042) |
| MultiPlant | −0.1857*** | (0.0368) | −0.1057 | (0.0750) | −0.0099 | (0.0840) |
| NoUplink | 0.6095*** | (0.0651) | 0.5141*** | (0.0652) | 0.5504*** | (0.0473) |
| NoDownlink | 0.3633*** | (0.0883) | 0.4321*** | (0.0904) | 0.4544*** | (0.0667) |
| Exporter | −0.3729*** | (0.0453) | −0.4105*** | (0.0599) | −0.5015*** | (0.0831) |
| Kint | 0.0383* | (0.0184) | 0.0283· | (0.0168) | 0.0294* | (0.0140) |
| R&D | 0.0240 | (0.0618) | 0.1614 | (0.1182) | 0.2074 | (0.1273) |
| FinDebt | −0.4648*** | (0.0662) | −0.4419*** | (0.0790) | −0.4849*** | (0.0707) |
| *Experience variables* | | | | | | |
| Fullnew | 0.1007· | (0.0526) | 0.1713* | (0.0794) | 0.2299* | (0.0930) |
| SameSector | −0.4619*** | (0.1267) | −0.3074· | (0.1843) | −0.1471 | (0.1806) |
| FormerSize | 0.0437*** | (0.0054) | 0.0592*** | (0.0121) | 0.0785*** | (0.0124) |
| FormerFage | −0.0824*** | (0.0084) | −0.0765** | (0.0267) | −0.0631*** | (0.0179) |
| FormerWage | 0.1257 | (0.0775) | 0.0436 | (0.1062) | −0.1570 | (0.1033) |
| FormerHHI | −0.2465** | (0.0846) | −0.1808· | (0.0964) | −0.3428*** | (0.0926) |
| FormerExit | −0.0332 | (0.0772) | −0.0904 | (0.0869) | 0.0389 | (0.1126) |
| UpSpinoff | −0.1264** | (0.0409) | −0.1102* | (0.0499) | −0.0838 | (0.0679) |
| DownSpinoff | 0.1957*** | (0.0376) | 0.1034 | (0.0960) | −0.0399 | (0.1052) |
| Observations | 1,301,864 | | 160,104 | | 92,717 | |
| Sq. Cor. | 0.0656 | | 0.0642 | | 0.0708 | |
| Pseudo $R^2$ | 0.1071 | | 0.1197 | | 0.1191 | |
| BIC | 297,033.6 | | 35,700.3 | | 24,499.1 | |

*Notes:* All models include time (quarterly), sector (NACE 2-digit), and province fixed effects. R&D-intensive are defined as sectors with R&D/sales ratio $\geq$ 0.5% in 2022. Growth are defined as sectors where employment increased at least 2.5 times from 2007 to 2020. Standard errors in parentheses. ***, **, *, and · denote statistical significance at 0.1%, 1%, 5%, and 10%, respectively.

a transition toward formalization—with its associated regulatory costs and rigidities—rather than genuine growth.

The experience variables (Table A.2) show considerable consistency. SameSector, FormerFage, and FormerHHI are significant in the expected directions across all four categories, confirming the universal value of sector-specific experience, employment in established firms, and concentrated prior employment networks. DownSpinoff is positive in all four groups, indicating that downstream supply-chain dependence on a former employer is a universal source of vulnerability. UpSpinoff, however, reverses sign across legal forms—negative (protective) for corporations but positive for partnerships—possibly reflecting differences in how supply-chain relationships function across organizational structures.

# 6 Conclusion

This paper has used the universe of Turkish firms from a comprehensive matched employer–employee database to study how workforce age composition and prior experience shape new-firm survival. Three main findings emerge.

First, the relationship between average employee age and survival is not a smooth inverted U, as commonly assumed. Using age-group dummies instead of the standard quadratic specification, we show that exit hazards are elevated only for firms with very young (15–20) or relatively old (45+) workforces. The broad 25–40 range shows no meaningful variation.

Second, even this tail effect is entirely confined to micro-firms with fewer than ten employees. For larger firms, workforce age composition has no significant effect on survival; instead, capital intensity, export orientation, supply-chain linkages, and financial access dominate. The methodological implication is that pooled estimates of the age–survival relationship conflate the micro-firm effect with a null effect for larger firms.

Third, the prior employment experience of the initial workforce is a powerful predictor of survival. Sector-specific experience (SameSector), the age of former employers (FormerFage), and the concentration of prior employment networks (FormerHHI) are the most robust experience variables. All of these entry-condition effects fade as firms age, consistent with models in which initial endowments are gradually supplanted by accumulated organizational capital (Jovanovic, 1982).

Our findings carry implications for policy in developing economies where micro-firms dominate new entries but face steep turnover. Policies aimed at improving micro-firm survival should focus on facilitating the transfer of sector-specific experience and supporting the formation of upstream supply-chain linkages in a startup's first year. As firms grow, the policy toolkit should shift toward measures that facilitate capital accumulation, export market access, and supply-chain integration.

Several limitations should be noted. We cannot observe the entrepreneur directly and use employee characteristics as a proxy. Our focus on entry conditions means we cannot capture post-entry workforce adjustments. The Turkish institutional context may limit generalizability. Future research should exploit within-firm variation in workforce composition over time and extend the analysis to other developing economies with comparable matched employer-employee data.

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## Appendix Tables

Table A.1: Descriptive Statistics by Firm Size — Manufacturing Corporations

| | Micro (1–10 emp.) | | Small (10–50 emp.) | | Medium & Large (50+) | |
|---|---|---|---|---|---|---|
| | Mean | St. dev. | Mean | St. dev. | Mean | St. dev. |
| *2008–2020 period* | ($n$ = 1,787,217) | | ($n$ = 428,955) | | ($n$ = 72,587) | |
| EmpAge | 33.168 | 6.137 | 32.311 | 3.620 | 32.323 | 3.064 |
| EmpAgeSdev | 0.180 | 0.115 | 0.254 | 0.053 | 0.255 | 0.044 |
| FirmSize | 1.044 | 0.722 | 2.899 | 0.427 | 4.630 | 0.620 |
| Wage | 3.850 | 0.648 | 3.795 | 0.599 | 4.053 | 0.531 |
| WageSdev | 0.054 | 0.124 | 0.128 | 0.154 | 0.251 | 0.153 |
| Female | 0.219 | 0.283 | 0.225 | 0.219 | 0.268 | 0.232 |
| MultiPlant | 0.082 | 0.275 | 0.243 | 0.429 | 0.497 | 0.500 |
| NoUplink | 0.091 | 0.288 | 0.052 | 0.222 | 0.070 | 0.255 |
| NoDownlink | 0.179 | 0.383 | 0.083 | 0.275 | 0.100 | 0.300 |
| Exporter | 0.180 | 0.384 | 0.307 | 0.461 | 0.496 | 0.500 |
| Kint | 0.974 | 5.471 | 0.560 | 5.334 | 1.796 | 4.690 |
| R&D | 0.015 | 0.120 | 0.027 | 0.163 | 0.101 | 0.301 |
| FinDebt | 0.345 | 0.475 | 0.509 | 0.500 | 0.687 | 0.464 |
| *2013–2020 period* | ($n$ = 1,229,507) | | ($n$ = 286,118) | | ($n$ = 60,814) | |
| Fullnew | 0.208 | 0.406 | 0.056 | 0.231 | 0.024 | 0.153 |
| SameSector | 0.121 | 0.230 | 0.205 | 0.251 | 0.296 | 0.284 |
| FormerSize | 2.149 | 1.797 | 3.334 | 1.296 | 4.493 | 1.111 |
| FormerFage | 1.959 | 1.346 | 2.430 | 0.901 | 2.534 | 0.701 |
| FormerWage | 0.127 | 0.259 | 0.168 | 0.224 | 0.286 | 0.268 |
| FormerHHI | 0.371 | 0.345 | 0.403 | 0.263 | 0.430 | 0.235 |
| FormerExit | 0.148 | 0.252 | 0.215 | 0.264 | 0.331 | 0.304 |
| UpSpinoff | 0.140 | 0.347 | 0.271 | 0.445 | 0.284 | 0.451 |
| DownSpinoff | 0.051 | 0.220 | 0.130 | 0.336 | 0.194 | 0.396 |

*Notes:* Sample restricted to manufacturing corporations. Experience variables (2013–2020 period) are calculated for employees employed in the first four quarters of a startup.

Table A.2: Determinants of Exit by Sector and Legal Form, 2013–2020 Entrants

| | Manuf. corp. | | Manuf. partner. | | Serv. corp. | | Serv. partner. | |
|---|---|---|---|---|---|---|---|---|
| *Employee age (base: 35–40)* | | | | | | | | |
| 15–20 | 0.3978*** | (0.1114) | −0.2104 | (0.1522) | 0.4750*** | (0.1030) | 0.1038 | (0.0811) |
| 20–25 | 0.0725 | (0.0621) | −0.1736** | (0.0529) | 0.0671 | (0.0634) | −0.1157*** | (0.0224) |
| 25–30 | 0.0013 | (0.0203) | −0.0804* | (0.0338) | −0.0466* | (0.0216) | −0.0799*** | (0.0131) |
| 30–35 | 0.0122 | (0.0193) | −0.0556* | (0.0283) | −0.0032 | (0.0196) | −0.0305*** | (0.0090) |
| 40–45 | 0.0450· | (0.0265) | 0.0464 | (0.0369) | 0.0416* | (0.0163) | 0.0329· | (0.0176) |
| 45+ | 0.1549*** | (0.0400) | 0.0916* | (0.0436) | 0.1512*** | (0.0396) | 0.1716*** | (0.0341) |
| FirmSize | −0.2402*** | (0.0428) | 0.1190*** | (0.0285) | −0.2305*** | (0.0686) | 0.0833*** | (0.0160) |
| Wage | −0.6221** | (0.2132) | −0.1703 | (0.1037) | −0.4874* | (0.2105) | −0.0990 | (0.0760) |
| WageSdev | 0.3965· | (0.2114) | 0.4700*** | (0.1346) | 0.4682· | (0.2543) | 0.4633*** | (0.0839) |
| EmpAgeSdev | 0.1067 | (0.1536) | 0.3407** | (0.1110) | 0.1481 | (0.2143) | 0.1304· | (0.0671) |
| Female | 0.6670*** | (0.1488) | 0.6939** | (0.2391) | 0.3632*** | (0.0884) | 0.2820· | (0.1570) |
| Wage × Female | −0.1528*** | (0.0361) | −0.1232* | (0.0599) | −0.1174*** | (0.0244) | −0.0494 | (0.0425) |
| MultiPlant | −0.1904*** | (0.0307) | −0.3209*** | (0.0440) | −0.1565*** | (0.0435) | −0.2063*** | (0.0372) |
| NoUplink | 0.6089*** | (0.0626) | 0.3079*** | (0.0352) | 0.4633*** | (0.0747) | 0.3094*** | (0.0279) |
| NoDownlink | 0.3380*** | (0.0849) | 0.0193 | (0.0313) | 0.3615*** | (0.0510) | −0.0071 | (0.0277) |
| Exporter | −0.3417*** | (0.0432) | −0.1229* | (0.0509) | −0.2680*** | (0.0288) | −0.0708** | (0.0236) |
| Kint | 0.0352* | (0.0163) | 0.0813* | (0.0359) | 0.0354* | (0.0172) | 0.0852* | (0.0410) |
| R&D | 0.0228 | (0.0531) | −0.0490 | (0.1067) | −0.0117 | (0.0361) | −0.1116· | (0.0601) |
| FinDebt | −0.4238*** | (0.0635) | −0.2059** | (0.0626) | −0.3676*** | (0.0586) | −0.2370*** | (0.0587) |
| *Experience variables* | | | | | | | | |
| Fullnew | 0.0794 | (0.0577) | −0.1028* | (0.0409) | 0.0793* | (0.0395) | −0.1206*** | (0.0268) |
| SameSector | −0.4828*** | (0.1239) | −0.3981*** | (0.0988) | −0.3424* | (0.1502) | −0.3094*** | (0.0617) |
| FormerSize | 0.0391*** | (0.0056) | 0.0276** | (0.0091) | 0.0302*** | (0.0027) | 0.0254*** | (0.0042) |
| FormerFage | −0.0820*** | (0.0078) | −0.0490*** | (0.0095) | −0.0523*** | (0.0074) | −0.0579*** | (0.0068) |
| FormerWage | 0.0955 | (0.0744) | −0.1451* | (0.0708) | −0.0136 | (0.0571) | −0.1549*** | (0.0377) |
| FormerHHI | −0.2320** | (0.0729) | −0.1830*** | (0.0313) | −0.2908*** | (0.0655) | −0.1230*** | (0.0214) |
| FormerExit | −0.0402 | (0.0781) | −0.0135 | (0.0556) | 0.0527 | (0.0631) | 0.0412· | (0.0249) |
| UpSpinoff | −0.1258*** | (0.0347) | 0.0904· | (0.0540) | −0.0772* | (0.0357) | 0.1728*** | (0.0344) |
| DownSpinoff | 0.1839*** | (0.0351) | 0.2677*** | (0.0469) | 0.0575* | (0.0262) | 0.1353*** | (0.0171) |
| Obs; Sq. Cor. | 1,566,934; 0.058 | | 255,536; 0.029 | | 6,544,624; 0.060 | | 1,299,645; 0.027 | |
| Pseudo $R^2$; BIC | 0.099; 349,247 | | 0.055; 100,254 | | 0.088; 1,867,818 | | 0.049; 493,406 | |

*Notes:* All models include time (quarterly), sector (NACE 2-digit), and province fixed effects. Standard errors in parentheses. ***, **, *, and · denote statistical significance at 0.1%, 1%, 5%, and 10%, respectively.