Why Don't Old Firms Do New Things?[*]

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Abstract

Since at least Schumpeter (1942), young firms are commonly associated with innovation. Yet limited economics research exists to explain when and why new technologies require new firms. We examine the view that old firms struggle especially when innovations require different organizational styles, which may clash with existing business models. We measure organizational styles based on occupation compositions and their corresponding workstyles. In the data, young firms grow significantly faster than old firms when new technologies in an industry generate greater changes in the industry's overall workstyles (due to the types of workers they require), whereas the sheer volume of new technologies (e.g., the number of all or breakthrough patents) does not matter. These results show the role of organizational frictions in shaping companies' adaptability, and provide new perspectives for the Coase (1937) boundary of the firm question. Venture investment and government policies that support entrepreneurship are especially important when innovations alter organizational styles.

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1 Introduction

Nearly one century ago, Schumpeter (1942) highlighted the importance of innovation for economic progress. In his own writing, as well as in academic, policy, and general public discussions ever since, the implementation of new technologies is commonly associated with new firms. While many studies emphasize the importance of young firms (Decker et al., 2014; Draghi, 2024)—and entrepreneurship is a core topic of economics research—some work has found that existing firms contribute substantially to innovation (Garcia-Macia, Hsieh, and Klenow, 2019; Braguinsky et al., 2024). We can name many new technologies that are successfully implemented by incumbents, such as polymers, smart phones, and cloud computing, which we discuss in more detail in Section 2. Indeed, the necessity of new firms for new technologies is not entirely self-evident.

When—and why—do new technologies require new firms? Although this question is essential for our understanding of "creative destruction" and its relationship with entrepreneurship, economics research so far offers limited theoretical guidance and systematic analyses. Influential models of creative destruction such as Aghion and Howitt (1992) do not address whether an entrant with a new technology is a new firm or an existing firm. Meanwhile, research motivated by the classic boundary of the firm question following Coase (1937) has focused on vertical integration (Williamson, 1971; Grossman and Hart, 1986; Hart and Moore, 1990), or "which transactions can be implemented within a firm?" Yet another aspect of the Coasian problem has attracted much less attention: "which ideas can be implemented within a firm?"

Case studies in management and reflections by managers often come to the view that old firms can implement new technologies if they are compatible with existing organizational processes and priorities, but struggle if they require new processes and priorities (Christensen, 1997; Gerstner, 2002; O'Reilly and Tushman, 2021). As Microsoft CEO Satya Nadella remarked at Chicago Booth's 125th anniversary celebration: "this is one of the foundational challenges—when the new thing comes not only as a technology challenge but also a business model challenge, most companies can't make it." This view also echoes the observations in Arrow (1964), who postulates that organizations form "codes...in accordance with the best expectations of the firm's creation," which will be "modified only slowly over time," so new technologies that require a different set of "codes" are most difficult for incumbents and most advantageous for new firms that start from scratch. Indeed, incompatibility between new technologies and existing organizational structures is key to the need for new organizations.

In this paper, we formalize this hypothesis theoretically, and conduct extensive empirical analyses to document its relevance for the performance of young vs old firms in the face of new technologies. Our primary challenge—conceptually and empirically—is finding a way to capture the extent to which new technologies require new organizational styles. Our entry point is to study the extent to which new technologies require different occupations to implement, which are associated with different workstyles. For example, in the car industry, technological advancements in software have proven especially challenging for old incumbents, because they require software engineers and emphasize flexibility and creativity rather than attention to detail and error prevention (whereas advancements in hardware were easy to plug into their existing systems). Numerous news reports attest to the difficulty for traditional car makers to adapt to the different workstyles associated with software (George, 2022; Davis, 2023). Accordingly, we present a model that lays out how new technologies associated with large changes in workstyles can lead to more severe organizational frictions, especially in old firms. We then develop a new and theoretically-grounded measure of changes in workstyles in an industry induced by new technologies, which allows us to perform large-scale empirical tests on the performance of young vs old firms.

In our model, firms initially operate an existing business model A. The occupation composition for A is pinned down by the productivity of each occupation given the technologies associated with that business model. Later on, a new business model B emerges. The desired occupation composition for B is pinned down by the productivity of each occupation given the technologies associated with this new business model, which can differ from the existing occupation composition under business model A. Each occupation has its set of workstyle (i.e., characteristics that it emphasizes), so that the overall (employment-weighted average) workstyle under the new business model B can differ from that under the existing business model A.

When differences in workstyle are larger, there is a higher probability that business model B wants to solve a problem differently from what business model A is used to. To address these conflicts, managers in business model B need to go through existing rules laid down by business model A—which were solutions to business model A's past problems—and justify their proposed solution. Doing so takes time and reduces the productivity of business model B, which shrinks its optimal size. Older firms have more existing rules, so the time and productivity losses are greater. Therefore, they end up with a smaller operation of B. Accordingly, they grow more slowly when new technologies require larger changes in style.

To validate that older firms indeed have more rules as well as more meetings that waste time, we process employee reviews from Revelio to measure the extent to which employees mention the presence of rules and the excess of meetings. Across different companies at a given point in time, we find that the fraction of reviews mentioning the presence of rules and the fraction of reviews mentioning the excess of meetings are positively correlated with firm age.

We build on the model to develop a new measure of style changes in an industry induced by new technologies, which can be applied systematically across industries and over time. We proceed in two steps. First, we predict future occupation composition in light of new technologies in an industry in a given year following Kogan et al. (2024). The key idea is to measure the textual similarity between new technologies (measured through patents) and occupations' routine and nonroutine tasks (using O*NET occupation task descriptions). As Kogan et al. (2024) have shown, when new technologies in an industry are more similar to an occupation's routine (nonroutine) tasks, substitutability (complementarity) is stronger, and the employment of the occupation falls (rises) going forward (according to Bureau of Labor Statistics data on employment at the industry-occupation level). Correspondingly, the similarity between patents in an industry-year and an occupation's tasks allows us to predict the occupation's future employment in the industry. Second, once we have future industry-level occupation composition predicted by new technologies, we can obtain the associated (employment-weighted average) overall future workstyle in the industry, relative to the current overall workstyle, using the workstyle associated with each occupation from O*NET data. The predicted industry-level workstyle change (over the next five years) induced by the new technologies is the key independent variable in our empirical analyses. The reliance of the measurement on O*NET and BLS data restricts our sample period to 2003 onward.

We use three sets of data to test the core hypothesis that young firms grow more than old firms when new technologies are associated with greater changes in workstyle. First, we investigate venture capital (VC) investment volume in an industry-year, which captures forward-looking valuation of startups that can reflect their growth potential. We find that a one standard deviation increase in predicted industry-level workstyle change is associated with around 0.3 log points higher VC investment in the industry, controlling for the log of total market capitalization of Compustat firms in industry n to capture other factors that may affect the prospects of firms in the industry. Importantly, the volume of new technologies per se, measured as the total number of patents, breakthrough patents (Kelly et al., 2021), or rapidly evolving patents (Bowen, Frésard, and Hoberg, 2023) in the industry does not have a significant relationship with VC investment, or affect the coefficient on workstyle change—our key variable of interest.

Second, we investigate variation among Compustat firms, including their equity valuation, as well as realized sales growth and employment growth over the next five years. Specifically, we regress firm-level equity valuation or subsequent growth on log firm age interacted with the predicted industry-level workstyle change (based on the new technologies in the industry as before). We find that young firms have significantly higher valuation and realized future growth relative to old firms when the technology-induced style change is larger. Meanwhile, the number of patents in the industry is not associated with significantly different outcomes for young vs old firms. We also show that the effects of firm age are not due to age being correlated with size or the severity of financial constraints.

Third, we investigate the population of firms in the Census Business Dynamics Statistics (BDS) dataset, which has broad coverage although many young firms in this case may not be aspirational entrepreneurship. BDS provides total employment of firms by age group: 0, 1-5, 6-10, 11-15, 16-20, 21-25, and the remaining age groups cannot be consistently defined over our sample period because firms' precise age is unknown if they are born before 1976. Therefore we restrict to firms with age between 1 and 25. We find that the young age groups grow significantly faster than the older ones when the technology-induced style change is larger. Again, the number of patents is not associated with significantly different outcomes for young vs old firms.

Taken together, these results support the importance of organizational frictions in shaping companies' adaptability. They show that new technologies per se do not necessarily challenge old firms. Incumbents are not ubiquitously incompetent in light of new technologies due to universal lack of learning or fear of cannibalization. However, when new technologies require changes in organizational styles, old firms struggle and young firms rise. In this case, venture investment and government policies that facilitate entrepreneurship can be especially useful when innovations alter organizational styles.

Literature Review Our work relates to three sets of literature. First, we contribute to research on the nature of innovation and creative destruction. We perform systematic analyses about the performance of young vs old firms in the face of new technologies, and highlight the role of organizational challenges (not just technological challenges). Prior work on innovation often sidesteps whether an entrant with a new technology is a new firm or an incumbent firm (Aghion and Howitt, 1992). Some maintain that young firms are important for innovation (Decker et al., 2014; Loderer, Stulz, and Waelchli, 2017; Acemoglu et al., 2018; Draghi, 2024; Ewens and Marx, 2024), while others show that incumbents contribute meaningfully (Garcia-Macia, Hsieh, and Klenow, 2019; Cohen, Gurun, and Nguyen, 2022; Braguinsky et al., 2024). Recent study by Bowen, Frésard, and Hoberg (2023) shows that a greater quantity of "rapidly evolving" patents is associated with startups exiting through initial public offering—thus remaining independent—instead of selling out. Caskurlu, Hoberg, and Phillips (2024) focus on firm size and show that a rise of new technologies highly correlated across multiple industries is associated with faster growth by small firms. Our focus is the importance of organizational frictions for understanding the implications of technological change for young vs old firms.

Second, we contribute to research on the nature of the firm. Many studies since Coase (1937) have focused on vertical integration (Williamson, 1971; Grossman and Hart, 1986; Hart and Moore, 1990; Aghion and Tirole, 1994; Anton and Yao, 1995),[1] using insights of incomplete contracts and property rights, but other considerations can also shape the activities that firms engage in (Atalay, Hortaçsu, and Syverson, 2014). Our work concerns another dimension of the boundary of the firm: which ideas can be implemented within a firm? We highlight challenges incumbents face that are not directly related to vertical integration, and point to a different set of mechanisms that restrict what a firm can do. In this regard, the most closely related work is Hart and Holmstrom (2010) on firm scope, which builds on the framework of Hart and Moore (2008) where authority rather than bargaining plays a central role in resolving ex post conflicts (Hart and Moore, 1990). The key concept in Hart and Holmstrom (2010) is shading, an action motivated by one party's grievance that imposes negative externalities on others, which becomes more severe with the integration of different business lines. This mechanism has resemblance with the frictions between existing and new business models in our framework, but we focus on conflicts due to old business insisting on old rules arising endogenously from a dynamic structure, rather than from ex post deviations of payoffs relative to the most preferred outcome specified in an ex ante contract that causes shading.

Third, we contribute to research on organizational economics. The extent to which incumbent firms can implement new technologies is a classic question in management, which has produced a large volume of qualitative assessments and cases (Penrose, 1959; Tushman and Anderson, 1986; March, 1991; Leonard-Barton, 1992; Teece, Pisano, and Shuen, 1997; Christensen, 1997; O'Reilly and Tushman, 2021). We draw on their insights to develop formal theoretical modeling and systematic empirical analyses. This research question is also related to Holmstrom (1989), who investigates why innovation is typically undertaken by smaller firms, using a complete contracting framework of Holmstrom and Milgrom (1991) unlike the incomplete contracting approach in the firm-boundary literature discussed above. The key idea is that combining hard-to-measure activities (e.g., innovation) with easy-to-measure activities (e.g., routine tasks) is costly due to the resulting misallocation of attention and effort. Another set of models study coordination and adaptation in organizations, emphasizing how firms use local

[1] Strictly speaking, the core takeaway for Grossman and Hart (1986), which highlights that asset ownership can be viewed as residual control rights, can apply to lateral integration too. Rajan and Zingales (2001) is an example which studies firm's organization structure based on the framework of property rights, showing that flat hierarchies features more distinctive technologies (than steep ones).

information in different settings (Milgrom and Roberts, 1992);[2] our focus is organizational conflicts even without informational frictions. Finally, our modeling relates to work on knowledge hierarchy (Garicano, 2000; Garicano and Rossi-Hansberg, 2004). Our mechanism incorporates the importance of managerial time, but our focus is the time loss from the conflict between business models, rather than time saving from the knowledge hierarchy.

The rest of the paper proceeds as follows. Section 2 presents stylized facts about the extent to which new technologies are implemented by new vs existing firms. Section 3 provides a model to motivate and organize our main empirical analyses. Section 4 explains the data and measurement. Section 5 shows the main empirical results. Section 6 concludes.

2 New Technologies and New Firms: Some Stylized Facts

In this section, we present stylized facts to show that significant technological inventions are not invariably implemented by young firms or vice versa. Old firms can implement new technologies, but not always. In other words, some new technologies may favor young firms, but others can be done by old firms. It is not simply that old firms are invariably incapable of implementing any new technologies, either because of slowness in learning or fear of cannibalization. The fact that the implementation of new technologies is split between young and old firms motivates our subsequent analyses that investigate the circumstances where new technologies favor new firms.

2.1 Technological Inventions Implemented by Young vs Old Firms

To obtain an intuitive sense of the extent to which new technologies are implemented by new firms, we proceed as follows. First, we collect a list of technological inventions over the 20th century by filtering Wikipedia titles, following Asirvatham (2024) who showed their usefulness for building catalogs of technologies.[3] Second, we use a Large Language Models (LLM) to summarize basic information about these inventions, including the time, location, type of inventor (i.e., private company, individual inventor, government, or university/non-profit), with the prompt shown in Appendix IA1.2. We also

[2]A long strand of the organizational economics literature underscores the role of local information and corresponding agency frictions across layers of decision makers, including formal versus real authority (Aghion and Tirole, 1997, 1995), corporate culture (Gorton and Zentefis, 2024), the design of functional units (Qian, Roland, and Xu, 2006; Dessein, Garicano, and Gertner, 2010), and adaptation to changing environments (Dessein and Santos, 2006).

[3]We download Wiki titles from Wikimedia English Wikipedia Dumps and use the steps in Appendix IA1.1 to filter for technological inventions.

ask the LLM to report whether the company that was most successful in its initial implementation and commercialization was a young firm (less than 10 years at the time) or an old incumbent, with the prompt shown in Appendix IA1.3. We focus on implementation and commercialization—not simply the invention—since several well-known examples show that incumbents may be able to invent a new technology, but organizational rigidity can prevent them from implementing the new technology (e.g., Bell Labs invented transistors but did not commercialize them, Xerox invented personal computers but did not commercialize them). Ultimately, new technologies need to be implemented to have an impact.

Figure 1 takes the 10,876 technological inventions in the 20th century from the Wikipedia-based dataset, and plots the fraction that is most successfully implemented by young vs old firms. The first two bars restrict to technological inventions in the U.S., where the left bar ("All") includes all inventions and the right bar ("Private") includes only inventions by private companies. The LLM cannot clearly determine the answer for a larger share of inventions by individuals, universities, and governments (included in the "All" bar but not in the "Private" bar) compared to inventions by private companies, which is understandable. The second two bars show the corresponding results for all technological inventions in the world. Overall, we see a mix: a substantial amount of new technologies are successfully implemented by old firms, though some are not. The share of old firms is somewhat comparable to their employment share of around 80% in the Census Business Dynamic Statistics dataset (United States Census Bureau, 2023).

2.2 Some Classic Examples

Business school classes on innovation often feature classic examples of new technologies that incumbent firms either succeeded or failed to implement. For example, Nylon (and polymers more generally) was invented and most successfully implemented by DuPont, when the company was already more than 100 years old (Ndiaye, 2007). Antibiotics were most successfully commercialized by established pharmaceutical companies. TVs and jet engines were also produced most extensively by companies that long existed by the time of their invention. More recently, smart phones were most successfully commercialized by Apple and cloud computing was pioneered by Amazon; both were established companies as well.[4]

Conversely, cars, aircraft, and semiconductors were most successfully produced by new companies at the time of their invention. Software was also mainly developed and commercialized by new companies,

[4]Apple was founded in 1976 and released iPhone in 2007; Amazon was founded in 1994 and launched Amazon Web Service (AWS) in 2002.

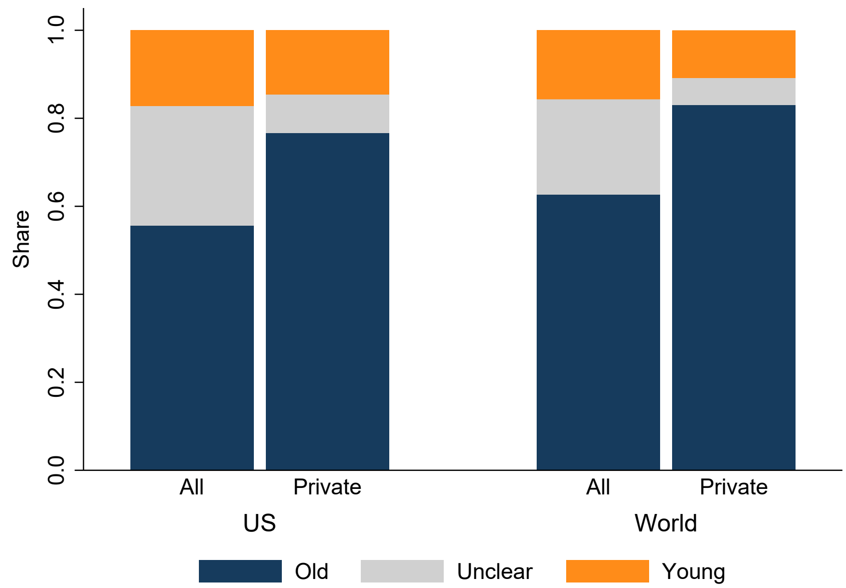


Figure 1. New Technologies Implemented by Young vs Old Firms (1900–2000)

Notes: This figure shows the fraction of technological inventions between 1900 and 2000 that are most successfully implemented by young firms (less than 10 years) vs old firms (otherwise). The first two bars restrict to technological inventions in the U.S., where the left bar includes all inventions and the right bar includes only inventions by private companies. The second two bars show all technological inventions in the world, where the left bar includes all inventions and the right bar includes only inventions by private companies. The shares are normalized to one within each group. Colors correspond to firm age categories.

despite existing companies such as General Electric repeatedly trying to enter this domain (Cohan, 2022). Discount retail and discount airlines—which represent new business models though not necessarily technological inventions—are also associated with new firms (O'Reilly and Tushman, 2021).

A common view in business school classes is that the former group largely represents new technologies that were compatible with existing organizational processes. Nylon had similarities with the production of Rayon for DuPont; antibiotics benefited from large-scale fermentation that Pfizer and Merck already used; TVs and jet engines built on GE's existing capabilities in manufacturing generators, turbines, and appliances; cloud computing was a product of computing infrastructure that Amazon already needed for its online platform; and iPhones follow from the production of other Apple devices. The latter group, however, led to organizational processes that differed from those in existing companies. The production of cars, aircraft, and semiconductors required flow that deviated from the procedures of their predecessors; software emphasized flexibility and maximizing upside, whereas hardware focused on attention to detail and minimizing downside; discount retailer and discount airlines relied on volume, whereas traditional retailer and airlines relied on margin.

How to capture the extent to which new technologies entail new organizational processes or priorities? These features of organizational styles are rich and difficult to measure in a uniform way. Our entry point is to extract information from the types of occupations required to implement new technologies. For example, as technological advancement leads to an increasing reliance on software in car manufacturing, the corresponding organizational processes will have to change given the different attributes of software versus hardware engineering that we later formalize as workstyle, which can be reflected by the shift in the occupation composition from hardware engineers to software engineers. Changes in the composition of occupations with different workstyles thus provide a window that can reveal corresponding changes in organizational processes. This angle has some limitations: subtle process changes may not be reflected in occupational composition, and the reliance on such data confines our main empirical analysis to the past two decades. However, this approach allows us to develop measurement methods that apply broadly across industries, with which we can perform systematic empirical tests.

3 Model

We formalize the core hypothesis in a simple model, which helps guide our subsequent empirical analyses. The key ingredients of the model are as follows. First, each firm has two business models: a pre-existing business model (A), which is already in place, and a new business model (B), which the firm is seeking to adopt. Second, each business model employs workers in occupations $j \in \{1, ..., J\}$. Each occupation has a different productivity depending on the business model. Additionally, each occupation is characterized by a workstyle, ws_j, which does not impact its productivity but will govern organizational frictions between the two business models. Third, a given business model has a continuum of identical operating units, each led by a manager that decides the occupation composition of the unit; we will explain why we need operating units later in Section 3.2 and Section 3.3. Finally, the firm owner oversees the choice of the number of operating units under each business model.

Our description of the model proceeds as follows. In Section 3.1, we first describe outcomes for a firm consisting only of operating units under business model A, which we interpret as the status quo, before business model B is introduced. Taking these choices as given, in Section 3.2 we then describe the decision to expand into business model B when that opportunity arises, subject to organizational frictions between the old and new business models. The simple one-shot expansion assumption helps explain clearly the key mechanisms of the model, but we relax it in Section 3.3, where we provide an explicit microfoundation for the organizational frictions in a more general model where the firm operates under business model A for some time, and the opportunity to adopt business model B arrives randomly. Finally, in Section 3.4, we use the simple model to derive explicitly the empirical predictions that we test in subsequent analyses.

3.1 Business Model A

We first describe the firm's optimization problem for the old business model A, before the emergence of the new business model B.

Technology and team composition At the beginning, firm i only operates units under business model A. Each unit is indexed by k, with one manager of type A who is in charge of hiring workers among J occupations for that unit, as illustrated in Figure 2. More specifically, for each unit under business model A, the corresponding manager solves the following problem:

$$Q_{A,i,k} = \max_{\{l_{A,i,k,j}\}_{j=1}^{J}} \left(\sum_{j=1}^{J} \theta_{A,j} \cdot (l_{A,i,k,j})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

$$s.t. \quad \sum_{j=1}^{J} l_{A,i,k,j} \leq \bar{l}. \qquad [\lambda_{A,i,k}] \tag{2}$$

Here, $\{\theta_{A,j}\}$ captures the productivity vector across the J occupations, and $\bar{l}$ captures the natural limit of team size that a manager can deal with.

The solution to problem (1) is as follows. For all k, we have $\lambda_{A,i,k} = \lambda_A = \left(\sum_{j=1}^{J} \theta_{A,j}\right)^{\frac{1}{\sigma-1}}$, and

$$l_{A,i,k,j} = \frac{\theta_{A,j}}{\sum_{j=1}^{J} \theta_{A,j}} \bar{l}. \tag{3}$$

This optimal composition of occupations implies the output per operating unit is

$$Q_{A,i,k} = Q_A = \left(\sum_{j=1}^{J} \theta_{A,j} \right)^{\frac{1}{\sigma-1}} \bar{l}. \tag{4}$$

Note that in each operating unit k across firm i in this industry, the manager will hire a team of workers with the same composition $\{l_{A,j}\}$ as in (3) and generate the same amount of output Q_A as in (4).

Workstyle of business model A We use ws_j to denote the workstyle associated with each occupation j. For firm i, the workstyle for its unit k under business model A is defined as

$$ws_A = ws_{A,i,k} \equiv \sum_{j=1}^{J} \frac{l_{A,i,k,j}}{l_{A,i,k}} ws_j, \tag{5}$$

where $l_{A,i,k} \equiv \sum_{j=1}^{J} l_{A,i,k,j}$. From (3) we see that $ws_{A,i,k} = ws_A$ is the same across all units k of firm i, and across all firms in the industry, simply because in each operating unit k its manager will hire a team of workers with the same composition $\{l_{A,j}\}$. The workstyle of business model A will play a role in shaping the organizational conflict when the new business model arrives.

Size of old business model A Because each unit is the same, at the firm level the problem is to choose how many operating units to have under business model A, taking the exogenous worker wage w and manager A's equilibrium wage (to be determined shortly) as given. We use $L_{A,i}$ to denote the number of operating units in business model A at firm i, which is also the total number of managers for business model A. The the firm solves:

$$\max_{L_{A,i} \geq 0} \left(Q_A - w\bar{l} - w_A \right) L_{A,i} - \frac{L_{A,i}^2}{2\xi_i}. \tag{6}$$

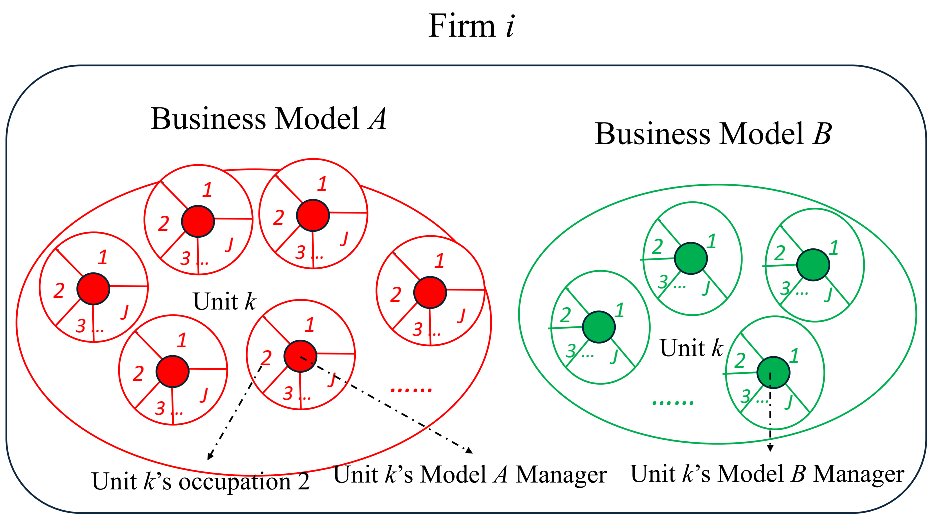
The fixed effect of the firm ξ_i, which can be interpreted as the inverse of adjustment cost, captures frictions that limit firm growth besides organizational rigidities. It does not play a central role in our analysis, other than generating ex-ante heterogeneity in scale between firms under the old business model; all our main results hold if $\xi_i = \xi$ for all firms i in the industry. Let $z_A \equiv Q_A - \left(w\bar{l} + w_A \right)$. The solution of (6) for the number of operating units of type A is

$$L_{A,i} = z_A \xi_i, \tag{7}$$

and the number of workers at the firm, denoted by $E_{A,i}$, is:

$$E_{A,i} = z_A \, \xi_i \, \bar{l}. \tag{8}$$

Equilibrium wage of A-managers We close the model by endogenizing the wage of managers of type A, denoted by w_A. Assume that the total number of managers of type A is exogenously given by L_A. Denote $\Xi \equiv \int_i \xi_i di$. Given the unit measure of identical firms, the market clearing condition



- Manager of each unit hires workers, and firm hires unit managers
- Business model A with rule list of length r_i increasing with age, matters for organization frictions

Figure 2. Model Structure

Notes: This figure illustrates the structure of business models A and B and the operating units in each business model.

$\int_0^1 L_{A,i}di = L_A$ for managers of type A allows us to solve for

$$w_A = \frac{L_A}{\Xi} - (Q_A - w\bar{l}), \text{ and } z_A = \frac{L_A}{\Xi}.$$

3.2 Business Model B

Later, a new business model B arrives, and firm i can now add new units under business model B, as illustrated in Figure 2.

Technology and team composition The new business is modeled as a different productivity vector $\{\theta_{B,j}\}$ over occupations. For simplicity, we assume that firm i cannot adjust existing business model A's units alongside its decision to expand into business model B. In each operating unit k under business model B, the manager solves a problem similar to that under business model A:

$$Y_{B,i,k} = \max_{\{l_{B,i,k,j}\}_{j=1}^{J}} \eta_i \cdot \underbrace{\left(\sum_{j=1}^{J} \theta_{B,j} \cdot (l_{B,i,k,j})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}}_{Q_{B,i,k}} \tag{9}$$

$$s.t. \quad \sum_{j=1}^{J} l_{B,i,k,j} \leq \bar{l} \qquad [\lambda_{B,i,k}] \tag{10}$$

The only difference from A's problem in (1) is the presence of the term η_i, which each manager of an individual operating unit takes as given. As we will explain shortly, this is a firm-level externality across type-B operating units that reflects organizational frictions within the firm, the key economic mechanism in our setting.

Because each manager for operating unit k takes η_i as given, the solution structure is identical to that of business model A. We therefore have $\forall k$, $\lambda_{B,i,k} = \lambda_B = \eta_i \left(\sum_{j=1}^{J} \theta_{B,j} \right)^{\frac{1}{\sigma-1}}$, and

$$l_{B,i,k,j} = \frac{\theta_{B,j}}{\sum_{j=1}^{J} \theta_{B,j}} \bar{l}, \tag{11}$$

$$Q_{B,i,k} = Q_B = \left(\sum_{j=1}^{J} \theta_{B,j} \right)^{\frac{1}{\sigma-1}} \bar{l}, \tag{12}$$

$$Y_{B,i,k} = Y_{i,B} = \eta_i Q_B. \tag{13}$$

Externality η_i across operating units of model B For each operating unit k of type B, we define the workstyle difference with business model A as:

$$\Delta_{i,k} \equiv \sum_{j=1}^{J} \frac{l_{B,i,k,j}}{l_{B,i,k}} ws_j - ws_A, \tag{14}$$

where $l_{B,i,k} \equiv \sum_{j=1}^{J} l_{B,i,k,j}$ and ws_A is given by (5). Here, the first term is the employment-weighted average workstyle in each new unit k of business model B. One can rewrite (14) as:[5]

$$\Delta_{i,k} = \sum_{j=1}^{J} \frac{l_{B,i,k,j} \delta_j}{l_{B,i,k}}, \quad \text{with} \quad \delta_j \equiv ws_j - ws_A.$$

[5]Note that so long as $w_j \neq w_{j'}$ for at least one pair (j, j'), then at least one of the δ_j's is strictly negative.

As before, we use $L_{i,B}$ to denote the total number of operating units under business model B (to be solved shortly). We can then define the average distance in workstyle between existing business model A and the new business model B:

$$|\Delta_i| \equiv \frac{1}{L_{i,B}} \int_0^{L_{i,B}} |\Delta_{i,k}| \, dk. \tag{15}$$

We assume that the externality term η_i is given by:

$$\eta_i = 1 - \gamma_i |\Delta_i| \,, \tag{16}$$

which decreases with the average workstyle difference between the old and new business models. The extent to which the workstyle distance affects the negative externality depends on the parameter $\gamma_i > 0$, which captures the severity of frictions in firm i for dealing with internal organizational conflicts, which we microfound in Section 3.3.

Using the solution to the problem of each operating unit described above, especially (11), we observe that the average workstyle difference is independent of firm i:

$$\forall k, \quad \Delta_{i,k} = \frac{\sum_{j=1}^{J} \theta_{B,j} \delta_j}{\sum_{j=1}^{J} \theta_{B,j}} \equiv \Delta. \tag{17}$$

Thus $\Delta_{i,k} = \Delta$ is constant across firms (in the particular industry we are studying) and across operating units of type B within a firm. This implies that the equilibrium firm-level externality is:

$$\eta_i = 1 - \gamma_i |\Delta| \,. \tag{18}$$

The upshot of the "externality" modeling of η_i in B-managers' problem (9) is that the resulting optimal team composition in each B unit is independent of the firm-specific organizational friction parameter γ_i, as evident from (11). That is, under our micro-foundation provided in Section 3.3, the B-manager's efficiency $\eta_i = 1 - \gamma_i |\Delta|$—especially $|\Delta|$ as in (15)—depends on the overall occupation composition of the business model B, instead of on $\Delta_{i,k}$ which is the occupation composition of the individual unit k that manager k controls. This follows from our assumption that the firm operates a continuum of units in each business model, so that atomistic managers cannot internalize the externalities that their allocation decisions create for the rest of the firm. Of course, the organizational friction will affect the number of units under business model B (hence the number of B-managers) for each firm, as shown in (13). We make this assumption for analytical convenience only, as homogeneous composition across all firms within an industry allows us to derive industry-level predictions and connect to empirical analyses in a clean way.

Size of new business model B The owner of firm i decides the optimal size of business model B by choosing the number of B-managers to solve:[6]

$$\max_{L_{B,i}\geq 0} \left(\underbrace{\eta_i Q_B}_{(1-\gamma_i|\Delta|)Q_B} - w\bar{l} - w_B \right) L_{B,i} - \frac{L_{B,i}^2}{2\xi_i}. \tag{19}$$

Here, ξ_i is the same adjustment cost as in (6) for business model A.

Given the B-manager's equilibrium wage w_B and productivity $\eta_i Q_B$ in (13), we denote $z_{B,i} \equiv (1-\gamma_i |\Delta|) Q_B - \left(w\bar{l} + w_B\right)$. The solution for the number of operating units of type B, $L_{B,i}$, and the number of total workers under business model B, $E_{B,i}$, is:

$$L_{B,i} = z_{B,i}\, \xi_i, \quad \text{and} \quad E_{B,i} = z_{B,i}\, \xi_i\, \bar{l}. \tag{20}$$

Finally, as before, we can close the model to pin down the equilibrium wage of B-managers, w_B, by assuming that there is a fixed number of managers of type B. Define:

$$\Gamma \equiv \frac{\int_i \xi_i \gamma_i di}{\int_i \xi_i di}.$$

Solving for w_B, we obtain:

$$\begin{aligned} w_B &= (1-\Gamma|\Delta|) Q_B - w\bar{l} - \frac{L_B}{\Xi}, \\ z_{B,i} &= (\Gamma - \gamma_i) |\Delta| Q_B + \frac{L_B}{\Xi}. \end{aligned}$$

Equation (21) gives one of the key properties of our model: the equilibrium size of new business model B is firm-dependent and decreases with the severity of firm i's organizational frictions.[7]

[6] Implicitly we assume that the firm owner will not adjust the occupation composition of business model A, and neither can contract with each type B manager on the occupation composition of each operating unit.

[7] To ensure that $z_{B,i}$ is always positive, so that employment in business model B is positive, it needs to be the case that:

$$\gamma_i \in [0, \overline{\gamma}], \quad \overline{\gamma} < \Gamma + \frac{L_B}{\Xi} \frac{1}{|\Delta| Q_B}. \tag{21}$$

In what follows we will assume that this restriction holds throughout. Additionally, note that for each firm i, equi-

3.3 A Microfoundation of Organizational Frictions between Business Models

In Section 3.2, we assume that the productivity of managers in business model B is affected by the workstyle differences between new and existing business models, via a simple functional form $\eta_i = 1 - \gamma_i |\Delta|$, which depends on the difficulty of resolving organizational conflict in firm i (γ_i). We now provide a microfoundation for this assumption, and illustrate how γ_i can increase with firm age. The key observation is that the old business model A builds up rules over time, which help solve the problems that business model A encounters efficiently. However, these rules may not be well-suited for business model B, especially when workstyles differ across business models. As a result, business model B runs into conflict with the existing rules, and resolving these conflicts takes time and work, which effectively reduces the productivity of B.

Rules for business model A We consider a simple dynamic model before the emergence of business model B, which is expected to arrive with some constant probability $\lambda \in (0, 1)$. Business model A operates exactly the same way as in Section 3.1; in particular, the occupation composition in each unit is decided by managers who will not take into account the externality caused by the composition of their unit.

Time is discrete and firm owners discount the future at a constant rate ρ. Each period, the firm, which initially operates under business model A, may run into a new incident $d \in \{1, 2, ..., R\}$. The probability of incident d occurring in each period is $1/R$, and incidents are i.i.d. over time. Suppose that $r \leq R$ incidents have occurred in the past, with r serving as the state variable. Then firm i's value function satisfies the following Bellman equation:

$$V(r) = \frac{\pi_A}{1+\rho} + \frac{1}{1+\rho} \left\{ \begin{array}{c} (1-\lambda)\left[\frac{r}{R}V(r) + \left(1-\frac{r}{R}\right)\left[-c + \max\left(V(r+1), V(r)\right)\right]\right] \\ +\lambda\left(\Pi_A + \Pi_B(r)\right) \end{array} \right\} \tag{22}$$

In (22), the first term captures the per-period profit π_A of business model A, which is the maximized value in (6). Moreover:

- With probability $1 - \lambda$, one of the following two events could potentially occur:

librium profits from all business units in models A and B are positive, as $\Pi_{A,i} = \frac{1}{2}\left(\frac{L_A}{\Xi}\right)^2 \xi_i$ and $\Pi_{B,i} = \frac{1}{2}\left(\frac{L_B}{\Xi} + (\Gamma - \gamma_i)|\Delta| Q_B\right)^2 \xi_i$, respectively. Thus if the market for managers is segmented (only A-managers can operate under business model A, and the same for business model B), then each firm would always want to expand into business model B.

- With probability $\frac{r}{R}$, the incident that arises is an old one, and the firm can resolve it with existing rules at no cost;
- With probability $1-\frac{r}{R}$, the incident that arises is a new one. The firm needs to pay c to resolve it, and can add new rules so that in the future this incident can be resolved at no cost following the rules. This is reflected by $\max\left(V\left(r+1\right),V\left(r\right)\right)$. The max operator captures the fact that the owner can decide not to add new rules to the list.

- With probability λ, business model B arrives. For simplicity, we assume that there are no new incidents in business model A going forward, but incidents in business model B start to occur. As explained shortly, the payoff in this state is the sum of the present values of two business models, with

$$\Pi_A=\frac{\pi_A}{\rho},\quad \Pi_B\left(r\right)=\frac{\pi_B\left(r\right)}{\rho}.$$

Here, the accumulation of rules helps formalize solutions to problems encountered by business model A and build its organizational capital (Rajan, 2012; Levitt, List, and Syverson, 2013). However, the length r of the rule list for business model A can negatively affect the productivity of business model B, as we model below.

Frictions between old and new business models Now suppose that business model B has arrived, and firm i has r_i rules developed by the existing business model A. For each operating unit k in business model B, new incidents may arise with probability dk. When a new incident arises, business model B proposes a solution. Business model A agrees with the solution with probability $1-|\Delta|$, and disagrees with probability $|\Delta|$ which is increasing in the distance between the workstyles of A and B.[8] In other words, if the workstyles of A and B misalign, they are more likely to disagree. We refer to an incident that triggers disagreement as a "conflict." Because conflicts provide learning opportunities across all units in business model B, all B-managers participate in resolving them.

When a conflict arises, managers in business model B need to form committees and show that the proposed solution is justified relative to existing rules laid down by business model A. Although existing rules—which apply to old business model A only—do not necessarily help solve the problem in question, A-managers insist that the existing rules are useful to follow. Accordingly, the length of rules that have accumulated in business model A will affect the process of resolving the conflict. We assume that each committee requires $\gamma(r_i)$ unit of time, with $\gamma(\cdot)$ a strictly increasing function. Recall that firm i has $L_{B,i}$ units under business model B. Because each conflict is i.i.d., the total number of conflicts

[8] Recall that $\Delta_{i,k}=\Delta$ for all firm i and operation unit k. For ease of exposition we assume that $|\Delta|\in(0,1)$. If $|\Delta|>1$ then any scaled version of $|\Delta|$ as the probability of conflict will work.

is $\int_0^{L_{B,i}} |\Delta| \, dk = |\Delta| \, L_{B,i}$, and hence the total conflict resolution time is $\gamma(r_i) L_{B,i} |\Delta|$. Because the committee work is shared among all B managers with a total measure of $L_{B,i}$, each individual B-manager spends $\gamma(r_i) |\Delta|$ units of time in resolving the conflict. Suppose that each B-manager is endowed with one unit of time. Following the spirit of Garicano (2000), the effective time that each B-manager can spend on production is one minus $\gamma(r_i) |\Delta|$. By rewriting $\gamma(r_i)$ as γ_i, this is exactly our assumption in (18). Finally, once an incident (whether it is a conflict or not) is resolved, business model B incorporates the resulting solution into its rule set for daily operations, analogous to the procedure followed under business model A; and the per period profit for model B is the value in the problem given in (19).[9]

The conflict between business models A and B assumes that the operations of B cannot be entirely insulated and separated from the operations of A, for example due to functions shared across the company (e.g., IT, production facilities, branding and marketing, human resources). In particular, in our perspective, the question regarding the boundary of the firm necessarily concerns real operations that take place within a given business organization. Businesses with distinct real operations that share financial investment (e.g., portfolio companies of a private equity investor) are not considered the same firm. Indeed, there are probably good reasons why companies with common investors often have separate real operations (e.g., venture capital portfolio companies, or even X, Tesla, and SpaceX).

Endogenizing the length of the rule list Recognizing the cost of appending the rule list in the existing business model A on the new business model B, we can work backward to solve the Bellman equation in (22) before business model B's arrival. In general, firm i will append its rule list in business model A until r_i reaches R^*, where $R^* \leq R$ is the endogenous maximum length of rules. In Appendix IA4.1, we provide a closed-form solution for $V(s)$ and give the characterization of R^*; note that R^* does not affect the key property that older firms have more rules.

Age, rules, and organizational frictions How do we interpret γ_i? In the microfoundation provided above, before the arrival of business model B, the firm keeps appending rules until the length r_i of its rule list reaches R^*. And, because r_i naturally increases with firm age (as it takes time to build a long list of rules), the friction between existing and new business models becomes worse with firm age. Essentially, our modeling captures the inefficiency or delay in how a firm's internal committee resolves conflicts—especially those sparked by new initiatives that challenge established practices. Older firms, often weighed down by outdated rules and entrenched bureaucratic norms, are more likely to exhibit

[9]Because there is no further arrival of new business models, it is always optimal to add to the rules for business model B. And, for simplicity, we assume $R \to \infty$ so that the length of the rule list in business model B does not matter for the value.

higher γ_i. Over time, procedural layers accumulate, leading to more boxes to check and a slower, more cumbersome decision-making process.

Although our microfoundation adopts the modeling of wasteful "committee time," this is not the only way to map the organizational friction parameter γ_i to real-world organizational features. Firms with larger γ_i may also feature rigid organizational structures–characterized by hierarchical decision–making, siloed departments, and low tolerance for bottom-up experimentation, which further hinder their ability to respond quickly to internal conflicts or external shocks. For instance, proposals that challenge existing practices might need to pass through multiple approval layers, each driven by status-quo-preserving incentives. This rigidity not only slows down the committee process but may also dilutes or suppresses innovative ideas before they can be implemented.

To substantiate the observation that old firms have more rules, we collect information through employee reviews from Revelio (Revelio Labs, 2025). First, we use LLM to screen for reviews that discuss rules at the employer company. Second, we use LLM to label the relevant reviews as those that mention the presence of rules vs those that mention the lack of rules. We detail our prompt in Appendix IA2.1. We calculate the intensity of rules in a GVKEY-year as:[10]

$$\text{Rule Index} = \frac{(\text{\# of reviews mentioning the presence of rules - \# of reviews mentioning the lack of rules})}{\text{\# of total reviews}}. \tag{23}$$

Similarly, we use employee reviews to substantiate the observation that old firms have more meetings, committees, and layers of approval that waste time. We detail our prompt in Appendix IA2.2. First, we use LLM to screen for reviews that discuss meetings, committees, and layers of approval at the employer company. Second, we use LLM to label the relevant reviews as those complaining the company has too many such activities that waste time vs praising the company for being efficient and not having too many such activities that waste time. We calculate the intensity of meetings that waste time in a GVKEY-year as:

$$\text{Meeting Index} = \frac{(\text{\# of reviews complaining too many - \# of reviews praising not too many})}{\text{\# of total reviews}}. \tag{24}$$

Figure 3 shows binscatter plots of the relationship between the Rule Index and the Meeting Index with respect to age. We see that both are strongly increasing with firm age.

[10]We map Revelio company ID RCID to GVKEY in a given year using parent-subsidiary bridge provided by Revelio to us directly.

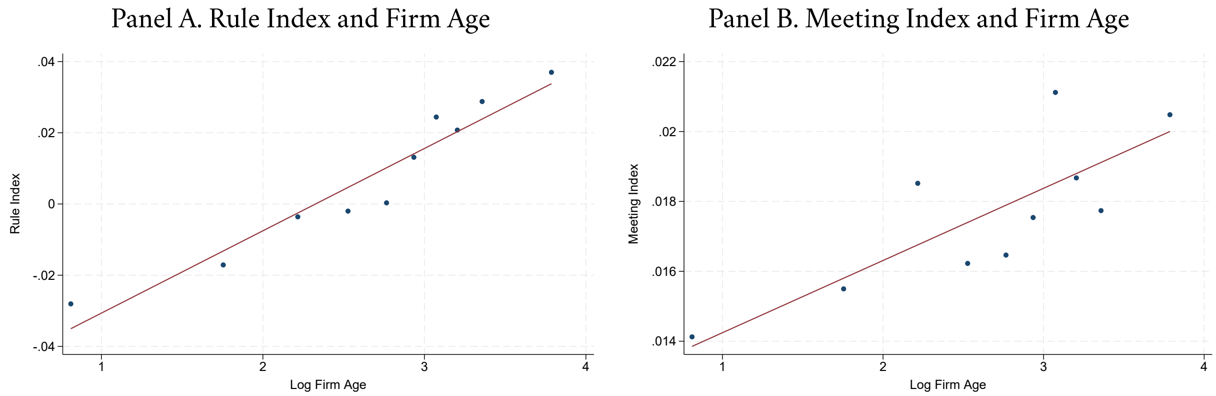


Figure 3. Firm Age, Rules, and Meetings that Waste Time

Notes: This figure shows binscatter plots of the Rule Index in (23) in Panel A and the Meeting Index in (24) in Panel B in 10 equal-sized bins based on log firm age for Compustat firms. We absorb year fixed effects.

3.4 Connection to Empirical Analyses

We now illustrate how the model guides the structure of our empirical analyses. A key hypothesis that we test in the data is that young firms grow more and old firms grow less when new technologies imply substantial style changes in an industry, which we formalize below. We focus on the simple, one-shot model to derive our testable implications.

Firm growth and change in workstyle First of all, the equilibrium change in overall workstyle, as a function of model primitives, is:

$$\Delta = \sum_j \frac{l_{B,j}}{l_B}\delta_j = \sum_j \left(\frac{\theta_{B,j}}{\sum_j \theta_{B,j}} - \frac{\theta_{A,j}}{\sum_j \theta_{A,j}} \right) ws_j. \tag{25}$$

Prior to the arrival of business model B, total employment at firm i is:

$$E_{pre,i} = E_{A,i} = z_A \xi_i \bar{l}.$$

After business model B has arrived, total employment at firm i expands to:

$$E_{post,i} = E_{A,i} + E_{B,i} = (z_A + z_{B,i})\, \xi_i \bar{l}.$$

Thus the growth rate of firm i is:

$$g_i = \frac{E_{post,i}}{E_{pre,i}} - 1 = \frac{E_{B,i}}{E_{A,i}} = \frac{z_{B,i}}{z_A} = \mu - \lambda Q_B \gamma_i \left|\Delta\right|,$$

where λ and μ are industry-wide constants given by:

$$\lambda \equiv \frac{\Xi}{L_A}, \quad \mu \equiv \frac{L_B}{L_A} + \lambda Q_B \left|\Delta\right| \Gamma.$$

Finally, we can compute industry-level changes in the overall workstyle. Before business model B arrives, the employment-weighted average workstyle in the industry is:

$$\overline{ws}_{\text{pre}} = \sum_j \frac{\int_i L_{A,i} l_{A,j} di}{\int_i L_{A,i} \bar{l} di} ws_j = \sum_j \frac{\theta_{A,j}}{\sum_j \theta_{A,j}} ws_j.$$

In the post-period, the weighted-average workstyle in the industry is:

$$\begin{aligned} \overline{ws}_{\text{post}} &= \sum_j \frac{\int_i L_{A,i} l_{A,j} di + \int_i L_{B,i} l_{B,j}}{\int_i (L_{A,i} + L_{B,i}) \bar{l} di} ws_j \\ &= \overline{ws}_{\text{pre}} + \frac{L_B}{L_A + L_B} \sum_j \left(\frac{\theta_{B,j}}{\sum_j \theta_{B,j}} - \frac{\theta_{A,j}}{\sum_j \theta_{A,j}} \right) ws_j. \end{aligned}$$

Thus the (absolute value of) the weighted-average change in workstyle in the industry is related to $|\Delta|$ through:

$$|d\overline{ws}| = |\overline{ws}_{\text{post}} - \overline{ws}_{\text{pre}}| = \frac{L_B}{L_A + L_B} \left| \sum_j \left(\frac{\theta_{B,j}}{\sum_j \theta_{B,j}} - \frac{\theta_{A,j}}{\sum_j \theta_{A,j}} \right) ws_j \right| = \frac{L_B}{L_A + L_B} \left|\Delta\right|.$$

Empirical regressions In what follows, we assume that there are multiple industries, indexed by n, and multiple firms within each industry. Each industry behaves according to the model described above. For simplicity, we assume that industries only differ in their occupation productivity vectors $\{\theta_{A,n,j}, \theta_{B,n,j}\}_{j=1}^J$, but that other industry-level variables are the same across industries, or have identical distributions.

We are interested in interpreting the results of the following regression:

$$g_{i,n} = \nu + \rho \, \text{age}_i + \kappa \, \left|d\overline{ws}\right|_n + \zeta \, \left(\text{age}_i \times \left|d\overline{ws}\right|_n\right) + \varepsilon_{i,n} \tag{26}$$

where $g_{i,n}$ is a measure of firm-level growth (of employment, in the model), $d\overline{ws}_n$ is the change in industry weighted average workstyle in industry n, and age_i is the age of firm i.[11] Our goal is to understand what determines the sign of the estimated coefficient ζ in the context of our model. In order to help interpret the regression coefficients, we make the following assumption.

Assumption 1. *The joint distribution of (age_i, γ_i) is identical across industries m. Moreover, the joint distribution of (age_i, γ_i) is independent from the distribution of $(d\overline{ws}_n)^2$ across industries.*

Note that in the microfoundation provided in Section 3.3, age and organizational frictions are perfectly correlated within and across firms. This motivates our empirical focus on age in this section and the remainder of the paper. However, our derivations below hold for any exogenous firm characteristic. Our main point is that the estimated coefficient ζ will only be positive if organizational rigidity covaries positively with those characteristics. This is formalized in the following result.

Result 1. *Under Assumption 1, the estimated coefficient $\hat{\zeta}$ in Equation (26) in terms of model objects is:*

$$\hat{\zeta} \;=\; -\frac{\Xi}{L_A}\left(1+\frac{L_A}{L_B}\right) \times \frac{cov(Q_{B,n}\,|\Delta|_n\,, |\Delta|_n)}{var(|\Delta|_n)} \times \frac{cov(\gamma_i, age_i)}{var(age_i)}, \tag{27}$$

where $|\Delta|_n$ is the change in workstyle in the industry, $Q_{B,n}$ is output in each business line of type B, and γ_i is the intensity of organizational frictions at firm i in industry n.

Proof. See Appendix IA4.2. □

To understand the economic content of this result, suppose that:

$$cov(Q_{B,n}\,|\Delta|_n\,, |\Delta|_n) > 0. \tag{28}$$

The estimated coefficient $\hat{\zeta}$, which captures the effect of the interaction of age and workstyle is negative, if and only if $cov(\gamma_i, \text{age}_i) > 0$, that is, if organizational frictions are larger within older firms. Thus, if age and organizational rigidity are positively correlated, this regression provides a direct test of our main economic mechanism: occupational misalignment ($|\Delta|_n$) between old and new business models hampers growth for firms with large organizational rigidities. The remainder of our empirical analysis will focus on testing this prediction across different data sources.

[11] We focus on a single cross-sectional regression with growth rates computed pre- to post-arrival of the new business model; in empirical counterparts to this regression, we use five-year changes in employment and workstyle instead.

There are good economic reasons to think that condition (28) is the relevant case empirically. Heuristically, (28) says that when business model B is performing well (so that $Q_{B,n}$, output in each unit, is high), the differences in workstyle with respect to business model A are large. Presumably, if firms are undertaking business model B, it is because it is sufficiently profitable to be worth the organizational cost, as captured by $|\Delta|_n$. If condition (28) were to fail, expanding into B may not be worthwhile to the firm, as it would require a high organizational cost for low incremental output. However, there is no explicit selection into B in our model (it is always profitable to expand into), and no opportunity cost (the firm cannot hire managers trained in business model A to work according to business model B). Appendix IA4.2 provides sufficient conditions for condition (28) to hold, specifically, that business model B raises the productivity of each new unit (relative to business model A) by an industry-specific factor, while reshuffling occupational composition.

4 Data and Measurement

We aim to measure industry-level workstyle changes $|d\overline{ws}|_n$ induced by new technologies. To do so, we combine two sets of data. First, we measure workstyle at the occupation level using the O*NET "Work Styles" dataset, which records the importance of 16 characteristics for the occupation (e.g., attention to detail, self control, stress tolerance, adaptability/flexibility, innovation). Second, we follow Kogan et al. (2024) to predict changes in occupation composition in each industry at a given point in time due to new technologies (measured using patents). In a nutshell, employment of an occupation in an industry decreases (increases) when the occupation's routine (nonroutine) tasks are similar to new technologies in the industry. Finally, we combine these two steps: new technologies predict future employment composition of different occupations in an industry, which then induces changes in the overall (occupation employment weighted average) workstyle in the industry. Our approach drawing information from occupation composition builds on prior work showing that similarity in occupations across industries relates to their compatibility in the case of firms' horizontal expansions and mergers (Lee, Mauer, and Xu, 2018; Beaumont, Hebert, and Lyonnet, 2025).

4.1 Measuring Workstyle

We first describe the measurement of workstyle at the occupation level using O*NET data by the U.S. Department of Labor. The O*NET dataset describes the key characteristics of occupations. The information comes from surveys of workers and occupational experts. The occupations in O*NET use a slight variant of the Bureau of Labor Statistics' Standard Occupational Classification (SOC) codes.

Workstyle for occupation j For each occupation, the O*NET Work Styles module provides the importance score of 16 characteristics, on a scale of 1 to 5. The characteristics are achievement/effort, persistence, initiative, leadership, cooperation, concern for others, social orientation, self-control, stress tolerance, adaptability/flexibility, dependability, attention to detail, integrity, independence, innovation, and analytical thinking. We use $\mathbf{ws}_j$ to denote this 16×1 vector at the occupation level. We download the data from the O*NET website (U.S. Department of Labor, Employment and Training Administration, 2025).[12]

Workstyle in industry n and year t We construct the industry-level workstyle in each year t as:

$$\mathbf{WS}_{n,t} = \sum_{j=1}^{J} \frac{l_{j,n,t}}{l_{n,t}} \mathbf{ws}_j, \tag{29}$$

where $l_{j,n,t}$ is the employment of occupation j in industry n and year t, and $l_{n,t} = \sum_j l_{j,n,t}$, which use data from the Occupational Employment and Wage Statistics (OEWS) dataset by U.S. Bureau of Labor Statistics (BLS). We use data at the 3-digit NAICS level, which are consistently available since 2003. We download the data from BLS website (U.S. Bureau of Labor Statistics, 2025).

Workstyle change in industry n from year t to year $t+5$ We define workstyle change in industry n from year t to year $t+h$ as the Euclidean distance between $\mathbf{WS}_{n,t}$ and $\mathbf{WS}_{n,t+h}$:

$$|d\overline{ws}|_{n,t,h} \equiv \|\mathbf{WS}_{n,t+h} - \mathbf{WS}_{n,t}\|, \tag{30}$$

which is the empirical counterpart to $|d\overline{ws}|_n$ in the model. We use $h = 5$ in our baseline analyses. We standardize $|d\overline{ws}|_{n,t,h}$ to facilitate the assessment of economic magnitude in the regressions.

4.2 Technology and Industry Workstyle Change

We then connect $l_{j,n,t+5}$ and correspondingly $\mathbf{WS}_{n,t+5}$ to new technologies using the methodology of Kogan et al. (2024). The core idea is to predict future employment by occupation in an industry based on the similarity between occupation tasks and new technologies measured using patents.

[12]For each occupation and characteristic, we take the average value across unique survey waves if there are multiple. If we only use the first value, then some occupations will have missing values in the early years.

Calculate a patent's similarity with occupation j's routine & nonroutine tasks We obtain the tasks of each occupation according to the ONET-SOC 2000 taxonomy (U.S. Department of Labor, Employment and Training Administration, 2005), so that the task descriptions predate our sample period. We then query LLM to label them as routine tasks vs non-routine tasks.[13] For each occupation, we combine the descriptions of routine tasks and nonroutine tasks, and will use each set to calculate the similarity with patent text later. We also compute the share of tasks that are routine or non-routine for each occupation. The median occupation has 16 tasks and 33.3% are routine.[14]

We follow Kogan et al. (2024) to represent each document—including each patent and each occupation's combined routine (nonroutine) task descriptions—X_i as a weighted average of its word embeddings x_k:

$$X_i = \sum_k q_{i,k} x_k,$$

where $q_{i,k}$ is the Term Frequency-Inverse Document Frequency (TF-IDF) weight,[15] and word embeddings x_k are obtained using the *GloVe* model.[16]

We then calculate the cosine similarity $s^r_{p,j}$ between a patent p and the routine or non-routine component of occupation j:

$$s^r_{p,j} = \frac{\mathcal{X}_p}{\|\mathcal{X}_p\|} \cdot \frac{\mathcal{X}^r_j}{\|\mathcal{X}^r_j\|}, \quad r \in \{R, NR\}.$$

We perform two adjustments of removing year fixed effects and imposing sparsity on $s^r_{p,j}$ to obtain an

[13]We follow Kogan et al. (2024) in querying LLM (GPT-4o) for this classification. The prompt is: "A routine task can be defined as follows: A routine task involves carrying out a limited and well-defined set of work activities, those that can be accomplished by following explicit rules. These tasks require methodical repetition of an unwavering procedure, and they can be exhaustively specified with programmed instructions and performed by machines. Tell me whether the following task is primarily routine or primarily non-routine; and explain your reasoning in one sentence.

Task: *task statement text from O*NET*

Output your answer in JSON like the following format: {"answer": "primarily routine/primarily non-routine", "reasoning": "your reasoning"}"

[14]The 2000 O*NET classification contains 15,643 different tasks, 98.3% of which are specific to a particular occupation in the O*NET-SOC classification. Examples of tasks include: "Manage and treat common health problems, such as infections, influenza and pneumonia, as well as serious, chronic, and complex illnesses, in adolescents, adults, and the elderly"; "Measures and marks location of studs, leaders, and receptacle openings, using tape measure, template, and marker"; "Receive mortgage, loan, or public utility bill payments, verifying payment dates and amounts due". By contrast, as explained above, the workstyle data which we use in our measures are lower-dimensional and score all occupations on the same set of characteristics.

[15]The weight $w_{i,k}$ reflects the frequency of a term within a document relative to its frequency across all documents, thereby emphasizing words that are distinctive to that document. We compute TF-IDF separately for the patent and occupation text corpora.

[16]We use the `glove-wiki-gigaword-300` model, trained on the Wikipedia and Gigaword corpora, which provides 300-dimensional word vectors that preserve semantic relationships among words.

adjusted similarity measure $\tilde{s}^r_{p,j}$[17].

Sum over patents in industry n and year t to get occupation j's exposure $\xi^R_{n,j,t}$ and $\xi^{NR}_{n,j,t}$ We sum over similarity between occupation j and all granted patents assigned to industry n in year t according to the mapping between Cooperative Patent Classification (CPC) and 3-digit NAICS industries provided by Goldschlag, Lybbert, and Zolas (2016). We refer to the total similarity between occupation j's routine (nonroutine) tasks and patents in industry n year t as $\xi^R_{n,j,t}$ ($\xi^{NR}_{n,j,t}$). Specifically, the exposure of industry n and occupation j to technology at year t is calculated as:

$$\xi^r_{n,j,t} = \theta^r_j \log\left(1 + \sum_{p\in\mathcal{P}_t} \tilde{s}^r_{p,j}\right), \quad r \in \{R, NR\}, \tag{31}$$

where θ^r_j is the routine/non-routine share of tasks for occupation j and $\mathcal{P}_t$ is the set of patents issued in industry n and year t.[18]

Predict future employment of occupation j in industry n We then follow Kogan et al. (2024) and use occupation exposure to technologies $\xi^R_{n,j,t}$ and $\xi^{NR}_{n,j,t}$ to predict future employment. Specifically, we run a regression of log employment of occupation j in industry n and year $t+5$ ($\log l_{n,j,t+5}$) on the occupation's exposure to year t technologies through routine tasks ($\xi^R_{n,j,t}$), the occupation's exposure to year t technologies through non routine tasks ($\xi^{NR}_{n,j,t}$), and current employment of occupation j in industry n ($\log l_{n,j,t+5}$). We obtain predicted employment of occupation j in industry n and year $t+5$ ($\widehat{\log l_{n,j,t+5}}$):

$$\widehat{\log l_{n,j,t+5}} = \underset{(0.066)}{0.293^{***}} - \underset{(0.009)}{0.056^{***}} \cdot \xi^R_{n,j,t} + \underset{(0.004)}{0.029^{***}} \cdot \xi^{NR}_{n,j,t} + \underset{(0.006)}{0.955^{***}} \cdot \log l_{n,j,t}. \tag{32}$$

Predicted workstyle change in industry n from year t to $t+5$ Finally, we obtain predicted workstyle in year $t+5$ using $\widehat{\log l_{n,j,t+5}}$:

$$\mathbf{WS}^e_{n,t+h} = \sum_{j=1}^{J} \frac{\widehat{l_{n,j,t+h}}}{\sum_j \widehat{l_{n,j,t+h}}} \mathbf{ws}_j. \tag{33}$$

[17]We remove year fixed effects from the similarity measures to account for time-varying semantic features. This adjustment is performed for routine and non-routine metrics and for each year separately. To focus on highly similar pairs, we set values below the 80th percentile to zero and rescale the remaining similarities to [0,1] by normalizing with the maximum such that the new maximum equals one.

[18]The Goldschlag, Lybbert, and Zolas (2016) bridge maps each CPC to an industry with a probability weight. We follow Kelly et al. (2021) to make the probability weights associated with a patent sum to one. In (31), we abstract away from explicitly writing out that a patent maps to an industry with a probability weight.

Accordingly, the predicted workstyle change in industry n from year t to $t+h$:

$$|d\overline{ws}|^e_{n,t,h} \equiv \|\mathbf{WS}^e_{n,t+h} - \mathbf{WS}_{n,t}\|. \tag{34}$$

This predicted industry-level workstyle change based on technologies, $|d\overline{ws}|^e_{n,t,h}$, will be the key independent variable in our analysis in Section 5.

5 Empirical Results

In this section, we present the main empirical results on how style changes in an industry help us understand the growth of young vs old firms. The key prediction is that such changes are especially difficult for old firms to accommodate. We test this hypothesis in several different datasets. In Section 5.1, we measure the strength of young firms using venture capital investment. In Section 5.2, we measure the growth of young firms vs old firms using Compustat data, which allow for a variety of measures including valuation, sales growth, and employment growth. In Section 5.3, we measure the growth of young firms vs old firms using employment growth Census Business Dynamic Statistic (BDS) data. The BDS dataset offers broad coverage of economy, although many young firms may be subsistence entrepreneurship rather than innovative entrepreneurship. In addition, firms' exact age is unknown for those formed before the start of the BDS dataset in 1976. All of our tests focus on nonfarm nonfinancial firms (i.e., excluding NAICS code starting with 11, 52, 53, and 55).

5.1 Venture Capital Investment

We start with measuring the strength of young firms through venture capital (VC) investment, which captures forward-looking valuation of startups that can reflect their growth potential. This test assumes that VC investors understand conditions that favor the growth of young firms (e.g., through examining their competitive advantages). First, we obtain venture capital investment from Refinitiv and calculate total VC investment in year t and industry n. We first obtain a list of deals from Refinitiv's Private Equity database (Refinitiv, 2025*a*), and select Fund Investors Type to be Venture Capital. Second, we use a fuzzy matching procedure to standardize industry names in Refinitiv data and map them to NAICS 2007 codes. Finally, sum over VC investment value by 3-digit NAICS and year.

In Table 1, we regress log VC investment in industry n following year t ($\log VC_{n,t+1}$) on the predicted workstyle change over the next 5 years due to year t technologies $|d\overline{ws}|^e_{n,t,5}$. We use the

Table 1 – Venture Capital Investment

	Forward 1-Year Log(VC)			
	(1)	(2)	(3)	(4)
Predicted Workstyle Change in Industry ($\|d\overline{ws}\|^e_{n,t,5}$)	0.331**	0.323**	0.276**	0.270**
	(0.117)	(0.118)	(0.115)	(0.113)
Log Compustat Market Cap in Industry	0.604***	0.561***	0.482***	0.568***
	(0.102)	(0.101)	(0.090)	(0.103)
Log Total Patents in Industry		0.049		
		(0.072)		
Log Breakthrough Patents in Industry			0.141**	
			(0.063)	
Log RETech Patents in Industry				0.058
				(0.077)
Year FE	X	X	X	X
Observations	743	737	715	691

Notes: This table presents regressions at the industry-year level in (35). The key dependent variable is the predicted workstyle change in industry n over the next 5 years due to year t technologies ($|d\overline{ws}|^e_{n,t,5}$), constructed in (30). We standardize $|d\overline{ws}|^e_{n,t,5}$ to unit variance and zero mean. We control for the log of total market capitalization of Compustat firms in industry n (log $MV_{n,t+1}$). Column (2) controls for the log number of total patents in industry n and year t. Column (3) controls for the log number of breakthrough patents in industry n and year t using data from Kelly et al. (2021). Column (4) controls for log of total rapidly evolving patent score for patents in industry n and year t using data from Bowen, Frésard, and Hoberg (2023). We include year fixed effects, and double cluster standard errors by 3-digit NAICS codes and year. Asterisks denote significance levels (***=1%, **=5%, *=10%). Sample years are 2003 to 2019.

dependent variable in year $t+1$ just to ensure that the year t predicted workstyle change is within the information set of investors. We control for the log of total market capitalization of Compustat firms in industry n to capture other factors that may affect the prospects of firms in the industry. We include year fixed effects to remove fluctuations in VC investment due to macroeconomic conditions. We double cluster standard errors by 3-digit NAICS codes and year.

$$\log VC_{n,t+1} = \alpha_t + \beta \, |d\overline{ws}|^e_{n,t,5} + \gamma z_{n,t} + \epsilon_{n,t}. \tag{35}$$

In Table 1 column (1), we see that VC investment value is significantly higher when an industry is hit by new technologies that are predicted to change its style. A one standard deviation increase in $|d\overline{ws}|^e_{n,t,5}$ is associated with higher VC investment by around 0.3 log points, which is meaningful. Columns (2) to (4) show that the sheer quantity of new technologies in the industry (also measured using patents) does not have such an effect, and these controls have a limited impact on the regression coefficients on $|d\overline{ws}|^e_{n,t,5}$. In column (2), we control for the log number of total patents in industry n and year t. Column (3) controls for the log number of breakthrough patents in industry n and year t

using data from Kelly et al. (2021). The breakthrough patents aim to capture particularly transformative new technologies, which are distinct from patents that came before them and followed by many similar patents afterwards. Column (4) controls for the log of total rapidly evolving patent score for patents in industry n and year t using data from Bowen, Frésard, and Hoberg (2023). Patents using words that are contemporaneously surging across the patent corpus receive a higher score.

5.2 Growth of Young Firms vs Old Firms: Compustat

We then measure the strength of young vs old firms using Compustat data (S&P Global Market Intelligence, 2025). To measure the age of Compustat firms (which is not directly available in Compustat), we get firms' incorporation date from Refinitiv (Refinitiv, 2025*b*) and IPO date from Compustat. We then calculate age as the number of years since the earlier one among incorporation date and IPO date, as in Lian and Ma (2021).

In Table 2, we perform regressions using the market value of equity (normalized by book value of equity) as the outcome variable. It captures forward-looking valuation of young vs old firms which can reflect their growth potential, similar to the VC investment analyses in Section 5.1, but now within the set of public companies (rather than startups relative to public companies). This test also assumes that investors understand conditions under which young firms are especially powerful (e.g., through examining their competitive advantages).

Specifically, the outcome variable is the market value of equity (normalized by book value of equity) of firm i in industry n (again we use dependent variable in year $t+1$ just to make sure year t technologies are within their information sets). The independent variables include the predicted workstyle change in industry n over the next 5 years due to year-t technologies ($|d\overline{ws}|^e_{n,t,5}$), and its interaction with log firm age. The controls include the patent variables in columns (2) to (4) of Table 1, as well as their interactions with log firm age. We include year fixed effects, and double cluster standard errors by 3-digit NAICS codes and year (since independent variables are measured at the industry level).

$$MV/BV_{i,t+1} = \alpha_t + \zeta \left(|d\overline{ws}|^e_{n,t,5} \times age_{i,t} \right) + \gamma z_{n,t} + \delta \left(z_{n,t} \times age_{i,t} \right) + \epsilon_{i,t}. \tag{36}$$

We see that when $|d\overline{ws}|^e_{n,t,5}$ is high, equity valuation is higher if firm age is low, and lower if firm age is high. Figure 4 visualizes the implied coefficient on $|d\overline{ws}|^e_{n,t,5}$ for different levels of firm age, using the specification in Table 2 column (1); we transform the coefficient on log firm age to that on firm age for ease of illustration. Meanwhile, the number of patents $z_{n,t}$ (all, breakthrough, or rapidly evolving) in

Table 2 – Equity Valuation among Compustat Firms

	Market to Book Value of Equity			
	(1)	(2)	(3)	(4)
Predicted Workstyle Change in Industry ($\lvert d\overline{ws}\rvert^{e}_{n,t,5}$)	0.440**	0.544**	0.402*	0.457*
	(0.151)	(0.186)	(0.208)	(0.216)
$\lvert d\overline{ws}\rvert^{e}_{n,t,5}$ × Log Firm Age	-0.146**	-0.191**	-0.158*	-0.180**
	(0.056)	(0.073)	(0.080)	(0.076)
Log Total Patents in Industry		-0.032		
		(0.065)		
Log Total Patents in Industry × Log Firm Age		0.034*		
		(0.017)		
Log Breakthrough Patents in Industry			0.039	
			(0.064)	
Log Breakthrough Patents in Industry × Log Firm Age			0.015	
			(0.022)	
Log RETech Patents in Industry				-0.037
				(0.060)
Log RETech Patents in Industry × Log Firm Age				0.031
				(0.019)
Log Firm Age	-0.421***	-0.623***	-0.433***	-0.601***
	(0.113)	(0.148)	(0.124)	(0.138)
Log Firm Sales	0.134*	0.148**	0.149*	0.144**
	(0.063)	(0.066)	(0.074)	(0.064)
Year FE	X	X	X	X
Observations	24,278	23,592	22,228	22,447

Notes: This table presents regressions at the firm-year level in (36). The key dependent variables are the predicted workstyle change in industry n over the next 5 years due to year t technologies ($\lvert d\overline{ws}\rvert^{e}_{n,t,5}$), constructed in Equation (30), and its interaction with firm age. We standardize $\lvert d\overline{ws}\rvert^{e}_{n,t,5}$ to unit variance and zero mean. Column (2) controls for the log number of total patents in industry n and year t, as well as its interactions with firm age. Column (3) controls for the log number of breakthrough patents in industry n and year t using data from Kelly et al. (2021), as well as its interactions with firm age. Column (4) controls for log of total rapidly evolving patent score for patents in industry n and year t using data from Bowen, Frésard, and Hoberg (2023), as well as its interactions with firm age. We include year fixed effects, and double cluster standard errors by 3-digit NAICS codes and year. Asterisks denote significance levels (***=1%, **=5%, *=10%). Sample years are 2003 to 2019.

the industry does not have any significant interaction with firm age. The coefficients on $\lvert d\overline{ws}\rvert^{e}_{n,t,5}$ and its interaction with firm age are also not affected by the controls on the quantity of patents.

In Tables 3 and 4, we perform similar regressions using realized sales growth and employment growth in the 5 years after t. The independent variables, control variables, and fixed effects are the same as those in Table 2.

$$\Delta Y_{i,t\to t+5} = \alpha_t + \zeta\left(\lvert d\overline{ws}\rvert^{e}_{n,t,5} \times age_{i,t}\right) + \gamma z_{n,t} + \delta\left(z_{n,t} \times age_{i,t}\right) + \epsilon_{i,t}. \tag{37}$$

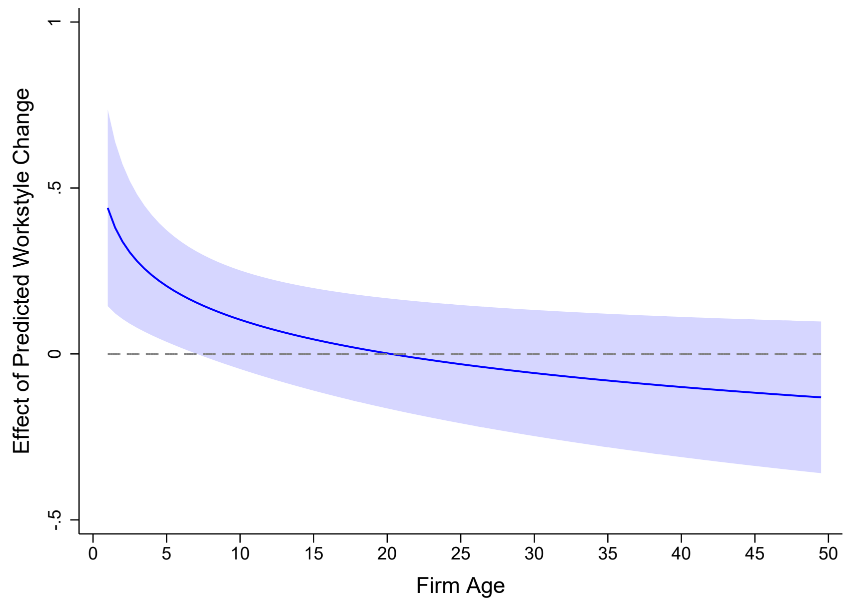


Figure 4. Equity Valuation among Compustat Firms: Implied Effect of $|d\overline{ws}|^e_{n,t,5}$

Notes: This figure shows the implied effect of $|d\overline{ws}|^e_{n,t,5}$ for different levels of firm age in Table 2, column (1).

The growth rates $\Delta Y_{i,t\rightarrow t+5}$ are calculated following Davis, Haltiwanger, and Schuh (1992), to be consistent with the specification we need to use in Census Business Dynamics Statistics dataset later in Section 5.3. It is defined as $\Delta Y_{i,t\rightarrow t+5} = (Y_{i,t+5} - Y_{i,t})/(0.5 \times Y_{i,t+5} + 0.5 \times Y_{i,t})$, which avoids missing values if the starting level is zero or extreme values when the starting level is small. In both Table 3 and Table 4, we see that when $|d\overline{ws}|^e_{n,t,5}$ is high, firm growth is faster if firm age is low, and slower when firm age is high. Figure 5 visualizes the implied coefficient on $|d\overline{ws}|^e_{n,t,5}$ for each level of firm age. In addition, as before, the quantity of patents does not have any significant interaction with firm age.

A natural question is whether the effects of firm age come from the correlation of age with size (Akcigit and Kerr, 2018): maybe young firms are more nimble in light of technology-induced style changes because they are small. In Table IA2, we redo the baseline regressions in Tables 2 to 4, with additional controls of $|d\overline{ws}|^e_{n,t,5}$ interacted with size, measured as either log sales or log employment in year t. Interestingly, we do not observe that size modulates how firm outcomes relates to technology-induced style change $|d\overline{ws}|^e_{n,t,5}$. We also check in Table IA3 that our results are not driven by firm age being correlated with financial constraints, by controlling for $|d\overline{ws}|^e_{n,t,5}$ interacted with standard financial friction proxies such as the Kaplan and Zingales (1997) index and an indicator of non-dividend payer. In principle, young firms are likely to have less abundant financial resources, which can make it

Table 3 – Sales Growth among Compustat Firms

	Sales Growth (5-Year DHS Rate)			
	(1)	(2)	(3)	(4)
Predicted Workstyle Change in Industry ($\lvert d\overline{ws}\rvert^{e}_{n,t,5}$)	0.052**	0.056***	0.046*	0.062***
	(0.020)	(0.018)	(0.021)	(0.018)
$\lvert d\overline{ws}\rvert^{e}_{n,t,5}$ × Log Firm Age	-0.020**	-0.021***	-0.018**	-0.025***
	(0.006)	(0.007)	(0.007)	(0.006)
Log Total Patents in Industry		-0.007		
		(0.009)		
Log Total Patents in Industry × Log Firm Age		0.002		
		(0.003)		
Log Breakthrough Patents in Industry			0.001	
			(0.013)	
Log Breakthrough Patents in Industry × Log Firm Age			-0.002	
			(0.004)	
Log RETech Patents in Industry				-0.007
				(0.009)
Log RETech Patents in Industry × Log Firm Age				0.002
				(0.003)
Log Firm Age	-0.110***	-0.117***	-0.095***	-0.123***
	(0.018)	(0.017)	(0.018)	(0.019)
Log Firm Sales	0.006	0.005	0.004	0.005
	(0.007)	(0.008)	(0.008)	(0.007)
Year FE	X	X	X	X
Observations	18,145	17,683	16,773	16,839

Notes: This table presents regressions at the firm-year level in (37), where the outcome variable $\Delta Y_{i,t\to t+5}$ is sales growth between year t and $t+5$ calculated following Davis, Haltiwanger, and Schuh (1992) as $\Delta Y_{i,t\to t+5} = (Y_{i,t+5} - Y_{i,t})/(0.5 \times Y_{i,t+5} + 0.5 \times Y_{i,t})$. The key dependent variables are the predicted workstyle change in industry n over the next 5 years due to year t technologies ($\lvert d\overline{ws}\rvert^{e}_{n,t,5}$), constructed in Equation (30), and its interaction with firm age. We standardize $\lvert d\overline{ws}\rvert^{e}_{n,t,5}$ to unit variance and zero mean. Column (2) controls for the log number of total patents in industry n and year t, as well as its interactions with firm age. Column (3) controls for the log number of breakthrough patents in industry n and year t using data from Kelly et al. (2021), as well as its interactions with firm age. Column (4) controls for log of total rapidly evolving patent score for patents in industry n and year t using data from Bowen, Frésard, and Hoberg (2023), as well as its interactions with firm age. We include year fixed effects, and double cluster standard errors by 3-digit NAICS codes and year. Asterisks denote significance levels (***=1%, **=5%, *=10%). Sample years are 2003 to 2019.

harder for them to accommodate technology-induced style changes, but the higher equity valuation of young growth firms might overturn this view. In the data, the effects of firm age remain largely unchanged with these additional controls.

Table 4 – Employment Growth among Compustat Firms

	Employment Growth (5-Year DHS Rate)			
	(1)	(2)	(3)	(4)
Predicted Workstyle Change in Industry ($\|\widehat{dws}\|^e_{n,t,5}$)	0.050**	0.054***	0.054*	0.061**
	(0.020)	(0.017)	(0.027)	(0.021)
$\|\widehat{dws}\|^e_{n,t,5} \times$ Log Firm Age	-0.018**	-0.018**	-0.019*	-0.023**
	(0.007)	(0.007)	(0.009)	(0.008)
Log Total Patents in Industry		-0.010		
		(0.009)		
Log Total Patents in Industry $\times$ Log Firm Age		0.001		
		(0.003)		
Log Breakthrough Patents in Industry			-0.003	
			(0.013)	
Log Breakthrough Patents in Industry$\times$ Log Firm Age			-0.001	
			(0.004)	
Log RETech Patents in Industry				-0.008
				(0.008)
Log RETech Patents in Industry $\times$ Log Firm Age				0.002
				(0.003)
Log Firm Age	-0.086***	-0.092***	-0.078***	-0.095***
	(0.015)	(0.010)	(0.009)	(0.010)
Log Firm Employment	0.001	-0.001	-0.001	0.000
	(0.006)	(0.008)	(0.007)	(0.007)
Year FE	X	X	X	X
Observations	17,396	16,951	16,098	16,166

Notes: This table presents regressions at the firm-year level in (37), where the outcome variable $\Delta Y_{i,t\to t+5}$ is employment growth between year t and $t+5$ calculated following Davis, Haltiwanger, and Schuh (1992) as $\Delta Y_{i,t\to t+5} = (Y_{i,t+5} - Y_{i,t})/(0.5 \times Y_{i,t+5} + 0.5 \times Y_{i,t})$. The key dependent variables are the predicted workstyle change in industry n over the next 5 years due to year t technologies ($|\widehat{dws}|^e_{n,t,5}$), constructed in Equation (30), and its interaction with firm age. We standardize $|\widehat{dws}|^e_{n,t,5}$ to unit variance and zero mean. Column (2) controls for the log number of total patents in industry n and year t, as well as its interactions with firm age. Column (3) controls for the log number of breakthrough patents in industry n and year t using data from Kelly et al. (2021), as well as its interactions with firm age. Column (4) controls for log of total rapidly evolving patent score for patents in industry n and year t using data from Bowen, Frésard, and Hoberg (2023), as well as its interactions with firm age. We include year fixed effects, and double cluster standard errors by 3-digit NAICS codes and year. Asterisks denote significance levels (***=1%, **=5%, *=10%). Sample years are 2003 to 2019.

5.3 Growth of Young Firms vs Old Firms: BDS

Finally, we turn to Census Business Dynamic Statistics (BDS), which has broader coverage of firms. Here the primary measure of size is employment (United States Census Bureau, 2023). In particular, the public use dataset provides total employment of firms by age group: 0, 1-5, 6-10, 11-15, 16-20, 21-25, and the remaining age groups cannot be consistently defined over our sample period because firms' precise age is unknown if they are born before 1976. Therefore we restrict to firms with age between 1

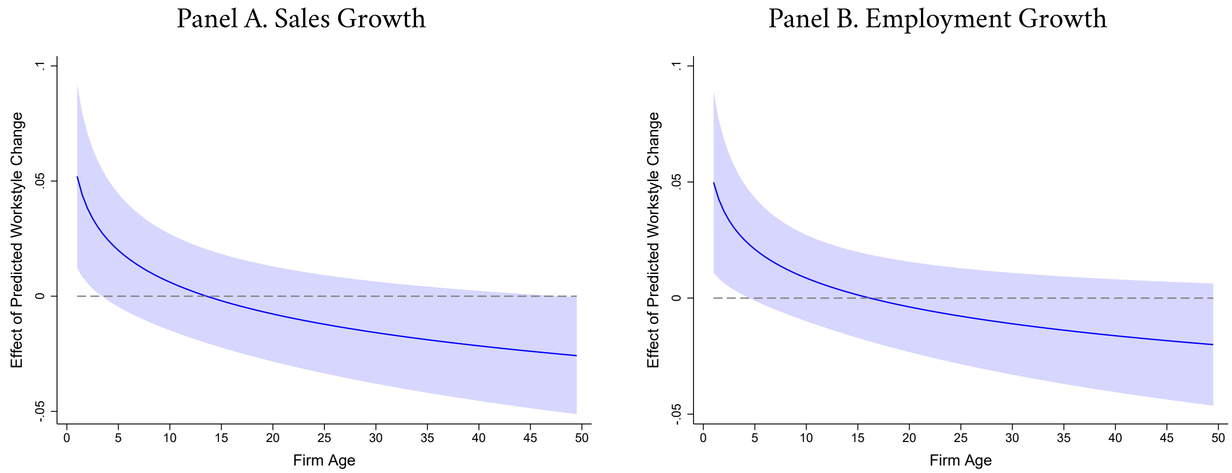


Figure 5. Sales and Employment Growth among Compustat Firms: Implied Effect of $|d\overline{ws}|^e_{n,t,5}$

Notes: Panel A shows the implied effect of $|d\overline{ws}|^e_{n,t,5}$ for different levels of firm age in Table 3, column (1). Panel B shows the implied effect of $|d\overline{ws}|^e_{n,t,5}$ for different levels of firm age in Table 4, column (1).

and 25. We perform regressions at the level of industry-year-age group level:

$$\Delta emp_{i,t\to t+5} = \alpha_t + \zeta \left(|d\overline{ws}|^e_{n,t,5} \times age_{i,t} \right) + \gamma z_{n,t} + \delta \, (\, z_{n,t} \times age_{i,t} \,) + \epsilon_{i,t}. \tag{38}$$

The outcome variable is the growth rate of employment among firm age group i in industry n between year t and $t+5$ (e.g., age group 1-5 becomes 6-10 after 5 years), calculated following Davis, Haltiwanger, and Schuh (1992). The independent variables include the predicted workstyle change in industry n over the next 5 years due to year-t technologies ($|d\overline{ws}|^e_{n,t,5}$), and its interaction with age group dummies. The controls include the patent variables in columns (2) to (4) of Table 1, as well as their interactions with age group dummies. We include year fixed effects, and double cluster standard errors by 3-digit NAICS codes and year (since independent variables are measured at the industry level). We see that when $|d\overline{ws}|^e_{n,t,5}$ is high, employment growth is faster for the young firm groups, and less so for the older firm groups.

Table 5 – Employment Growth among BDS Firms

	Employment Growth (5-Year DHS Rate)			
Patent Measure =	(1) N/A	(2) All Patents	(3) Breakthrough	(4) RETech
Predicted Workstyle Change in Industry ($\lvert\overline{dws}\rvert^{e}_{n,t,5}$)	0.035*	0.036**	0.032*	0.028*
	(0.016)	(0.016)	(0.016)	(0.015)
$\lvert\overline{dws}\rvert^{e}_{n,t,5}$ × Age 6–10	0.008	0.009	0.007	0.009
	(0.010)	(0.010)	(0.010)	(0.011)
$\lvert\overline{dws}\rvert^{e}_{n,t,5}$ × Age 11–15	-0.024	-0.024*	-0.026*	-0.020
	(0.013)	(0.013)	(0.014)	(0.014)
$\lvert\overline{dws}\rvert^{e}_{n,t,5}$ × Age 16–20	-0.024**	-0.023**	-0.024**	-0.023**
	(0.010)	(0.010)	(0.010)	(0.009)
Log Patents in Industry		-0.004	-0.002	-0.003
		(0.008)	(0.007)	(0.007)
Age 6–10 × Log Patents in Industry		0.002	0.003	0.003
		(0.004)	(0.004)	(0.004)
Age 11–15 × Log Patents in Industry		0.003	0.004	0.002
		(0.006)	(0.006)	(0.006)
Age 16–20 × Log Patents in Industry		-0.001	0.001	0.002
		(0.006)	(0.006)	(0.006)
Age 6–10	0.038**	0.030	0.032	0.018
	(0.016)	(0.023)	(0.019)	(0.023)
Age 11–15	0.030	0.018	0.024	0.015
	(0.019)	(0.035)	(0.025)	(0.035)
Age 16–20	0.056**	0.062	0.058**	0.045
	(0.020)	(0.039)	(0.024)	(0.039)
Log Employment in Industry	-0.005	-0.006	-0.006	-0.007
	(0.017)	(0.017)	(0.018)	(0.017)
Year FE	X	X	X	X
Observations	3,456	3,432	3,332	3,220

Notes: This table presents regressions at the industry-age group-year level in (38), where the outcome variable $\Delta Y_{i,t\rightarrow t+5}$ is employment growth of age group i in industry n between year t and $t+5$, calculated following Davis, Haltiwanger, and Schuh (1992) as $\Delta Y_{i,t\rightarrow t+5} = (Y_{i,t+5} - Y_{i,t})/(0.5 \times Y_{i,t+5} + 0.5 \times Y_{i,t})$. The key dependent variables are the predicted workstyle change in industry n over the next 5 years due to year t technologies ($\lvert\overline{dws}\rvert^{e}_{n,t,5}$), constructed in Equation (30), and its interaction with age group dummies. We standardize $\lvert\overline{dws}\rvert^{e}_{n,t,5}$ to unit variance and zero mean. Column (2) controls for the log number of total patents in industry n and year t, as well as its interactions with age group dummies. Column (3) controls for the log number of breakthrough patents in industry n and year t using data from Kelly et al. (2021), as well as its interactions with age group dummies. Column (4) controls for log of total rapidly evolving patent score for patents in industry n and year t using data from Bowen, Frésard, and Hoberg (2023), as well as its interactions with age group dummies. We include year fixed effects, and double cluster standard errors by 3-digit NAICS codes and year. Asterisks denote significance levels (***=1%, **=5%, *=10%). Sample years are 2003 to 2019.

6 Conclusion

Every year, over 200 NBER working papers are written on entrepreneurship (National Bureau of Economic Research, 2025). Given the popularity of this subject, it is essential to address the fundamental question: why do we need new firms to do new things? Our work highlights the importance of organizational frictions for understanding organizational change and disruption. In particular, existing firms are not always incapable of implementing new technologies, due to slowness of learning or fear of cannibalization. They are especially vulnerable when new technologies require changes in organizational processes and priorities, which naturally favor new organizations that start fresh. With the advancement in data and measurement—thanks to more ways to extract information from texts—future research can make more progress to capture organizational frictions, and investigate their role in innovation, productivity, and growth.

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Internet Appendix

IA1 Processing Wikipedia Titles

This appendix describes in detail how we obtain and process Wikipedia titles on technological inventions used in Section 2.

IA1.1 Wikipedia Titles on Technological Inventions

We extract English Wikipedia titles from the Wikimedia English Wikipedia Dumps and filter them in two steps to identify titles related to technological inventions.

Step 1 We first do batch filtering to obtain a broad set of technology-related titles using GPT-4o-mini. The LLM is instructed to identify Wikipedia titles corresponding to technological inventions. Wikipedia titles are processed in batches of 50, and the LLM returns only those classified as technological inventions.

```
Instructions:
- You are tasked with filtering a list of Wikipedia article titles to
include only those of technological inventions. A technological invention is
a novel device, method, process, or system that applies scientific or
engineering principles to solve a problem or improve efficiency. These
inventions typically introduce new functionalities, enhance existing
technologies, or create entirely new categories of tools or systems.
- Focus ONLY on technological inventions, which are devices, systems, and
components with novel technological advancements, such as ''wheels'',
''artificial intelligence'', ''eletric vehicle'', ''mobile phone'', ''Watt
steam engine'', etc.
- EXCLUDE names of people, movies, books, songs, food, animals, places,
companies, organizations, social movements, slogans, cultural phrases, and
any non-technology items.
- EXCLUDE specific models, product names, versions of weapons and vehicles,
unless they represent a significant technological advancement (e.g.,
''iPhone'' is a technological invention, but ''iPhone 13'' is not. Airplane
is a technological invention, but ''Boeing 747'' is not).
- Do NOT include scientific phenomena unless they describe a concrete
technological invention or device.
```

```
- If multiple titles are extremely similar (such as variations in
capitalization, punctuation, or wording), ONLY include ONE representative
title.

For each title, first assess if it represents a technological invention.
Then, return ONLY the valid titles (keeping the original format of input,
including the ''_'' character).

Respond in a JSON array of strings like this:
[''Title 1'', ''Title 2'', ''Title 3'']

Titles:
{titles_list}
```

Step 2 We validate each Wikipedia title from Step 1 using its Wikipedia summary to obtain the final set of technological inventions. For each title, we use the Wikipedia API library to retrieve the corresponding English Wikipedia summary. We then supply both the title and the summary to Deepseek-Reasoner model, which is prompted to determine whether the article indeed describes a technological invention, following the same definition used in Step 1. The LLM's responses indicate whether the Wikipedia title should be retained.

```
Instructions:
- You are tasked with determining whether a given Wikipedia article is about
a technological invention based on the title and summary provided. A
technological invention is a novel device, method, process, or system that
applies scientific or engineering principles to solve a problem or improve
efficiency. These inventions typically introduce new functionalities,
enhance existing technologies, or create entirely new categories of tools or
systems.
- EXCLUDE specific models, product names, versions of weapons and vehicles,
unless they represent a significant technological advancement (e.g.,
''iPhone'' is a technological invention, but ''iPhone 13'' is not. Airplane
is a technological invention, but ''Boeing 747'' is not). Example of titles
that should be EXCLUDED: ''AJS_Model_16'', ''AMD_2900'',
''A340_(aircraft)'', ''A.T_Mine_E.P._Mark_II''.

Wikipedia Article Title: {title}
```

```
Wikipedia Article Summary:
\''\''\''{summary}\''\''\''

Based on the above summary, determine if this article is about a
technological invention.
Respond ONLY with a JSON object in the following format:
{{''is_valid'': true}}
or
{{''is_valid'': false}}
```

IA1.2 Technology Information

We use the following prompt to summarize basic information about the technological inventions with Gemini-2.0-Flash, including the time and location of the invention, as well as the type of inventor (i.e., private company, individual inventor, government, or university/non-profit).

```
Instructions:
You are an expert in the history of technologies. Your task is to answer
questions about when, where, who invented the technology, and which category
of application it best fits into, based on the given information about the
technology and your domain knowledge.

Provide the following information along with a brief reason (less than 20
words) for each:

1) When the technology first became workable. If the exact year is
unavailable or uncertain, provide the closest approximation. Be as accurate
as possible. Include ''BCE'' in your response if the date is before 0
CE/very ancient.

2) Where it was first created (country where the first workable version was
created).

3) Who invented it (choose one of these categories by the type of inventor):
- ''Private Company'': For-profit company/companies or people working for
these companies developed the technology (e.g. Apple, Google);
```

- ''University/Non-Profit'': Non-profit institution or organization developed it, such as universities, non-profit institutions, open-source projects (e.g. UC Berkeley, SRI, Mozilla);
- ''Government Project'': Developed via government-funded or military project (e.g. NASA, the Apollo program, the Manhattan Project);
- ''Individual Inventor'': Developed by an individual or a small team of inventors unaffiliated with large institutions or companies (e.g. Nikola Tesla, Philo Farnsworth);

Note: Some inventions involve collaboration. When multiple parties are involved, choose the category that best reflects the majority of developers or the most responsible entity. Aim for the most accurate classification based on available evidence. When inventors are not explicitly mentioned, use your best judgment to classify the technology based on the context and purpose of the invention
For example:
- A collaboration between private companies is still classified as ''Private Company''.
- A small team of unaffiliated inventors is still ''Individual Inventor''.
- If an individual works under a government-funded initiative, classify it as ''Government Project''.
- If it was published by an industry association, it should be either ''Private Company'' or ''University/Non-Profit'' depending on the inventor and purpose of the technology. For example, SAE (Society of Automotive Engineers) is mostly ran by engineers from private companies, so it should be classified as ''Private Company''. W3C (World Wide Web Consortium) is ran by university researchers, so it should be classified as ''University/Non-Profit''.
- If it was designed for commercial use or production efficiency, it's likely ''Private Company''.
- If it served military, national defense, or public interest, it's likely ''Government Project''.
- If it was developed for academic research or knowledge advancement, it's likely ''University/Non-Profit''.
- If it was created by individuals not working for large institutions, it's likely ''Individual Inventor''.

```
4) The 'domain_of_application' (choose exactly one from the list below):
   [''Agriculture, Forestry, Fishing and Hunting'', ''Mining, Quarrying, and
   Oil and Gas Extraction'', ''Utilities'', ''Construction'',
   ''Manufacturing'', ''Wholesale Trade'', ''Retail Trade'',
   ''Transportation and Warehousing'', ''Information'', ''Finance and
   Insurance'', ''Real Estate and Rental and Leasing'', ''Professional,
   Scientific, and Technical Services'', ''Health Care and Social
   Assistance'', ''Military and Defense'', ''Basic Research'']

Importantly: Use only the listed categories above. Do not invent new
categories.

Technology Name: {title}

Wikipedia Page:
\''\''\''{wiki_text[:5000]}\''\''\''

Return ONLY a JSON object in the following format:
{{
  ''technology'': ''Title'',
  ''when'': year or ''Not Available'',
  ''when_reason'': ''Brief reason for chosen year'',
  ''where'': country name or ''Not Available'',
  ''where_reason'': ''Brief reason for chosen country'',
  ''who'': one of the 4 listed categories,
  ''who_reason'': ''Brief reason for chosen category'',
  ''domain_of_application'': one of the 15 listed categories,
  ''domain_reason'': ''Brief reason for chosen domain''
}}

Example Output #1:
{{
  ''technology'': ''iPhone'',
  ''when'': ''2007'',
  ''when_reason'': ''Apple released the first iPhone in 2007.'',
  ''where'': ''USA'',
  ''where_reason'': ''Apple developed the iPhone in the United States.'',
```

```
  ''who'': ''Private Company'',
  ''who_reason'': ''Developed by Apple, which is a for profit company.'',
  ''domain_of_application'': ''Information'',
  ''domain_reason'': ''Primarily used for communication and computing.''
}}

Example Output #2:
{{
  ''technology'': ''CRISPR'',
  ''when'': ''2012'',
  ''when_reason'': ''First practical demonstration of gene editing was in
  2012.'',
  ''where'': ''USA'',
  ''where_reason'': ''Initial research conducted at UC Berkeley.'',
  ''who'': ''University Lab'',
  ''who_reason'': ''Developed at UC Berkeley by academic researchers.'',
  ''domain_of_application'': ''Health Care and Social Assistance'',
  ''domain_reason'': ''Primarily applied to medicine and biotechnology.''
}}

Use this JSON schema:
{{
  ''technology'': ''str'',
  ''when'': ''str'',
  ''when_reason'': ''str'',
  ''where'': ''str'',
  ''where_reason'': ''str'',
  ''who'': ''str'',
  ''who_reason'': ''str'',
  ''domain_of_application'': ''str'',
  ''domain_reason'': ''str''
}}
```

IA1.3 Technology Implementation and Commercialization

We use the following prompt to ask web-enabled Gemini-2.0-Flash whether the company that was most successful in its initial implementation and commercialization was a young firm, or an old incumbent.

```
You are a historian of technology and innovation.
You must use web search (Google Search tool is available) to verify the
answer.

Here is a technological invention. Your task is to determine **whether the
company that was most successful in its initial implementation and
commercialization was a new firm or an established firm**.

---
### Instructions
1. Use web search to identify which company first commercialized or
implemented this technology.
2. Then decide whether that company was:
   - **1** → a *young firm* (founded <10 years before commercialization)
   - **-1** → an *old incumbent* that existed long before the invention
   - **0** → *Not sure or ambiguous*
3. Provide the company’s name, short reasoning, and the approximate period
of commercialization.

---
### Examples
Dropbox → young firm (founded 2007, same year commercialized)
iPhone → established firm (Apple founded 1976)

---
### Input
Technology: {title}
Wikipedia summary:
\''\''\''{summary_text[:5000]}\''\''\''

---
### Output (JSON only)
```

```
Return only valid JSON:
{{
  ''technology'': ''{title}'',
  ''firm_name'': ''Name of company or 'Unknown''',
  ''firm_type'': 1 or -1 or 0,
  ''firm_type_reason'': ''Short explanation (<30 words)'',
  ''year_or_period'': ''Approximate year/decade of first commercialization
  if available, else 'Unknown'''
}}
```

IA2 Processing of Employee Reviews

We collect information through employee reviews from Revelio (Revelio Labs, 2025). We process the reviews using the prompts below.

IA2.1 Prevalence of Rules

Step 1 We process all employee reviews with Gemini-2.0-Flash to screen for those that discuss rules.

```
You are analyzing employee reviews of companies. Your task is to determine
whether this review discusses rules, protocols, procedures, policies, or
norms that the employee's company has. Rules include formal policies and
processes as well as strong unwritten norms.

- Ignore comments about pay, culture, or leadership that do not explicitly
mention rules or norms.
- We are looking for reviews about rules in the reviewer's employer company,
not rules imposed by the regulators, suppliers, or clients of the reviewer's
employer company.

Here is a piece of employee review:
''{text}''

Does the review discuss rules, protocols, procedures, policies, or norms
that the employee's company has?

- Yes (return 1)
- No (return -1)
- Unclear (return 0)

Respond ONLY with a JSON object in the following format:
{{''flag'': 0, ''confidence'': 0.5}}
```

Step 2 We process reviews labeled as 1 or 0 from Step 1 with Gemini-2.0-Flash to determine whether they mention the presence or the lack of rules.

```
Here is a piece of employee review for a company:
```

```
''{text}''

Please determine which of the following best describes this review:
- This review discusses the presence of rules and processes in the company
(return 1)
- This review discusses the lack of rules and processes in the company
(return -1)
- This review does not discuss rules and processes in the company (return 0)

Respond ONLY with a JSON object in the following format:
{{
    ''label'': 0,
    ''confidence'': 0.5,
    ''snippets'': (if the label is not 0, report the snippets from the
    review that was most important for your determination of the label)
}}
```

Rule index We use the results from Step 2 in the numerator of the rule index, and calculate the intensity of rules in a GVKEY-year as:

$$\text{Rule Index} = \frac{(\text{\# of reviews mentioning the presence of rules - \# of reviews mentioning the lack of rules})}{\text{\# of total reviews}}.$$

We map Revelio company ID RCID to GVKEY in a given using parent-subsidiary bridge provided by Revelio to us directly.

Examples of employee review discussions

- Presence of rules:
  - "It's a very structured place with a lot of rules, hierarchy, etc."
  - "Stick to the rules and not flexible."
  - "Lots of rules and guidelines."
  - "A stable and well structured corporation that follows the rules."
  - "Company follows strict rules in all type of scenario."
- Absence of rules:
  - "Unstructured work environment. Lack of leadership. Lack of accountability - Job Functions are not very well defined and will change constantly."

- “’Lack of, or nonexistent enforcement of policy results in extremely inconsistent standards.”
- “Make many changes at the last minute...schedules, resource guide, rules. etc."
- “Need to improve culture and standardize HR rules.”
- “Rules of engagement and process were not always clear.”

IA2.2 Too Many Meetings

Step 1 We process all employee reviews with Gemini-2.0-Flash to screen for those that discuss meetings, committees, and layers of approval.

```
You are analyzing employee reviews of companies. Your task is to determine
whether this review discusses work activities that waste time at the
employee’s company, such as too many meetings, committees, and layers of
approval., slow decision making, red tape, or bureaucratic procedures.
- We are looking for reviews about time-wasting work such activities in the
reviewer's employer company, not those imposed by the regulators, suppliers,
or clients of the reviewer's employer company or social meetings and
parties.
- Do not include employees wasting time on personal, non-work related
activities, such as smoking, drinking, eating, or playing games.
- Do not include general discussions about office politics, slow promotion,
or bad management.

Here is a piece of employee review:
''{text}''

Does the review discuss work activities that waste timemeetings, committees,
and layers of approval at the employee's company?

- Yes (return 1)
- No (return -1)
- Unclear (return 0)

Respond ONLY with a JSON object in the following format:
{{''flag'': 0, ''confidence'': 0.5}}
```

Step 2 We process reviews labeled as 1 or 0 from Step 1 with Gemini-2.0-Flash to determine whether they complain that the company has too many meetings, committees, and layers of approval or praise the company for not having too many.

```
Here is a piece of employee review for a company:

''{text}''

Please determine which of the following best describes this review:
- This review complains about work activities at the company that waste
time, such as too many meetings, committees, and layers of approval, slow
decision making, red tape, or bureaucratic procedures that waste time.
(return 1)
- This review praises the company for being efficient and the company does
not have work activities that waste timenot having too many meetings,
committees, and layers of approval that waste time. (return -1)
- It is difficult to tell (return 0)

Respond ONLY with a JSON object in the following format:
{{
    ''label'': 0,
    ''confidence'': 0.5,
    ''snippets'': (if the label is not 0, report the snippets from the
    review that was most important for your determination of the label)
}}
```

Meeting index We use the results from Step 2 in the numerator of the meeting index, and calculate the intensity of meetings that waste time in a GVKEY-year as:

$$\text{Meeting Index} = \frac{\text{(\# of reviews complaining too many - \# of reviews praising not too many)}}{\text{\# of total reviews}}.$$

We map Revelio company ID RCID to GVKEY in a given using parent-subsidiary bridge provided by Revelio to us directly.

Examples of employee review discussions

- Too many meetings:

  - "Way too many meetings. Took forever to make changes and/or decisions."
  - "More meetings and games than work."
  - "Too many internal mandatory calls which takes away time best served somewhere else."
  - "A lot of meaningless meetings."
  - "Too much internal fighting, more competition with folks inside rather than outside."
- Not too many meetings:
  - "Meeting-light: this was a HUGE unlock for me. My previous job had me back to back in meetings from 9a-5p so the only time I had to get work done was AFTER work."
  - "Good work environment, not too many meetings during the day."
  - "The weekly meetings were not excessive."
  - "There are lots of resources and projects going on, and very few fiefdoms or silos to get in the way of you contributing."
  - "Not being micro-managed, feeling challenged, being a part of something bigger than just a job, but a disruption of an industry, with camaraderie along the way are things I value."

IA3 Additional Tables

Table IA1 – Summary Statistics

	P25	P50	P75	Mean	SD
Panel A: Venture Capital Sample					
Predicted Workstyle Change in Industry ($\lvert\overline{dws}\rvert^{e}_{n,t,5}$)	-0.49	-0.32	0.03	-0.00	1.00
Log VC Investment in Industry	2.40	3.79	5.28	3.86	2.29
Log Compustat Market Cap in Industry	9.51	10.86	12.15	10.69	2.10
Log Total Patents in Industry	3.12	5.09	7.04	4.91	2.89
Log Breakthrough Patents in Industry	0.28	2.41	4.65	2.30	3.04
Log RETech Patents in Industry	3.21	5.17	7.21	4.98	3.07
Panel B: Compustat Sample					
Predicted Workstyle Change in Industry ($\lvert\overline{dws}\rvert^{e}_{n,t,5}$)	-0.39	-0.05	0.33	0.18	0.92
Market Value/Book Value of Equity	0.84	1.60	3.16	2.21	9.48
Sales Growth Next 5 Years	-0.05	0.27	0.66	0.32	10.27
Employment Growth Next 5 Years	-0.14	0.12	0.44	0.14	0.64
Log Firm Age	1.79	2.40	2.94	2.29	0.89
Log Firm Employment	-2.38	-0.64	1.19	-0.68	2.56
Log Firm Sales	3.34	5.22	6.97	4.98	2.87
Log Total Patents in Industry	5.07	7.00	9.42	6.71	3.34
Log Breakthrough Patents in Industry	2.89	5.37	6.43	4.52	3.23
Log RETech Patents in Industry	5.43	7.41	9.47	6.85	3.58
Panel C: BDS Sample					
Predicted Workstyle Change in Industry ($\lvert\overline{dws}\rvert^{e}_{n,t,5}$)	-0.49	-0.32	0.04	0.00	1.01
Employment Growth Next 5 Years	-0.23	-0.09	0.02	-0.10	0.26
Log Employment in Industry	12.71	13.41	14.25	13.31	1.49
Log Total Patents in Industry	3.31	5.40	7.25	5.19	2.87
Log Breakthrough Patents in Industry	0.32	2.97	5.03	2.58	3.03
Log RETech Patents in Industry	3.41	5.56	7.52	5.29	3.01

Notes: This table reports summary statistics for the main variables used in the analysis. Panel A presents statistics for the venture capital sample at the industry-year level. Panel B presents statistics for the Compustat sample at the firm-year level. Panel C presents statistics for the BDS sample at the industry-age group-year level. Reported values include the 25th, 50th, and 75th percentiles (P25, P50, P75), mean, and standard deviation (SD).

Table IA2 – Baseline Regressions in Compustat: Controlling for Firm Size

	MTB		**Sales Growth**		**Employment Growth**	
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Workstyle Change in Industry ($\lvert d\overline{ws}\rvert^{e}_{n,t,5}$)	0.382	0.416**	0.030	0.059**	0.004	0.064***
	(0.271)	(0.139)	(0.028)	(0.022)	(0.027)	(0.017)
$\lvert d\overline{ws}\rvert^{e}_{n,t,5} \times$ Log Firm Age	-0.152**	-0.144**	-0.022***	-0.023**	-0.025***	-0.024***
	(0.064)	(0.059)	(0.007)	(0.008)	(0.007)	(0.007)
$\lvert d\overline{ws}\rvert^{e}_{n,t,5} \times$ Log Firm Sales	0.014		0.005		0.012***	
	(0.049)		(0.003)		(0.004)	
$\lvert d\overline{ws}\rvert^{e}_{n,t,5} \times$ Log Firm Employment		0.009		0.010**		0.013***
		(0.052)		(0.004)		(0.003)
Log Firm Age	-0.419***	-0.440***	-0.110***	-0.102***	-0.078***	-0.084***
	(0.113)	(0.127)	(0.018)	(0.018)	(0.017)	(0.015)
Log Firm Sales	0.130*		0.005	-0.065***	0.051***	
	(0.069)		(0.007)	(0.015)	(0.007)	
Log Firm Employment		0.098		0.087***	-0.051***	-0.002
		(0.075)		(0.020)	(0.006)	(0.005)
Year FE	X	X	X	X	X	X
Observations	24,278	23,984	18,145	17,246	16,943	17,396

Notes: This table performs the regressions in column (1) of Tables 2, 3, and 4, controlling for firm size interacting with predicted workstyle change $\lvert d\overline{ws}\rvert^{e}_{n,t,5}$ (standardized to have zero mean and unit variance). The size measure is log sales in year t in the odd columns, and log employment in year t in the even columns. The outcome variable is the firm's market-to-book ratio of equity in columns (1) and (2), next 5 year sales growth a la Davis, Haltiwanger, and Schuh (1992) in columns (3) and (4), and next 5 year employment growth a la Davis, Haltiwanger, and Schuh (1992) in columns (5) and (6). We include year fixed effects, and double cluster standard errors by 3-digit NAICS codes and year. Asterisks denote significance levels (***=1%, **=5%, *=10%). Sample years are 2003 to 2019.

Table IA3 – Baseline Regressions in Compustat: Controlling for Financial Constraint Proxies

	MTB		Sales Growth		Employment Growth	
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Workstyle Change in Industry ($\lvert\widehat{dws}\rvert^e_{n,t,5}$)	0.421***	0.440**	0.040*	0.055**	0.046*	0.058**
	(0.133)	(0.185)	(0.020)	(0.023)	(0.022)	(0.019)
$\lvert\widehat{dws}\rvert^e_{n,t,5}$ × Log Firm Age	-0.148***	-0.153**	-0.016**	-0.020**	-0.017*	-0.019**
	(0.046)	(0.056)	(0.007)	(0.007)	(0.008)	(0.007)
$\lvert\widehat{dws}\rvert^e_{n,t,5}$ × KZ Index	-0.053		0.002		-0.003	
	(0.030)		(0.002)		(0.002)	
$\lvert\widehat{dws}\rvert^e_{n,t,5}$ × No dividend		-0.005		-0.004		-0.009
		(0.094)		(0.010)		(0.012)
Log Firm Age	-0.325**	-0.399***	-0.099***	-0.109***	-0.080***	-0.084***
	(0.108)	(0.106)	(0.017)	(0.017)	(0.016)	(0.014)
KZ Index	-0.157***		-0.010***		-0.009**	
	(0.032)		(0.003)		(0.003)	
No dividend		-0.107		0.026		0.041
		(0.196)		(0.028)		(0.027)
Log Firm Sales			0.006	0.007		
			(0.007)	(0.008)		
Log Firm Employment					0.001	0.003
					(0.006)	(0.007)
Year FE	X	X	X	X	X	X
Observations	24,458	25,104	17,595	18,145	17,045	17,396

Notes: This table performs the regressions in column (1) of Tables 2, 3, and 4, controlling for financial constraint proxies interacting with predicted workstyle change $\lvert\widehat{dws}\rvert^e_{n,t,5}$ (standardized to have zero mean and unit variance). The financial constraint proxy is the Kaplan and Zingales (1997) index in year t in the odd columns, and an indicator of non-dividend payer in year t in the even columns. The outcome variable is the firm's market-to-book ratio of equity in columns (1) and (2), next 5 year sales growth a la Davis, Haltiwanger, and Schuh (1992) in columns (3) and (4), and next 5 year employment growth a la Davis, Haltiwanger, and Schuh (1992) in columns (5) and (6). We include year fixed effects, and double cluster standard errors by 3-digit NAICS codes and year. Asterisks denote significance levels (***=1%, **=5%, *=10%). Sample years are 2003 to 2019.

IA4 Appendix for Models

IA4.1 Closed-form Solution for the Model in Section 3.3

We now provide closed-form solution for our value function before the arrival of business model B for the microfoundation proposed in Section 3.3 .

Recursive definition: $$rV(r) = \pi_A + \frac{S-s}{S}\Big(-c + V(s+1) - V(s)\Big), \qquad V(S) = \bar{V}.$$

Step 1: Rearranging into standard form.

$$\frac{S-s}{S}\Big(V(s+1) - V(s) - c\Big) = rV(s) - \pi_A,$$
$$V(s+1) = \left(1 + \frac{Sr}{S-s}\right)V(s) + \left(c - \frac{S\pi_A}{S-s}\right).$$

Hence define

$$a_n = 1 + \frac{Sr}{S-s}, \qquad b_n = c - \frac{S\pi_A}{S-s}.$$

Step 2: General solution of a first–order linear recurrence.

$$V(s) = \bar{V}\prod_{k=s}^{S-1} a_k \; + \; \sum_{j=s}^{S-1}\left(b_j \prod_{k=s}^{j-1} a_k\right),$$

where an empty product equals 1.

Substituting a_k, b_k:

$$\boxed{V(s) = \bar{V}\prod_{k=s}^{S-1}\left(1 + \frac{Sr}{S-k}\right) + \sum_{j=s}^{S-1}\left(\left(c - \frac{S\pi_A}{S-j}\right)\prod_{k=s}^{j-1}\left(1 + \frac{Sr}{S-k}\right)\right).}$$

Step 3: Reindexing with $M := S-s,\ \alpha := Sr$.

Let $m = S-k,\ t = S-j$. Then

$$\boxed{V(s) = \bar{V}\ \prod_{m=1}^{M}\left(1 + \frac{\alpha}{m}\right) + \sum_{t=1}^{M}\left(\left(c - \frac{S\pi_A}{t}\right)\prod_{m=t+1}^{M}\left(1 + \frac{\alpha}{m}\right)\right),}$$

with an empty product equal to 1.

It is often convenient to factor out the full product $P(M) := \prod_{m=1}^{M}(1+\alpha/m)$:

$$V(s) = P(M)\left(\bar{V} + \sum_{t=1}^{M} \frac{c - \dfrac{S\pi_A}{t}}{P(t)}\right), \qquad P(t) = \prod_{m=1}^{t}\left(1+\frac{\alpha}{m}\right).$$

Step 4: Gamma-function closed form.

Use

$$P(t) = \frac{\Gamma(t+1+\alpha)}{\Gamma(1+\alpha)\,\Gamma(t+1)}.$$

Then

$$\boxed{V(s) = \frac{\Gamma(M+1+\alpha)}{\Gamma(1+\alpha)\Gamma(M+1)}\left[\bar{V} + \sum_{t=1}^{M}\left(c - \frac{S\pi_A}{t}\right)\frac{\Gamma(1+\alpha)\Gamma(t+1)}{\Gamma(t+1+\alpha)}\right], \qquad M = S-s,\ \alpha = Sr.}$$

This expression gives the closed-form solution for $V(s)$ consistent with the boundary condition $V(S) = \bar{V}$.

IA4.2 Proof of Result 1

To make notation lighter we write $w_n = |d\overline{ws}|_m$. The regression we are interested in analyzing is:

$$g_{i,n} \quad = \quad \nu + \beta\,\text{age}_i + \gamma\, w_n + \zeta\,\left(\text{age}_i \times w_n\right) + \varepsilon_{i,n} \tag{IA1}$$

The corresponding normal equations are:

$$Y_1 \quad = \quad M_1 \begin{pmatrix} \beta \\ \gamma \\ \zeta \end{pmatrix},$$

where:

$$M_1 \quad = \quad \begin{pmatrix} var(\text{age}_i) & cov(\text{age}_i, w_n) & cov(\text{age}_i w_n, \text{age}_i) \\ cov(\text{age}_i, w_n) & var(w_n) & cov(\text{age}_i w_n, w_n) \\ cov(\text{age}_i w_n, \text{age}_i) & cov(\text{age}_i w_n, w_n) & var(\text{age}_i w_n) \end{pmatrix}$$

$$Y_1 \quad = \quad \begin{pmatrix} cov\left(g_{i,n}, \text{age}_i\right) \\ cov\left(g_{i,n}, w_n\right) \\ cov\left(g_{i,n}, \text{age}_i w_n\right) \end{pmatrix}$$

Assumption 1 implies the following moment restrictions:

$$\begin{aligned}
cov(\text{age}_i, w_n) &= 0 \\
cov(\text{age}_i w_n, \text{age}_i) &= \mathbb{E}(w_n) var(\text{age}_i) \\
cov(\text{age}_i w_n, \text{age}_i) &= \mathbb{E}(\text{age}_i) var(w_n) \\
cov(\text{age}_i w_n, \text{age}_i w_n) &= \mathbb{E}(\text{age}_i)^2 var(w_n) + \mathbb{E}(w_n)^2 var(\text{age}_i) + var(\text{age}_i) var(w_n)
\end{aligned}$$

Introduce the following notation:

$$\begin{aligned}
\mathbb{E}(\text{age}_i) &= E_a \\
var(\text{age}_i) &= var_a \\
\mathbb{E}(w_n) &= E_w \\
var(w_n) &= var_w \\
cov(g_{i,n}, \text{age}_i) &= cov_{ga} \\
cov(g_{i,n}, w_n) &= cov_{gw} \\
cov\left(g_{i,n}, \text{age}_i w_n\right) &= cov_{gaw}
\end{aligned}$$

Then the matrices M_1 and Y_1 can be written as:

$$M_1 = \begin{pmatrix} var_a & 0 & E_w var_a \\ 0 & var_w & E_a var_w \\ E_w var_a & E_a var_w & E_a^2 var_w + E_w^2 var_a + var_a var_w \end{pmatrix}$$

$$Y_1 = \begin{pmatrix} cov_{ga} \\ cov_{gw} \\ cov_{gaw} \end{pmatrix}$$

implying the following expression for ζ:

$$\zeta = \frac{cov_{gaw} - E_w \cdot cov_{ga} - E_a \cdot cov_{gw}}{var_a \cdot var_w}$$

The equilibrium conditions of the model are:

$$
\begin{aligned}
g_{i,n} &= \mu_n - \lambda Q_{B,n} \left|\Delta\right|_n \gamma_i, \\
\lambda &= \frac{\Xi}{L_A}, \\
\mu_n &= \frac{L_B}{L_A} + \lambda Q_{B,n} \left|\Delta\right|_n \Gamma \\
Q_{B,n} &= \left(\sum_{j=1}^{J} \theta_{B,j,n} \right)^{\frac{1}{\sigma-1}} \bar{l} \\
w_n &= \xi \left|\Delta\right|_n \\
\xi &= \frac{L_B}{L_A + L_B} \\
\left|\Delta\right|_n &= \left| \sum_j \left(\frac{\theta_{B,j}}{\sum_j \theta_{B,j}} - \frac{\theta_{A,j}}{\sum_j \theta_{A,j}} \right) ws_j \right|.
\end{aligned}
$$

Let us introduce the following further notation:

$$
\begin{aligned}
cov_{\gamma a} &= cov(\gamma_i, \text{age}_i) \\
cov_{Q|\Delta|} &= cov(Q_{B,n} \left|\Delta\right|_n, \left|\Delta\right|_n) \\
var_{|\Delta|} &= var(\left|\Delta\right|_n)
\end{aligned}
$$

The equilibrium conditions imply the following additional moment restrictions:

$$
\begin{aligned}
\mathbb{E}_n(g_{i,n}) &= \frac{L_B}{L_A} \\
cov_{gw} &= \mathbb{E}(cov_n(g_{i,n}, w_n)) + cov(\mathbb{E}_n(g_{i,n}), w_n) = 0 \\
cov_{ga} &= -\lambda \mathbb{E}(Q_{B,n} \left|\Delta\right|_n) cov_{\gamma a} \\
E_w cov_{ga} &= -\lambda \xi \mathbb{E}(Q_{B,n} \left|\Delta\right|_n) \mathbb{E}(\left|\Delta\right|_n) cov_{\gamma a} \\
cov_{gaw} &= \mathbb{E}(cov_n(g_{i,n}, \text{age}_i w_n)) + cov(\mathbb{E}_n(g_{i,n}), w_n \mathbb{E}(age_i)) \\
&= \mathbb{E}(w_n cov_n(g_{i,n}, \text{age}_i))
\end{aligned}
$$

$$
\begin{aligned}
&= -\lambda \mathbb{E}(w_n Q_{B,n} \left|\Delta\right|_n) cov_{\gamma a} \\
&= -\lambda \xi \mathbb{E}(Q_{B,n} (\Delta_n)^2) cov_{\gamma a} \\
cov_{gaw} - E_w cov_{ga} &= -\lambda \xi cov_{Q|\Delta|} cov_{\gamma a} \\
var_w &= \xi^2 var_{|\Delta|}
\end{aligned}
$$

In turn, substituting into the expression for ζ above, we obtain:

$$
\zeta = -\frac{\lambda}{\xi} \frac{cov_{Q|\Delta|}}{var_{|\Delta|}} \frac{cov_{\gamma a}}{var_a},
$$

which is the expression reported in Result 1.

IA4.2.1 Conditions guaranteeing that $\zeta > 0$

Suppose that the random vectors $\{\theta_{A,j,n}\}$ and $\{\theta_{B,j,n}\}$ can be written as:

$$
\begin{aligned}
\theta_{A,j,n} &= s_{A,j,n}\, \theta_n \\
\theta_{B,j,n} &= s_{B,j,n}\, (1+\nu_n)\theta_n
\end{aligned}
\tag{IA2}
$$

where $\{\theta_{A,j,n}\}$ and $\{\theta_{B,j,n}\}$ are independently distributed from the scalars θ_n and ν_n, and satisfy:

$$
\sum_j s_{A,j,n} = \sum_j s_{B,j,n} = 1. \tag{IA3}
$$

Economically, this is a case where business model B raises the overall productivity of each business line relative to A (by a factor of ν_n), but also alters the composition of occupations required relative to A, as captured by the term $\left|\Delta\right|_n$. Then we have:

$$
Q_{B,n} = (1+\nu_n)^{\frac{1}{\sigma-1}} \theta_n^{\frac{1}{\sigma-1}} \bar{l}, \quad \left|\Delta\right|_n = \left| \sum_j \left(s_{B,j,n} - s_{A,j,n}\right) w s_j \right|, \tag{IA4}
$$

and the two quantities are independent. Thus:

$$
cov\left(Q_{B,n} \left|\Delta\right|_n, \left|\Delta\right|_n\right) = \mathbb{E}(Q_{B,n}) var(\left|\Delta\right|_n), \tag{IA5}
$$

and so:

$$
\zeta = -\frac{\Xi}{L_A}\left(1+\frac{L_A}{L_B}\right) \times \mathbb{E}\left[((1+\nu_m)\theta_m)^{\frac{1}{\sigma-1}}\right] \bar{l} \times \frac{cov(\gamma_i, \text{age}_i)}{var(\text{age}_i)} \tag{IA6}
$$

Therefore, under Assumptions (IA2), the sign of the coefficient is driven by the relationship between organizational frictions and age.