Skill Mismatch over the Technology Life Cycle

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Abstract

Despite rapid technological progress, the diffusion of new technologies across firms remains slow and uneven. Skill mismatch is widely viewed as a central explanation for this gap, yet we know little about how skill mismatch itself arises and evolves over the diffusion process. This paper studies how multidimensional skill mismatch—the misalignment between firms' skill requirements and workers' capabilities—endogenously develops and shapes the diffusion of information technologies. We construct granular measures of skill demand and supply using large language models applied to matched data on firm job postings and worker résumés. Consistent with our model, the data reveal a U-shaped pattern over the technology life cycle: mismatch is high when new technologies are adopted, declines as firms and workers adjust, and rises again as technologies mature into legacy systems. Diffusion bottlenecks reflect combinations of technical and complementary nontechnical skills, such as managerial capabilities, rather than technical skill gaps alone. We further show that skill mismatch helps explain the persistence of firms operating legacy systems with low marginal returns to investment. Together, these findings highlight skill mismatch as a dynamic force shaping technology diffusion.

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1 Introduction

Technological progress has accelerated in recent decades, yet the diffusion of new technologies across firms remains strikingly slow and uneven (Kalyani et al., 2025). A growing literature points to the labor market as a central factor behind this diffusion gap. In particular, many studies argue that the adoption and productivity of frontier technologies is constrained by the limited supply of workers with complementary skills (Adão et al., 2024; Brunello and Wruuck, 2021; Acemoglu and Zilibotti, 2001). Consistent with this view, the business press is replete with accounts of firms' extraordinary—and often unsuccessful—efforts to recruit workers with technology-complementary capabilities.[1]

Yet despite the central role of skill mismatch in discussions of technological change, we have a limited understanding of how mismatch itself arises and evolves as technologies diffuse. Much of the existing literature takes mismatch as exogenous, abstracting from firm incentives to adjust skill requirements and from worker incentives to acquire new skills as technologies mature. As a result, we know little about how skill mismatch changes over the technology life cycle or how skill gaps differ between firms adopting new technologies and those operating legacy systems. Moreover, prior research typically relies on univariate measures of skill, providing limited insight into the particular—and potentially multidimensional—skills that constrain diffusion. Identifying the specific skills demanded by firms and supplied by workers is inherently challenging, as many relevant capabilities are unobservable and difficult to infer from job descriptions. For example, a job posting requiring "Java programming," may reflect demand for a narrow technical task, broad problem-solving ability, and/or social skills needed for collaborative software development. Disentangling these dimensions is crucial for identifying which skills—and *combinations* of skills—impede technology adoption.

In this paper, we propose and empirically test a model of information technology diffusion with multidimensional skill mismatch. Our conceptual framework builds on the seminal

[1] ManpowerGroup's 2024 Global Talent Shortage survey reveals that 75% of employers worldwide report difficulty finding workers with appropriate skills (ManpowerGroup, 2024).

work of Chari and Hopenhayn (1991), who provide a general equilibrium theory of technology diffusion and vintage human capital. We borrow insights from several literatures to adapt their model in three ways. First, we introduce multidimensional skill mismatch——defined as the distance between the vector of skill weights required by firms and the vector of skill weights possessed by workers (Lazear, 2009)——to capture both technical and nontechnical dimensions of human capital that relate to technology diffusion. Differences in skill requirements across firms arise from variation in the tasks embodied in the information technologies and complementary organizational structures that firms adopt (Acemoglu and Autor, 2011; Brynjolfsson and Hitt, 2000). In the model, skill mismatch between firms and newly hired employees arises naturally as a consequence of market participants behaving individually rationally; there are no search frictions or other market distortions needed for mismatch to arise. Second, we use skill mismatch to microfound the productivity dynamics of workers that are otherwise assumed in the original model; we assume greater mismatch implies lower marginal productivity (Lise and Postel-Vinay, 2020; Guvenen et al., 2020; Coraggio et al., 2025). Third, we model firms' responses to skill mismatch through capital investments, following the established literature on technology diffusion and productivity (Brynjolfsson et al., 2021). These investments encompass employee training, work practices, and other organizational assets that facilitate worker skill acquisition (Bartel et al., 2007). Together, these adaptations generate novel predictions about three key issues: how multidimensional skill mismatch endogenously evolves over the technology life cycle, what skill attributes serve as technology diffusion bottlenecks, and how skill mismatch can help explain the prevalence of legacy technologies with low marginal returns of investment.

To test these predictions, we construct a matched employer–employee dataset that links U.S. firms' online job postings with workers' online résumés. The job postings data contain detailed information on firm skill requirements while the résumé data allow us to observe the skills supplied by workers with comparable granularity. Linking the two data sources enables us to measure the skill attributes of new hires in close temporal proximity to firms'

posted skill requirements. The job postings data also provide information that reflects firms' adoption of specific information technologies. We identify the year of inception for each of the technologies in our sample, and use these data to characterize the diffusion of information technologies across firms over time.

We harmonize the raw, unstructured skills text from job postings and résumés by applying large language models (LLMs) and standard natural language processing (NLP) techniques to construct multidimensional measures of skill demand and supply. Specifically, we use BERT (Bidirectional Encoder Representations from Transformers; Devlin et al. (2019)) in a zero-shot classification framework (Yin et al., 2019) to map each list of reported skills into a vector of weights across 25 broad skill categories, including managerial, financial, and technical competencies.[2] These deep learning tools (Dell, 2025) are well suited to our setting for several reasons. Most importantly, because LLMs are trained on a vast corpus of text, they are able to capture the semantic meaning of skill descriptions expressed by firms and workers more effectively than researcher-defined keyword dictionaries. For example, a skill requirement such as "Java programming" simultaneously conveys various skills that are difficult to encode using manually constructed taxonomies. LLM's, in contrast, are able to codify skill descriptions using high-dimensional embeddings that capture much (if not all) of the information that market participants associate with these terms in practice, thereby mitigating the limitations of ad-hoc skill measures for our analysis.

In our main empirical specifications, we measure skill mismatch as the Euclidean distance between firms' skill-demand vectors and the skill-supply vectors of newly hired workers.[3] This continuous measure provides an intuitive characterization of the extent to which newly hired workers possess skills that meet firms' requirements, with larger distances indicating greater mismatch. Because skill weights sum to one, this measure captures the degree to which

[2]The 25 skill categories are defined by the résumé data provider and are designed to parsimoniously and efficiently span the skill space observed in the data. As discussed later, our results are robust to alternative skill categorizations that have been used in the prior literature.

[3]We also present similar results using alternative distance metrics, such as Hellinger distances between skill vectors.

workers' comparative advantages across skill dimensions align with firms' needs. Our vector-based approach allows us to compare skill mismatch consistently across firms and over time while incorporating a broad range of skill dimensions.

We document several empirical findings that support the predictions of the model. The first finding is that skill mismatch between firms and newly hired workers follows a U-shaped pattern over the technology life cycle: mismatch is high when new technologies are adopted, declines as firms and workers adjust, and rises again as technologies mature into legacy systems. Importantly, this process is slow, unfolding over several decades. Consistent with the model, mismatch is initially high because workers lack the specific combinations of skills required to work with new technologies. As adoption expands, workers acquire relevant skills and firms adjust their skill requirements, leading to closer alignment between skill supply and demand. Over time, however, as newer and more productive technologies emerge, workers have weaker incentives to join firms that continue to rely on older technologies, causing skill mismatch at these firms to increase. The empirical relationship between skill mismatch and technology diffusion that we document is new to the literature, and arises theoretically from relaxing the standard assumptions of exogenous, one-dimensional human capital. By modeling the joint, endogenous evolution of multidimensional skill mismatch and technology adoption, we show that skill mismatch is a quantitatively important constraint not only for new technologies but also for legacy systems.

Our second set of results identifies the specific skill attributes that act as bottlenecks to information technology diffusion. We show that diffusion is constrained not by technical skills alone, but by shortages in combinations of technical and non-technical, IT-complementary skills. We build up to this conclusion through several findings. First, we document a U-shaped pattern in skill mismatch for technical occupations such as engineers and data scientists, mirroring the aggregate relationship over the technology life cycle. Strikingly, we find that mismatch is even more pronounced for non-technical occupations—such as managers and business analysts—that are central to the organizational transformations accompanying IT

adoption. Second, examining mismatch at the level of individual skill dimensions, we find that the largest gaps between firm requirements and worker capabilities arise in non-technical, IT-complementary skills, particularly managerial and business capabilities, alongside substantial shortfalls in technical skills such as advanced manufacturing and network security. By contrast, skills associated with tasks less central to IT diffusion (e.g., hospitality or public speaking) exhibit little mismatch and are, in some cases, relatively oversupplied. Taken together, these patterns indicate that skill mismatch reflects broader scarcities in complementary skills and organizational competencies (Bresnahan et al., 2002; Bartel et al., 2007) that underpin the effective use of information technologies, rather than narrow deficits in technical expertise alone. Consistent with this interpretation, we find evidence that firms face persistent difficulty hiring workers who combine managerial and business expertise with sufficiently deep technological knowledge to meet evolving job requirements.

Our third set of findings shows how skill mismatch contributes to the persistence of legacy technologies, even when their marginal returns to investment are low. In the model, firms operating older technologies remain viable because they attract workers whose skill portfolios are poorly aligned with frontier systems. Skill mismatch at the technological frontier therefore reduces labor market competition for legacy firms, allowing them to retain workers and continue operating despite inferior investment opportunities. Consistent with this mechanism, we document that firms' market-to-book ratios—a standard proxy for Tobin's q—decline monotonically with technology age, indicating systematically lower marginal returns to investment among firms deploying older systems in our sample. Our results thus complement existing explanations for the persistence of legacy technologies that emphasize adjustment costs, switching frictions, or technological lock-in. By highlighting how skill mismatch endogenously segments labor markets across technology vintages, our framework provides a distinct economic mechanism for the coexistence of frontier and legacy systems.

We conduct an extensive set of robustness checks to assess the sensitivity of our results. Our findings are robust to alternative skill taxonomies proposed in prior work, including

those developed by Deming and Kahn (2018). We also show that our results are robust to alternative choices of job-posting and résumé sampling windows and consistent across different measures of technology vintage. We further show that the estimated patterns are even stronger when we replace BERT with alternative large language models, such as ModernBERT. Finally, we discuss several limitations of our approach. In particular, our methodology captures mismatch in workers' comparative advantages across skill dimensions rather than mismatch in absolute skill levels, which may represent an additional, empirically relevant dimension of skill mismatch.

The main contribution of this paper is to show how multidimensional skill mismatch endogenously evolves and shapes technology diffusion. We advance the literature on technological change and mismatch by relaxing the standard assumption that mismatch is exogenous and by allowing both firms' skill requirements and workers' skill portfolios to be multidimensional. These innovations yield several new insights into labor market dynamics that are otherwise obscured in existing frameworks. First, skill mismatch evolves following a U-shaped pattern over the technology life cycle and is pronounced not only for firms adopting new technologies, but also for firms deploying legacy systems. Second, diffusion bottlenecks arise from shortages of specific combinations of nontechnical and technical skills rather than from purely technical skill gaps alone. Third, labor market segmentation induced by skill mismatch helps explain the persistence of legacy technologies despite their low marginal returns to investment.

A secondary contribution of our paper is methodological. We introduce a new empirical approach for measuring multidimensional skill demand and supply using large language models applied to unstructured text from job postings and résumés. This approach allows us to construct granular measures of skill combinations that capture firms' job requirements and workers' capabilities at scale. Our methodology complements prior approaches based on univariate classifications or manually-curated taxonomies by enabling a high-dimensional characterization of skill mismatch in settings where skill content is heterogeneous, difficult

to observe, and continuously evolving.

The rest of the paper proceeds as follows. Section 2 discusses the related literature, Section 3 presents our theoretical framework, Section 4 details our empirical approach, Section 5 describes our data, Section 6 presents our findings, Section 7 assesses the robustness of our conclusions, and Section 8 concludes.

2 Related Literature

A longstanding question in economics concerns the gap between the rapid pace of technological progress and the much slower diffusion of new technologies across firms and countries. A growing literature emphasizes labor market forces as central to technology adoption and productivity dynamics. A prominent contribution is Acemoglu and Zilibotti (2001), who show that productivity differences across countries reflect mismatches between the skill requirements of frontier technologies and the human capital of the local workforce. Related work by Adão et al. (2024) argues that the speed of technological adoption depends critically on the size of skill gaps between workers and new technologies. Together with practitioner surveys documenting skill shortages as a primary barrier to adoption (MIT Technology Review Insights, 2023), these studies provide compelling evidence of skill mismatch as a central determinant of technology diffusion and aggregate productivity.

A common feature of this literature, however, is that skill mismatch is taken as exogenous. Gaps between technological requirements and individual worker skills are treated as fixed constraints, rather than as endogenous outcomes that are continuously shaped by firms' and workers' responses to technological diffusion. This abstraction is well suited to studying the consequences of skill mismatch for adoption and productivity, but it leaves open a fundamental question: what determines the evolution of skill mismatch in the first place?

Understanding the forces that shape skill mismatch is crucial for assessing how mismatch dissipates or persists as technologies diffuse, thereby influencing long-run adoption patterns

and the coexistence of new technologies with legacy systems. Absent a clear account of the mechanisms that shape mismatch, it is difficult to interpret observed skill shortages or to distinguish temporary adjustment frictions from persistent bottlenecks. For example, skill mismatch is not confined to firms adopting new technologies; firms operating legacy technologies also frequently report difficulty hiring workers with desirable skills (Monaghan and Bass, 2020). The nature of skill mismatch facing these firms, however, may reflect fundamentally different economic forces. Finally, understanding the endogenous determination of skill mismatch is a prerequisite for evaluating policies aimed at workforce development, as effective policy design requires separating market-driven adjustment dynamics from exogenous skill constraints.[4]

Progress on these issues also requires understanding the multidimensional nature of skill gaps between firm requirements and worker capabilities. Empirical studies of technological change and skill mismatch have typically examined mismatch through a univariate lens, focusing on broad categorizations of skill or education. This abstraction is sufficient for existing work to explain aggregate patterns of technology diffusion and productivity, however, it is insufficient for identifying the specific skill attributes that explain technology differences across firms. For example, we have a limited understanding of the extent to which technology diffusion is constrained by technical skill gaps alone or by gaps in IT-complementary nontechnical skills such as managerial and organizational capabilities. Moreover, there is little established evidence on the *combinations* of these skills as diffusion bottlenecks, even though there are numerous accounts of hiring managers reporting difficulties in finding employees with the right mix of skills (OECD, 2024).

The relevance of multidimensional skill mismatch for technology diffusion is further underscored by a growing literature that studies multidimensional mismatch more broadly.[5] On the empirical side, Baley et al. (2022) and Lise and Postel-Vinay (2020) examine multi-

[4]See Goldin and Katz (2008) for a comprehensive discussion of these issues in the context of technical change and the wage structure.

[5]Prominent theoretical contributions include Lindenlaub and Postel-Vinay (2023) and Moscarini (2001).

dimensional skill mismatch arising from job search frictions, while Guvenen et al. (2020) study mismatch driven by uncertainty about workers' own skills. These studies rely on occupation-level skill requirements, drawn from O*NET, which are well suited to analyzing the implications of mismatch for worker earnings, mobility, and productivity in frictional labor markets.

Our paper complements this literature by studying multidimensional skill mismatch in a different economic setting: the diffusion of new technologies across firms. Rather than taking mismatch as a consequence of search frictions or informational constraints, we model skill mismatch as an endogenous outcome of firms' technology choices and workers' skill acquisition decisions over the technology life cycle. Empirically, we depart from occupation-level abstractions by measuring skill demand and supply at the firm level using job postings and résumés, allowing us to capture substantial heterogeneity in skill requirements even within narrowly defined occupations. This approach enables us to study how multidimensional skill mismatch evolves as technologies diffuse and to identify the specific combinations of skills that act as bottlenecks to adoption—dimensions that are difficult to observe using standard occupational classifications.

To study multidimensional skill mismatch and technology diffusion, we build on the classic theory of technology diffusion and vintage human capital developed by Chari and Hopenhayn (1991). Their general equilibrium framework provides a workhorse model of how human capital evolves endogenously as firms adopt successive waves of more productive technologies. In the original model, workers are differentiated along a single skill dimension—skilled versus unskilled—and newly hired workers enter firms with a common initial skill level. This parsimonious structure is well suited to explaining aggregate patterns of diffusion and human capital accumulation, but it abstracts from heterogeneity in the degree and composition of skill mismatch across firms and technologies.

We adapt this framework to allow for multidimensional skill mismatch between firms and newly hired workers, reflecting the rich, high-dimensional nature of human capital em-

phasized in contemporary discussions of technology adoption and skill gaps. In our model, firms differ in their skill requirements across multiple dimensions, and newly hired workers vary in the extent to which their skill portfolios align with these requirements. This extension allows mismatch to vary systematically across firms, technologies, and stages of the technology life cycle. We further incorporate firm investment in capital and organizational assets, enabling us to study how skill mismatch shapes returns to technology investment. Together, these extensions generate new empirical predictions about the joint evolution of multidimensional skill mismatch and technology diffusion that go beyond the original scope of Chari and Hopenhayn (1991) and speak directly to the central questions of this paper.

3 Theoretical Framework

We present our conceptual framework by first summarizing the relevant aspects of Chari and Hopenhayn (1991). The model is an overlapping-generations economy with an infinite horizon (time t = 0,1,2...), where workers of two types (young and old, each of mass 1) live for two periods. In each time period t, a new technology is introduced that is more productive than all previous vintages, where a specific vintage is denoted by τ (which means that the technology was first introduced at time t-τ). Firms adopt a technology of a particular vintage and hire U unskilled workers (type u) and S skilled workers (type s); the production function $Y = \gamma^{t-\tau} f(U, S)$ is constant returns to scale, strictly increasing and concave in the number of skilled workers, and the productivity parameter γ is greater than 1.

A key assumption in the model is that unskilled workers and skilled workers are complements: the marginal productivity of an unskilled worker increases in the number of skilled workers who are simultaneously working in the same firm (i.e. $\frac{\partial f_U}{\partial S_t} > 0$). Young workers, who begin life unskilled, choose to work at a firm with a particular technology vintage. After one period of experience, they become skilled workers by acquiring technology vintage-specific human capital. When old, these workers can either join a firm with the same technology or

switch to a firm that uses a different technology, in which case the workers are now considered unskilled. Equilibrium requires that workers sort across firms to maximize lifetime utility, firms choose technologies and make hiring decisions to maximize profits, and markets clear. Chari and Hopenhayn (1991) prove the existence of a unique stationary equilibrium in which the distribution of skilled workers (s_τ) over technology vintages $\tau \in \{0,1,2...\}$ is single-peaked: human capital specialization in a given technology rises with vintage, peaks, and then declines to zero once the technology becomes obsolete and adoption ceases.

Our first adaptation is to introduce an intuitive and well-accepted definition of multidimensional skill mismatch to provide a richer characterization of skilled and unskilled workers. Specifically, we define skill mismatch between firms and workers as the discrepancy between firms' multidimensional skill requirements and workers' multidimensional skill attributes, each measured using skill weight vectors following Lazear (2009). This measure has precedence in the academic literature and the practitioner sphere (International Labour Organization, see https://www.ilo.org/skills-mismatches). In the context of our model, when a firm adopts information technology of a particular vintage, the firm designs a production system with complementary assets built around the technology (Brynjolfsson et al., 2002; Brynjolfsson and Hitt, 2000). Production entails the completion of various tasks; the skills required of workers to perform these tasks represent the firm's skill requirements. This connection between technology, tasks, and skill requirements is rooted in the task-based approach to human capital (Acemoglu and Autor, 2011).[6]

Formally, a firm that adopts information technology of vintage τ will have skill requirements for a worker of type $j \in (u,s)$ denoted by $F^{\tau,j} \equiv (F_1^{\tau,j}, F_2^{\tau,j}...F_N^{\tau,j})$, where $0 \leq F_i^{\tau,j} \leq 1$ for N skills indexed by $i = 1,2,...N$ and $\sum_{i=1}^{N} F_i^{\tau,j} = 1$. The magnitude of each skill requirement $F_i^{\tau,j}$ measures the relative weight of the skill among the total set of skill requirements

[6]There is a vast literature that examines the channels through which information technologies shape firm production decisions and organizational scope, worker tasks, and skill requirements. See for example, Bartel et al. (2007), Bresnahan et al. (2002), Autor et al. (2003), Caroli and vanReenen (2001), Acemoglu and Zilibotti (2001), Acemoglu and Restrepo (2018), Beaudry et al. (2010), Goos and Manning (2007), Goos et al. (2014), Akerman et al. (2015), Michaels et al. (2014), Autor et al. (2024).

of the firm. Workers of type $j \in (u,s)$ possess multidimensional skill attributes, denoted by $W^{\tau,j} \equiv (W_1^{\tau,j}, W_2^{\tau,j}...W_N^{\tau,j})$ where $0 \leq W_i^{\tau,j} \leq 1$ for N skills indexed by i = 1,2,...N and $\sum_{i=1}^{N} W_i^{\tau,j} = 1$. The magnitude of each skill attribute $W_i^{\tau,j}$ measures the relative weight of the skill within a worker's skill portfolio.

We denote mismatch for skill i between a firm using technology of vintage τ and a worker of type $j \in (u,s)$ by $M_i^{\tau,j} \equiv F_i^{\tau,j} - W_i^{\tau,j}$ for $i \in$ (1,2,...N). Mismatch across all skills between a firm using technology of vintage τ and a worker of type $j \in (u,s)$ is denoted by Euclidean distance $M^{\tau,j} \equiv \|F^{\tau,j} - W^{\tau,j}\|_2 = \sqrt{\sum_{i=1}^{N}(F_i^{\tau,j} - W_i^{\tau,j})^2}$. We use these definitions to recast unskilled and skilled workers in the original model to be defined in terms of multidimensional skill mismatch. Specifically, we redefine a skilled worker as one who possesses skill attributes $W^{\tau,s}$ that equal the skill requirements $F^{\tau,s}$ of a firm using technology of vintage τ (i.e., $W_i^{\tau,s}$=$F_i^{\tau,s}$ for all individual skill dimensions i=1,2,...N). The skill mismatch $M^{\tau,s}$ of a firm-worker pairing of this type will thus be *zero*; vintage-specific human capital in the original model is thus represented by the specific skill weights desired by the firm, consistent with the notion of specific human capital defined by Lazear (2009). We redefine an unskilled worker as one who possesses skill attributes $W^{\tau,u}$, where $W_i^{\tau,s} \neq F_i^{\tau,s}$ for at least one $i \in \{1,2,...N\}$; the skill mismatch $M^{\tau,u}$ of this firm-worker pairing will be *non-zero*.

Our second adaptation is to use our definition of skill mismatch to microfound the production complementarity between unskilled and skilled workers that is otherwise assumed in Chari and Hopenhayn (1991). Specifically, we decompose the original assumption of $\frac{\partial f_U}{\partial S_t} > 0$ into the product of two components: $(\frac{\partial M^{\tau,u}}{\partial S_t}) \times (\frac{\partial f_U}{\partial M^{\tau,u}}) > 0$. For the first term, we assume that as the firm employs more skilled workers s_τ, the firm becomes better able to assign tasks and facilitate knowledge transfer to unskilled workers so that the skill requirements facing unskilled workers $F^{\tau,u}$ align more closely with unskilled workers' skill endowments $W^{\tau,u}$, thereby reducing skill mismatch $M^{\tau,u}$. Formally, this means $\frac{\partial M^{\tau,u}}{\partial S_t} < 0$. For the second term, we assume that the marginal productivity of an unskilled worker $f_U(U_t, S_t)$ is decreasing and concave in the degree of skill mismatch $M^{\tau,u}$ between the worker and the firm. Formally, this

implies $\frac{\partial f_U}{\partial M^{\tau,u}} < 0$ and $\frac{\partial^2 f_U}{\partial (M^{\tau,u})^2} < 0$. This assumption is supported by prior work that finds a negative association between mismatch and worker productivity (Coraggio et al., 2025; Guvenen et al., 2020; Lise and Postel-Vinay, 2020). Taken together, the two assumptions and the decomposition that we introduce to the model imply that an increase in the number of skilled employees allows the firm to raise the marginal productivity of its unskilled workers by altering their skill requirements and reducing the mismatch they exhibit with the firm.

Our third adaptation of Chari and Hopenhayn (1991) is to introduce capital investment as the mechanism through which firms respond to skill mismatch and facilitate workers' acquisition of IT-complementary skills. This approach is motivated by a large literature showing that firms' IT expenditures are key drivers of workers' IT-complementary human capital. Such expenditures include investments in training, organizational practices, and IT software and hardware. Our modification opens the original model's "black box" governing the transition of workers from unskilled to skilled and links this process, via mismatch, directly to firms' IT-related investment decisions.

For tractability, we model capital investment as a function of skill mismatch $M^{\tau,u}$, abstracting from other determinants, so that investment occurs only when mismatch is present: $I_t = Investment_t \times \mathbb{1}_{\{M^{\tau,u} \neq 0\}}$. This specification isolates the role of mismatch in shaping investment behavior in a parsimonious manner. We further assume that investment follows standard q-theory under price taking and convex adjustment costs (Lucas, 1967; Treadway, 1969; Hayashi, 1982). The firm's production function is thus $Y_t = \gamma^{t-\tau} f(U_t, S_t) + \gamma^{t-\tau} g(K_t)$, where K_t represents capital; additive separability ensures that U_t and S_t do not depend on K_t. Capital evolves according to $\dot{K}_t = I_t - \delta K_t$, where δ is the depreciation rate. Firms face convex adjustment costs of the form $\Phi(I_t, K_{t-1}) = \frac{\phi}{2}\left(\frac{I_t}{K_{t-1}} - \delta\right)^2 K_{t-1}$.

Taken together, the adaptations that we introduce microfound key primitives of Chari and Hopenhayn (1991) without altering its mechanics. As a result, we are able to generate the same equilibrium conditions and comparative statics as the original model. For example, the distribution of skilled workers s_τ remains single-peaked across technology vintages. The

enriched foundations that we provide, however, yield novel testable implications that enable us to address issues that are beyond the scope of the original framework: namely, the relationship between multidimensional skill mismatch and information technology diffusion. We derive these implications below, and provide a graphic illustration of our model in Figure 1.

Prediction 1: U-shaped skill mismatch over the technology life cycle.

In equilibrium, our model predicts that the mismatch between firms and unskilled workers, $M^{\tau,u}$, follows a U-shaped pattern with respect to technology vintage τ. The production complementarity between skilled and unskilled workers implies that $\frac{\partial M^{\tau,u}}{\partial S_t} < 0$; that is, skill mismatch for unskilled workers decreases as the firm employs more skilled workers. Because the equilibrium distribution of skilled labor, s_τ, is single-peaked across technology vintages, it follows that $M^{\tau,u}$ declines as s_τ rises, reaches its minimum when s_τ attains its peak, and increases thereafter as s_τ falls.

Intuitively, skill mismatch is high for newly introduced technologies because few workers initially possess the capabilities required to utilize them effectively. As technologies mature and greater numbers of unskilled workers accumulate experience and become skilled, firms can assign tasks more efficiently, reducing mismatch for new entrants. However, once technologies become sufficiently old and less productive, workers have dampened incentives to join these firms and become skilled in these technologies. Firms then find it harder to reorganize tasks and skill requirements for new employees, causing skill mismatch to rise once again.

Prediction 2: IT-complementary skill requirements exceed worker capabilities

Although our framework can be broadly applied across a range of technologies, in this paper, we focus on the diffusion of information technologies. For the model to be consistent with observed patterns of IT adoption, we should observe firm skill requirements exceed worker capabilities for IT-complementary skills, as these are the skills that are critical for IT diffusion. That is, we should observe positive skill mismatch, $M_c^{\tau,u} > 0$, for unskilled workers across IT-complementary skills $c \in \{1, 2, \ldots, N\}$. Conversely, we should observe negative

mismatch for IT-neutral skills, since skill weights sum to one. Thus we predict that $M_n^{\tau,u} < 0$ for $n \neq c$, reflecting the relative over-supply of skills that are less relevant for explaining information technology diffusion.

Prediction 3: U-shaped skill mismatch for IT-complementary skills

Our assumption that the marginal productivity of unskilled workers is decreasing and concave in the degree of skill mismatch implies that productivity losses rise disproportionately with larger mismatches. Because of this concavity, firms have stronger incentives to close the largest, rather than the smallest, individual skill gaps $M_i^{\tau,j}$ between firm requirements and worker capabilities. Following Predictions 1 and 2, this reasoning implies that as s_τ increases, firms will prioritize adjustments in tasks and skill requirements for IT-complementary skills—those that initially exhibit the largest gaps between firm demands and worker capabilities. As technology vintage increases and s_τ rises, the magnitude of these adjustments declines until s_τ peaks. Thereafter, as s_τ falls, firms find it increasingly difficult to reallocate tasks and reduce mismatch, leading to a rise in misalignment. Consequently, the model predicts a U-shaped relationship between IT-complementary skill mismatch and technology vintage.

Prediction 4: Tobin's Q decreases with technology vintage when skill mismatch $M^{\tau,u}$ is non-zero

Our model predicts that the firm's equilibrium marginal product of capital, and thus Tobin's q, are decreasing in technology vintage τ. As τ increases, technologies become older and less productive than frontier technologies, as captured by the productivity term $\gamma^{t-\tau}$. Consequently, the expected marginal return on new investment declines. In the presence of convex adjustment costs $\Phi(I_t, K_t) = \frac{\phi}{2}\left(\frac{I_t}{K_{t-1}} - \delta\right)^2 K_t$ and non-zero skill mismatch $M^{\tau,u}$, firms optimally reduce investment I_t as q_t falls to avoid incurring high adjustment costs when returns to new capital are low.[7]

[7]Firm value at time t can be written as:

$$V_t = \gamma^{t-1-\tau} f(U_{t-1}, S_{t-1}) + \gamma^{t-1-\tau} g(K_{t-1}) - I_t - \frac{\phi}{2}\left(\frac{I_t}{K_{t-1}} - \delta\right)^2 K_{t-1} + E[M_{t+1} V_{t+1}]$$

Intuitively, firms using newer technologies (low τ) face high q and strong incentives to invest in both tangible and intangible capital in order to reduce skill mismatch and help new employees acquire IT-complementary skills. These incentives change with technology vintage, however. As technologies mature and τ increases, declining productivity and lower expected returns reduce the firm's incentives to make such investments. Firms gradually invest less in capital that facilitates worker adaptation, and workers have less incentive to join these firms. Eventually, these dynamics culminate in technologies becoming obsolete.

4 Empirical Approach

4.1 Challenges

Empirically characterizing skill mismatch and its relationship with firm technologies is challenging. Ideally, we would like to be able to identify the specific skills that different firms seek and the specific skills that workers possess. We could then compute the distance between the skill attributes of firms and matched workers to estimate skill mismatch, and examine how skill mismatch varies over the technology life cycle.

There are numerous challenges with implementing this procedure in practice. First, there are limited data of sufficient granularity that adequately describe the skill attributes of firms and workers. Prior studies of skill mismatch either rely on survey data of managers and workers, or administrative datasets that contain information on worker demographics,

The Lagrangian is:

$$\mathcal{L}_t = \gamma^{t-1-\tau} f(U_{t-1}, S_{t-1}) + \gamma^{t-1-\tau} g(K_{t-1}) - I_t - \frac{\phi}{2}\left(\frac{I_t}{K_{t-1}} - \delta\right)^2 K_{t-1} + E[M_{t+1}V_{t+1}] - q_t[K_t - (1-\delta)K_{t-1} - I_t]$$

FOC wrt I_t

$$q_t = 1 + \phi\left(\frac{I_t}{K_{t-1}} - \delta\right)$$

FOC wrt K_t

$$q_t = E_t\left[M_{t+1}\left\{\gamma^{t-\tau}\cdot\frac{\partial g(K_t)}{\partial K_t} + \frac{\phi}{2}\left(\frac{I_{t+1}}{K_t}\right)^2 - \frac{\phi\cdot\delta^2}{2} + q_{t+1}\cdot(1-\delta)\right\}\right]$$

education, and experience. These data lack the detail required to meaningfully characterize skill mismatch across firms that utilize different information technologies. Firms relying on different IT systems, for example, will often require broadly similar levels of education, yet very different levels of expertise with specific technologies.

Second, it is conceptually challenging to identify the specific skills that firms truly demand, as these skills are fundamentally unobservable and difficult to discern from observable data on firm skill requirements. For example, a job posting that asks for "Java programming" skills may signal demand for a specific coding task, general problem-solving ability, and/or social skills that facilitate teamwork with software engineers. Additionally, firms will have implicit demand for many skills that are not explicitly specified in job postings, such as basic language and communication skills. The same points apply when attempting to identify workers' true skill portfolios from observed skills listed on workers' resumes.

Prior studies that analyze skills data in job postings frequently devise keyword tables to classify skill requirements. For example, one might look for keywords in job postings and then use those keywords to label skills as "cognitive" or "routine". This bag-of-words approach is well-suited for many applications, however, this approach is inappropriate for our setting, because any mapping of observable skills-to-unobservable skills defined by the econometrician may fail to resemble the skill mapping used by market participants. This disparity can lead to severe measurement error that distorts estimates of skill mismatch.

Third, it is computationally challenging to process skills data from job postings and worker resumes. There are typically thousands of unique and inconsistently defined skill requirements that vary significantly across firms. Deming and Kahn (2018) study U.S. job postings and find that skill requirements vary greatly across narrowly defined occupations; they estimate that firm-specific factors account for nearly 30% of the variation in posted skill requirements. Similar problems apply to the lexecon of skills that workers use to describe their human capital on resumes. These aspects of skills data make it challenging to produce estimates of skill mismatch that are computationally feasible and comparable across firms.

4.2 Empirical Methodology

We devise an empirical methodology that helps us overcome the aforementioned challenges and empirically characterize skill mismatch over the technology life cycle. First, we construct a novel matched employer-employee panel dataset that combines information from U.S. firm job postings (provided by Lightcast, formerly known as Burning Glass) with information from workers' online professional profiles (provided by Revelio). The job postings data contain detailed information on the skill requirements of firms for various positions. Job postings also list the specific technologies that companies want workers to be familiar with. The online professional profile data provide detailed information on the skills that workers possess, along with the start and end dates at various companies where workers have previously been employed. These raw data represent the most detailed information currently available for describing the skill attributes of firms and workers across the U.S.

From these data, we construct new firm-worker matches each year by identifying workers who join a firm within one year of the posting of a job ad and aggregating all such workers and associated job ads for each firm-year. This method provides a first approximation to the actual firm-worker matches realized each year; there are many workers who do not have online professional profiles and there are many vacancies that are not advertised online. We evaluate these sampling issues and discuss the robustness of our findings to alternative sampling criteria and different matching specifications in Section 5. We merge our data with firm-level information from Compustat and CRSP to characterize firms' annual balance sheet characteristics, investment and operating activities, and market valuations. Estimates of TFP are provided by Imrohoroglu and Tuzel (2014) and estimates of investment in intangible capital are provided by Peters and Taylor (2017). We describe the construction of the dataset and relevant sources in more detail in Appendix A.

We then employ the zero-shot classification algorithm developed by Yin et al. (2019) and the BERT large language model (Devlin et al., 2019) to map the raw, free-text skill descrip-

tions reported by firms and workers into a common set of 25 predefined skill groups. This classification step addresses the conceptual challenges noted above by producing comparable measures of skill attributes that can be used to estimate mismatch. The key advantage of using the BERT large language model is that it leverages contextual information in text to interpret what firms and workers mean when they report skills in unstructured form. In effect, we rely on the model's semantic representation of skill descriptions to approximate how market participants themselves interpret and categorize observable skills. We believe that this procedure provides a more accurate and relevant mapping for our context than could be achieved by an econometrician manually coding skill attributes using a bag-of-words approach.

To describe this classification step more precisely, we employ a predefined set of 25 skill categories developed by Revelio Labs. These categories are constructed by Revelio using clustering algorithms applied to the large corpus of skills that they extract from online professional profiles. Distinct skill expressions are first grouped into unique skills, which are then iteratively clustered into broader categories. Each cluster is assigned a representative label chosen to be both frequent within the cluster and central to its semantic meaning.[8] We adopt Revelio's skill taxonomy rather than define our own skill taxonomy, under the assumption that their large-scale clustering procedure spans the raw skill space more efficiently and systematically than any ad hoc grouping. We believe that this approach minimizes measurement error and reduces "researcher bias" that could arise when classifying raw skills into comparable skill groups used to generate estimates of mismatch.

The zero-shot classification algorithm maps the raw skill data for each firm or worker into a 25-dimensional vector, where each coordinate j=1,2,...,25 represents the model's estimated confidence that the raw skill profile entails Revelio skill category j. Formally, for each input skill profile k and predefined skill label j, the language model computes a logit score for the hypothesis "label j is true given input k." This entailment score, or degree of entailment,

[8]See Revelio's full methodology description at: https://www.data-dictionary.reveliolabs.com/methodology.html#clustering-skills.

is defined relative to the alternative hypotheses that skill label j is contradicted or neutral given input k. Entailment logits are computed for each of the 25 skill categories and then passed through a softmax transformation, producing a normalized distribution that sums to one. Intuitively, a higher score for skill category j indicates greater model confidence that raw skill input k is consistent with category j relative to the other predefined skill groups. The resulting vector of scores captures the degree of alignment between the reported raw skills and each standardized category, providing a harmonized representation that can be directly compared across firms and workers.

We use these skill vector outputs from zero-shot classification to estimate skill mismatch. Specifically, for each firm-year observation, we define skill mismatch between the firm and its workers as the Euclidean distance between firm skill vector $\mathbf{f} = (f_1, f_2, \ldots, f_{25})$ and worker skill vector $\mathbf{w} = (w_1, w_2, \ldots, w_{25})$:

$$m(\mathbf{f}, \mathbf{w}) = \sqrt{\sum_{j=1}^{25} (f_j - w_j)^2}.$$

for skill attributes j=1, 2,...25. Intuitively, our skill mismatch measure captures how far apart a firm's skill requirements and a worker's skill portfolio are in the 25-dimensional "skill space". If a firm and a worker place similar weight on the same skill categories, their vectors will be close together, resulting in a low level of skill mismatch. By contrast, if the firm emphasizes skills the worker does not possess—or the worker has skills that are not demanded by the firm—their vectors will differ more sharply, leading to a higher level of mismatch.

Finally, we follow the prior literature (eg. Tambe (2014)) to characterize firms' information technologies by identifying the vintage years of each of the technologies that are listed in firms' job postings, where the vintage year is the year in which a technology is invented. We compute the average (and median) vintage year of all the technologies that appear in the firms' job postings. This measure captures the stage of the technology cycle that corresponds

to the information technologies that are being adopted by firms and listed in job postings to convey worker skill requirements.

Armed with measures of skill mismatch and firm IT capital vintages, we perform a number of empirical analyses to present new facts that characterize skill mismatch in the context of firms' technology decisions. We examine how skill mismatch varies across firms and within-firms, we examine how mismatch varies across specific skill categories, and we study how skill mismatch is related to measures of firm performance such as operating profitability and total factor productivity. We also perform a number of analyses to establish the robustness of our conclusions to alternative variable definitions and empirical specifications.

5 Data

We construct a matched employer-employee dataset that combines information from three separate databases. First, we obtain job postings for U.S. firms from Lightcast for the years 2010 to 2024. Second, we merge these data with firm-level information from Compustat. Third, we merge our firm-year data with Revelio job profile data for workers. Most of the job profile data in Revelio comes from Linkedin. The data thus allow us to classify the starting years for employees of firms in the sample. The Revelio and Lightcast data contain information on the multidimensional skill attributes of workers and firms, respectively, and are the key data that we use to constructing our measures of skill mismatch. The specific skill categories that Revelio uses to classify worker skills is presented in Table A2. We break these skills up into three groups, based on the literature on IT and productivity: IT-complementary technical skills, IT-complementary nontechnical skills, and Peripheral skills that are unrelated to information technology deployment.

Table 1 describes our sample of firms (Panel A); we present data from Compustat to illustrate the population of firms and describe how our sample compares with the population. Our sample firms are generally larger and more productive than the average Compustat

firm, reflecting sample selection toward technology-intensive companies that are more likely to post jobs online and have employees with LinkedIn profiles. Table 1 also describes firm characteristics such as age, capital intensity, etc.

[Insert Table 1]

Figure 2 presents a histogram that depicts the ages of information technologies utilized by firms in our sample. The figure depicts the distribution of firm-year observations that correspond to different age buckets. The most commonly observed technology vintage in our sample of job postings reflects information technologies that have an age of approximately 28 to 31 years. A substantial portion of our firms utilize older technologies that have been in place for greater than 36 years.

To get a sense of the types of technologies that appear in job postings, Table A1 presents the top ten most frequently cited technologies that are listed in each technology bin in our sample. As the table indicates, we see that frontier technologies in our sample include cloud computing and modern programming languages, while technologies listed in the latest bins correspond to lower level programming languages and applications that are associated with mainframe systems and older IT systems.

[Insert Figure 2]

Table 3 presents summary statistics that describe our central measures of multidimensional skills, across each of the 25 skill groups that we use in our main analysis. The statistics for demand corresponds to the entailment scores for a given skill group across all job postings in the sample, while the mean statistic for supply corresponds to the entailment scores for workers in our sample. The "gap" measure corresponds to the absolute value of the difference between the demand and supply measures for every firm-year observation in the sample.

[Insert Table 3]

6 Empirical Findings

6.1 Skill mismatch over the technology life cycle

The model's first empirical prediction is that multidimensional skill mismatch follows a U-shaped pattern over the technology life cycle. We test this prediction using both graphical evidence and regression analysis.

Figure 3 plots average skill mismatch against technology vintage for all firm–year observations in the sample. Technology vintage is grouped into ten equal-weighted bins spanning more than 40 years. The figure reveals a pronounced U-shaped relationship: skill mismatch is relatively high for firms implementing new technologies, declines steadily as technologies mature, and rises again for older vintages. The standard-error bars indicate that differences in mismatch across vintages are statistically significant for a range of bin comparisons. Skill mismatch is highest among firms using the newest technologies (2.1), declines by approximately 40 percent to its minimum after 33.8 years, and subsequently increases (to 1.2) for the oldest technologies in the sample—overlapping the levels observed at earlier stages of the life cycle.

Several additional features of Figure 3 shed light on the relationship between skill mismatch and the technology diffusion process. The long time-series of observed technology vintages in the sample reflects the slow pace of adoption in the data, consistent with studies of gradual diffusion relative to the rate of technological progress (Kalyani et al., 2025). The declining slope of mismatch among younger technologies aligns with the model's diminishing-adjustment mechanism: as the stock of skilled workers expands, firms first close their largest skill gaps, generating progressively smaller reductions in mismatch over time. Finally, mismatch reaches its minimum roughly 35 years after technology inception, suggesting that it can take several decades for information technologies to fully diffuse and for skill mismatch to be minimized.

Table 2 formalizes these patterns using regression estimates of skill mismatch as a function of technology vintage. Across specifications, the coefficient on the linear term in vintage is negative (between -2.2 and -2.3), while the quadratic term is positive (between 3.3 and 3.5), confirming the U-shaped relationship observed in the figure. These results are robust to the inclusion of year and industry fixed effects, indicating that the predicted relationship holds both across and within industries. We also observe statistically significant results consistent with the model using specifications with year and firm fixed effects, with the caveat that these results rely on significantly less variation than other specifications, as technology vintage varies little within most firms over time. The robustness of the results across specifications shows that the U-shaped pattern observed in Figure 3 is not an artifact of particular industry characteristics or firm attributes, but instead reflects a systematic relationship between skill mismatch and technology vintage that is consistent with the adjustment dynamics emphasized in the model.

Taken together, Figure 3 and Table 2 show that skill mismatch evolves endogenously over the technology life cycle. Mismatch declines as technologies mature and the supply of skilled workers expands, consistent with the model's prediction that firms initially close the largest skill gaps as complementary skills accumulate. Once technologies become sufficiently old, however, mismatch rises again as worker incentives to join firms using less productive technologies weaken.

These findings rule out several plausible alternative priors. First, skill mismatch is not confined to firms adopting new technologies: it remains an empirically relevant constraint for firms operating legacy systems. This pattern is consistent with practitioner surveys and business-press accounts documenting hiring difficulties among firms reliant on older technologies. Second, mismatch is not a persistent, technology-invariant feature of labor markets. Instead, the U-shaped pattern indicates that systematic forces govern how skill mismatch increases and decreases over the technology life cycle.

An important implication is that similar observed levels of skill mismatch can reflect

fundamentally different economic forces. We observe comparable mismatch among firms deploying very new technologies and among firms using very old technologies. According to the model, mismatch in the former case reflects a scarcity of workers who have accumulated the skills required to operate frontier technologies, whereas mismatch in the latter case reflects weak worker incentives to join firms using relatively less productive technologies. Distinguishing between these mechanisms is essential for interpreting observed skill shortages and for evaluating policies aimed at workforce development and technology adoption.

6.2 Characterizing Skill Dimensions of Mismatch

The model also makes predictions about the skill attributes that serve as bottlenecks to information technology diffusion. Prediction 2 states that firm requirements should exceed worker capabilities for IT-complementary skills. These skills may include technical skills such as programming and troubleshooting, as well as non-technical skills such as management and organizational capabilities Brynjolfsson and Hitt (2000). To test this prediction, we examine skill mismatch across each of the individual skill categories in our data. We graphically depict average levels of mismatch between firm requirements and worker skills in Figure 4. We also aggregate the skills in our sample into three groups following prior work on IT and productivity (Bartel et al., 2007): IT-complementary technical skills, IT-complementary nontechnical skills, and IT-neutral skills, and present these aggregated skills in Figure 6.

Consistent with this prediction, Figures 4 and 6 show that mismatch for IT-complementary skills—and especially for IT-complementary nontechnical skills—is substantially larger than for IT-neutral skills across all technology vintages. These results indicate that firms' skill requirements exceed workers' capabilities precisely in the dimensions most relevant for IT adoption. Notably, the largest bottlenecks to diffusion arise not only in technical competencies but also in nontechnical, IT-complementary skills that the literature identifies as critical for organizational and process changes accompanying new technologies (Bartel et al., 2007; Bresnahan et al., 2002).

For example, the most pronounced mismatches emerge for nontechnical capabilities such as managerial ability and related organizational skills, as well as for technical capabilities tied to IT infrastructure—technology support, networking, and manufacturing-related software. These attributes are directly complementary to IT-intensive production systems. By contrast, attributes that are in relatively low demand and exhibit little sensitivity to technology vintage—such as legal writing, biotech, and risk management—display minimal mismatch and, in several cases, excess supply. Taken together, these findings demonstrate that overall mismatch does not simply reflect a shortfall of "STEM skills" alone, but rather a targeted scarcity in high-weight, IT-complementary attributes, including managerial and finance-related capabilities. This pattern aligns with the model's weighting mechanism: gaps in attributes receiving the highest weights become the most binding for aligning worker skills with firm requirements.

To test the model's third main prediction, we next examine Euclidean distance measures of mismatch for each of the three skill groups. Figure 7 shows that the U-shaped pattern in overall mismatch is driven primarily by IT-complementary nontechnical skills. This evidence supports the hypothesis that firms reduce mismatch by prioritizing adjustments in the attributes that are farthest from workers' capabilities—which, in our setting, are precisely the IT-complementary nontechnical skills.

6.3 Multidimensional skill mismatch and the returns to investment across technology vintages

A final prediction of the model is that production systems relying on older technologies exhibit lower marginal returns to investment than those relying on newer technologies. In the model, older technologies persist because workers lack the skills needed to work with newer, more productive technologies; instead of working with frontier technologies, many workers instead instead sort into firms using older technologies where they can earn higher wages than they would at firms deploying new technologies for which they are poorly matched.

This prediction echoes the inverse relationship between technology vintage and productivity in the original model of Chari and Hopenhayn (1991). However, by explicitly incorporating capital investment as a response to skill mismatch, our framework allows us to directly measure marginal returns to investment and to examine how those returns vary across firms operating technologies of different vintages and thus verify that our adapted model shows that multdimensional skill mismatch affects technology diffusion.[9]

We test this prediction by examining how firms' market-to-book ratios vary with technology vintage. Figure 8 presents graphical evidence showing that market-to-book ratios decline monotonically with technology vintage. Table 4 formalizes this relationship using regression analysis. Across specifications that control for year and industry fixed effects, the estimated coefficient on technology vintage is negative and statistically significant, ranging from -1.2 to -2.8.

These findings are consistent with the model's prediction that technologies with lower marginal returns to investment persist because of labor market mismatch rather than because they remain equally attractive investment opportunities. These results reject several alternative priors. First, they rule out the possibility that, in our sample, older technologies generate marginal returns to investment comparable to those of newer technologies. Second, they are inconsistent with explanations in which the coexistence of old and new technologies reflect persistent industry-level differences unrelated to technology vintage. Finally, the results reject the view that the persistence of legacy technologies is driven primarily by technological or adjustment frictions on the capital side alone; instead, they point to skill mismatch and worker sorting as central forces shaping firms' investment opportunities across the technology life cycle.

[9]Estimating market-to-book ratios provides a more precise proxy for marginal investment returns than total factor productivity, particularly in settings where intangible capital and information technologies play a central role (Brynjolfsson et al., 2021).

7 Robustness Analysis

Our empirical approach to measuring skill mismatch and characterizing its relationship with technology vintage takes advantage of recent computational advances in large language models. Our approach has many strengths, but it also has several potential limitations. In this section, we discuss various concerns about our empirical methodology and we present additional analyses to assess the robustness of our findings.

7.1 Choice of language model

In our analysis, we rely on the BERT large language model. BERT has become the workhorse model for text classification because it is bidirectional (relative to uni-directional large models that only read text in one direction), and therefore better suited for capturing contextual information than many other language models. This makes BERT well-suited for our skill classification task, because it can capture the meaning of explicit raw skill data and it can also capture the skills that are implied but not explicitly mentioned in observable data.

There have been recent advances to BERT, such as ModernBERT, that are reportedly even better at capturing contextual information than BERT. The problem with these more advanced models is that they are computationally intensive; running ModernBert on our sample requires several weeks of run-time. Neverthless, to explore the robustness of our results to the choice of large language model, we repeat our analysis for firm-worker matches in the year 2020 using ModernBert. We find results that are even stronger than what we find using Bert. For example, as shown in Table 5, column 4, the U-shape of skill mismatch over technology vintage is even more pronounced than what we estimate using BERT. Thus our findings do not appear to be driven solely by the particular choice of large language model that we use for our analysis.

[Insert Table 5]

7.2 Technology vintage measure

In our main specifications, we use the average vintage for all information technologies listed in a firm's job postings as an estimate of the IT capital vintage of the firm. The average IT vintage that we estimate might be skewed by software that is particularly old and so commonplace that it may not be particularly relevant for characterizing changes in production systems that are empirically most relevant in the context of skill mismatch. For example, around 25% of the information technologies listed in job postings belong to Microsoft Office suite.

We address this concern in two ways. First, we show that using alternative measures for IT capital vintage, such as median vintage year for IT capital, does not significantly alter our results. Second, we re-run our analysis, excluding Microsoft office software from our measures of IT capital vintage, and we find that our results remain the same. Our findings thus show that the patterns of skill mismatch that we present are not significantly related to the particular measures of IT capital vintage that we employ.

7.3 Unobserved skill proficiency

Our analysis does not account for the relative level of proficiency associated with skills in our sample. For example, when two workers list "Python programming" on their professional profiles, we do not distinguish between the two workers based on their relative levels of proficiency with Python. Similarly, if two firms list the same skill requirements in their job postings, we do not distinguish between minimum levels of proficiency in the skills required by the two firms. In reality, there is likely to be significant heterogeneity in unobserved ability that further adds to the degree of skill mismatch that we measure in our sample.

One concern for our analysis is that firm-worker matches that exhibit large mismatch using our measures may actually be close skill matches once unobservable proficiency is taken into account. This concern is important, but it is unlikely to significantly alter our main

conclusions. First, our analysis implicitly assumes that firms and workers have a common (minimum) standard of proficiency in a particular skill when it is explicitly listed online. Thus, our measure of skill mismatch is still informative about relative differences in skill attributes between firms and workers, taking into account skill proficiency in the decision to list a particular skill online or not. Second, we note that our measure of skill mismatch is associated with lower firm productivity and lower wages, which suggests that our measures of skill mismatch are unlikely to be systematically biased by unobserved levels of skill proficiency.

7.4 Misidentifying firm-worker matches

We show that our results are robust to using alternative time windows for matches firms with workers. For example, we show that our results are similar when we match workers who join the firms within the same year of the firm's job postings. We also find that the results are the same when we identify workers who join firms two years after jobs are posted online.

7.5 Alternative skill labels

We show that our results are also robust to alternative skill labels, such as the categories of skills specified in Deming and Kahn (2018). In the literature, it is common for skills associated with technology to be classified as cognitive, routine, etc. When we use these skill classifications in place of the skill classifications defined by Revelio, we observe similar results for all of our tests. Thus our findings are not driven by specific skill labels per se; the results reflect skill mismatch that is consistent with the predictions of our model.

8 Conclusion

This paper provides theory and evidence showing that skill gaps in the labor market constitute a central friction in the diffusion of new technologies. Focusing on information-

technology adoption, we document that skill mismatch is U-shaped in technology vintage and is especially pronounced for IT-complementary skills—both technical and nontechnical. We also show that the patterns of capital investment across vintages are consistent with the view that skill mismatch shapes firms' investment in both intangible and tangible capital. In particular, our results help rationalize J-curve dynamics in which early investment in intangible assets is high, measured TFP appears low at the onset of new technology adoption, and productivity gains materialize only gradually as skills adjust. Together, these findings support models of technological change in which delays in skill adjustment play a key role in generating firm-level heterogeneity in productivity.

Our analysis highlights several promising directions for future research. On the theoretical side, understanding the incentives of workers to acquire skills that complement new technologies—and the incentives of firms to adopt new technologies given workers' human-capital investment behavior—remains an open and important question. More broadly, identifying which specific skills are most critical for facilitating technology diffusion, and how these skills can be acquired or developed most efficiently, is central to understanding the productivity impact of ongoing technological change. These issues have particular urgency today, as policymakers and business leaders increasingly point to skill gaps as a first-order barrier to innovation and growth. On the empirical side, our findings underscore the potential of large language models and other modern computational tools for measuring and analyzing the evolving nature of multidimensional skill demand and supply in the labor market. Such tools offer a powerful way to study the micro-foundations of technological diffusion and may help open new avenues for understanding how skills, technology, and productivity co-evolve.

References

Acemoglu, D. and Autor, D. (2011). *Skills, Tasks and Technologies: Implications for Employment and Earnings*, volume 4, Part B.

Acemoglu, D. and Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6):1488–1542.

Acemoglu, D. and Zilibotti, F. (2001). Productivity differences. *Quarterly Journal of Economics*, 116(2):563–606.

Adão, R., Beraja, M., and Pandalai-Nayar, N. (2024). Fast and slow technological transitions. *Journal of Political Economy Macroeconomics*, 2(2):183–227.

Akerman, A., Gaarder, I., and Mogstad, M. (2015). The skill complementarity of broadband internet. *Quarterly Journal of Economics*, 130(4):1781–1824.

Autor, D., Chin, C., Salomons, A., and Seegmiller, B. (2024). New frontiers: The origins and content of new work, 1940–2018. *Quarterly Journal of Economics*, 139(3):1399–1465.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, 118(4):1279–1333.

Baley, I., Figueiredo, A., and Ulbricht, R. (2022). Mismatch cycles. *Journal of Political Economy*, 130(11):2943–2984.

Bartel, A., Ichniowski, C., and Shaw, K. (2007). How does information technology affect productivity? plant-level comparisons of product innovation, process improvement, and worker skills. *Quarterly Journal of Economics*, 122(4):1721–1758.

Beaudry, P., Doms, M., and Lewis, E. (2010). Should the personal computer be considered a technological revolution? evidence from u.s. metropolitan areas. *Journal of Political Economy*, 118(5):988–1036.

Bresnahan, T. F., Brynjolfsson, E., and Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *Quarterly Journal of Economics*, 117(1):339–376.

Brunello, G. and Wruuck, P. (2021). Skill shortages and skill mismatch: A review of the literature. *Journal of Economic Surveys*, 35(4):1145–1167.

Brynjolfsson, E. and Hitt, L. M. (2000). Beyond computation: Information technology, organizational transformation and business performance. *Journal of Economic Perspectives*, 14(4):23–48.

Brynjolfsson, E., Hitt, L. M., and Yang, S. (2002). Intangible assets: Computers and organizational capital. *Brookings Papers on Economic Activity*, 2002(1):137–181.

Brynjolfsson, E., Rock, D., and Syverson, C. (2021). The productivity j-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeco-*

nomics, 13(1).

Caroli, E. and vanReenen, J. (2001). Skill-biased organizational change? evidence from a panel of british and french establishments. *Quarterly Journal of Economics*, 116(4):1449–1492.

Chari, V. V. and Hopenhayn, H. (1991). Vintage human capital, growth, and the diffusion of new technolog. *Journal of Political Economy*, 99(6):1142–1165.

Coraggio, L., Pagano, M., Scognamiglio, A., and Tåg, J. (2025). Jaq of all trades: Job mismatch, firm productivity and managerial quality. *Journal of Financial Economics*, 164:103992.

Dell, M. (2025). Deep learning for economists. *Journal of Economic Literature*, 63(1):5–58.

Deming, D. and Kahn, L. (2018). Skill requirements across firms and labor markets: Evidence from job postings. *Journal of Labor Economics*, 36(S1).

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2019). Bert: Pre-training of deep bidirectional transformers for language understanding. *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186.

Goldin, C. and Katz, L. F. (2008). *The Race Between Education and Technology.* Belknap Press for Harvard University Press.

Goos, M. and Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in britain. *Review of Economics and Statistics*, 89(1):118–133.

Goos, M., Manning, A., and Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, 104(8):2509–2526.

Guvenen, F., Kuruscu, B., Tanaka, S., and Wiczer, D. (2020). Multidimensional skill mismatch. *American Economic Journal: Macroeconomics*, 12(1):210–244.

Hayashi, F. (1982). Tobin's marginal q and average q: A neoclassical interpretation. *Econometrica*, 50(1):213–224.

Imrohoroglu, A. and Tuzel, S. (2014). Firm-level productivity, risk, and return. *Management Science*, 60:2073–2090.

Kalyani, A., Bloom, N., Carvalho, M., Hassan, T., Lerner, J., and Tahoun, A. (2025). The diffusion of new technologies. *Quarterly Journal of Economics*, 140(2):1299–1365.

Lazear, E. P. (2009). Firm-specific human capital: A skill-weights approach. *Journal of Political Economy*, 117(5):914–940.

Lindenlaub, I. and Postel-Vinay, F. (2023). Multidimensional sortingunder random search. *Journal of Political Economy*, 131(12):3267–3540.

Lise, J. and Postel-Vinay, F. (2020). Multidimensional skills, sorting, and human capital accumulation. *American Economic Review*, 110(8):2328–2376.

Lucas, R. E. (1967). Adjustment costs and the theory of supply. *Journal of Political Economy*, 75(4):321–334.

ManpowerGroup (2024). 2024 global talent shortage: Infographic. https://go.manpowergroup.com/hubfs/Talent%20Shortage/Talent%20Shortage%202024/MPG_TS_2024_GLOBAL_Infographic.pdf. ManpowerGroup surveyed over 40,000 employers in 41 countries on difficulty finding needed talent, October 2023.

Michaels, G., Natraj, A., and Reenen, J. V. (2014). Has ICT poliazied skill demand? Evidence from elevent countries over twenty-five years. *Review of Economics and Statistics*, 96(1):60–77.

MIT Technology Review Insights (2023). New approaches to the tech talent shortage. Technical report, MIT Technology Review Insights. Executive briefing paper, sponsored by HCLTech.

Monaghan, B. D. and Bass, J. M. (2020). Redefining legacy: A technical debt perspective. In Morisio, M., Torchiano, M., and Jedlitschka, A., editors, *Product-Focused Software Process Improvement*, pages 254–269, Cham. Springer International Publishing.

Moscarini, G. (2001). Excess worker reallocation. *Review of Economic Studies*, 68(3):593–612.

OECD, editor (2024). *Understanding Skill Gaps in Firms: Results of the PIAAC Employer Module*. OECD Skills Studies. OECD Publishing, Paris. Accessed: February 13, 2026.

Peters, R. and Taylor, L. (2017). Intangible capital and the investment-q relation. *Journal of Financial Economics*, 123:251–272.

Tambe, P. (2014). Big data investment, skills, and firm value. *Management Science*, 60(6):1452–1469.

Treadway, A. B. (1969). On rational entrepreneurial behavior and the demand for investment. *Review of Economic Studies*, 36(2):227–239.

Yin, W., Hay, J., and Roth, D. (2019). Benchmarking zero-shot text classification: Datasets, evaluation and entailment approach. *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3914—-3923.

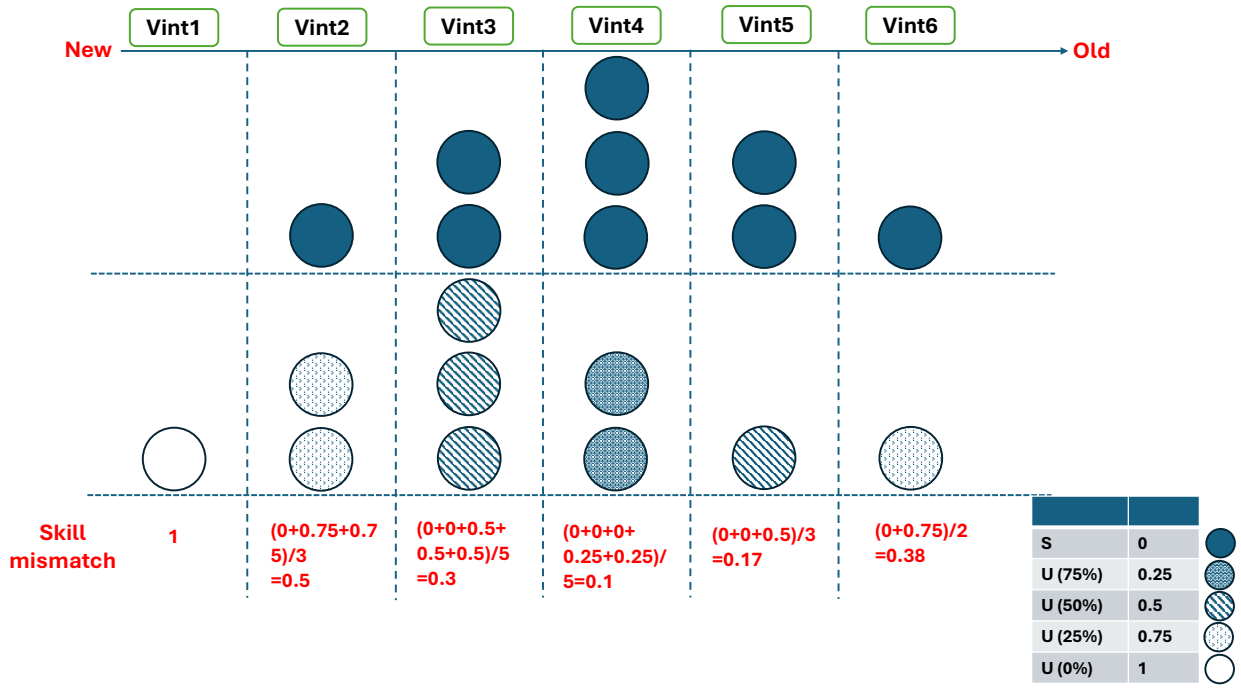


Figure 1: Model Overview

This figure provides a graphic illustration of our model. Each column corresponds to a technology vintage, increasing from the youngest to oldest vintage. In the first period, a single unskilled worker joins a firm employing the newest technology. Because the firm has no existing skilled employees, the level of mismatch between the new worker and the firm is normalized to 1. After one period of experience, this worker becomes skilled, and then two new unskilled workers join the firm. The skilled worker has 0 mismatch with the firm, while the two unskilled workers each reflect mismatch 0.25, since the skilled worker enables the firm to rearrange tasks and skill requirements that more closely align with unskilled workers' capabilities. The evolution of mismatch and employment growth of the firm continues each period until the technology reaches vintage 4. At that time, fewer unskilled workers join the firm, subsequently increasing the mismatch that new workers exhibit each period, until the technology become obsolete.

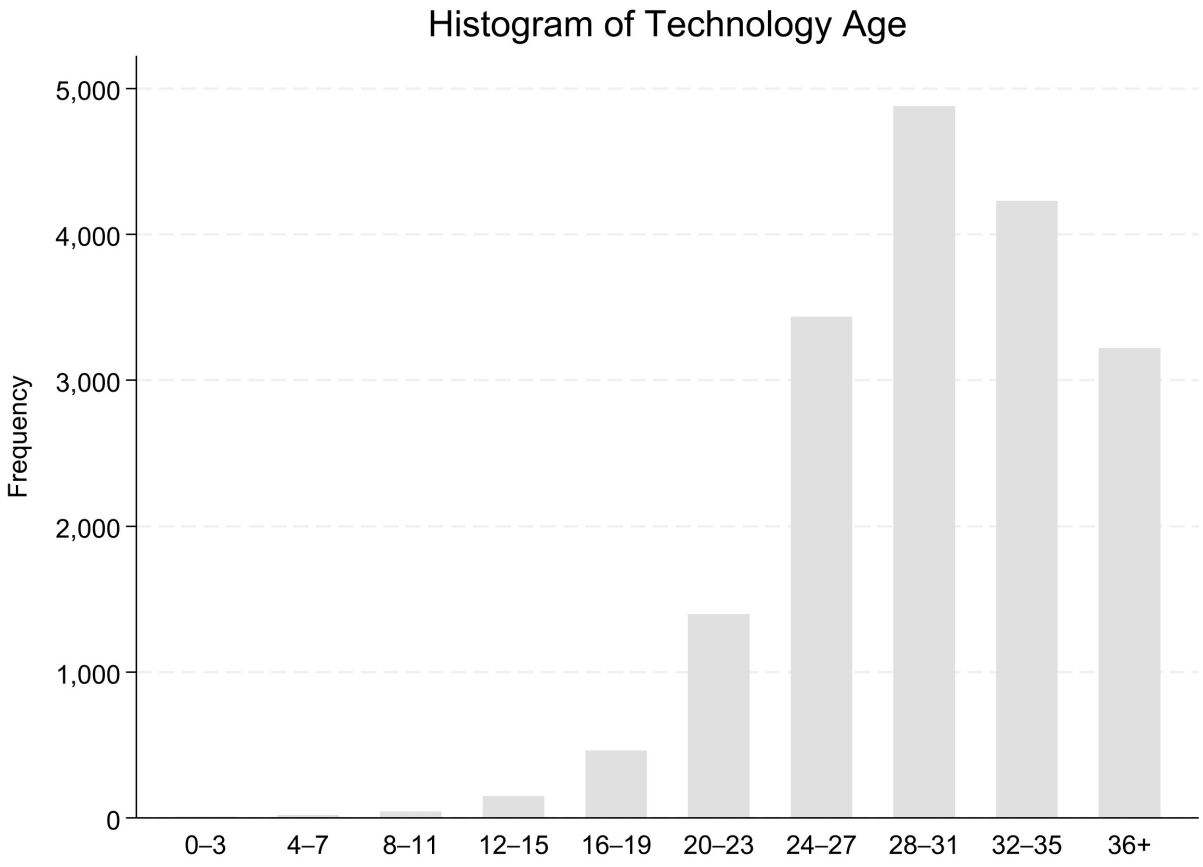


Figure 2: Skill Mismatch by Firm Technology Vintage
This figure presents a histogram of technology vintage in our sample. Each data point corresponds to a firm-year observation. The x-axis depicts the average technology vintage, computed as the average information technology age in the firm's job postings as of the year of observation.

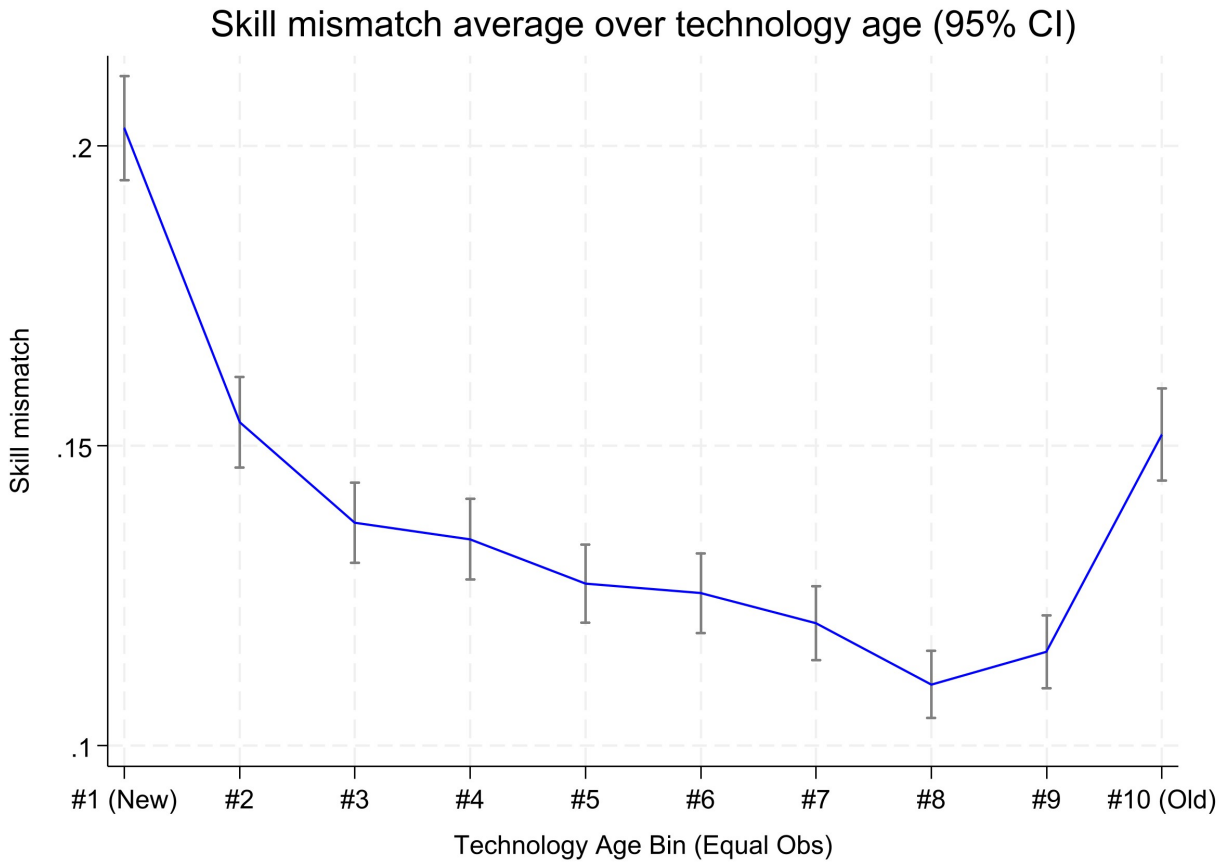


Figure 3: Skill Mismatch Over The Technology life cycle

This figure presents the empirical relationship between firm technology vintage and average skill mismatch between the firm and its new employees. Skill mismatch is defined as the Euclidean distance between the firm's skill requirements and new employees' skill portfolios. Technology vintage is measured as the relative age of the technologies used by the firm; newer technologies corresponding to lower technology vintage values. Bin#1 corresponds to firm-year observations whose technology vintage between 0 and 23.4 years. Bin#2 corresponds to firm-year observations whose technology vintage between 23.4 and 26.1 years. Bin#3 corresponds to firm-year observations whose technology vintage between 26.1 and 27.8 years. Bin#4 corresponds to firm-year observations whose technology vintage between 27.8 and 29.3 years. Bin#5 corresponds to firm-year observations whose technology vintage between 29.3 and 30.8 years. Bin#6 corresponds to firm-year observations whose technology vintage between 30.8 and 32.2 years. Bin#7 corresponds to firm-year observations whose technology vintage between 32.2 and 33.8 years. Bin#8 corresponds to firm-year observations whose technology vintage between 33.8 and 35.6 years. Bin#9 corresponds to firm-year observations whose technology vintage between 35.6 and 38.2 years. Bin#10 corresponds to firm-year observations whose technology vintage between 38.2 and 91.5 years. The figure demonstrates that firms using newer technologies tend to experience larger skill mismatch, consistent with the rapid evolution of skill requirements in technology-intensive industries.

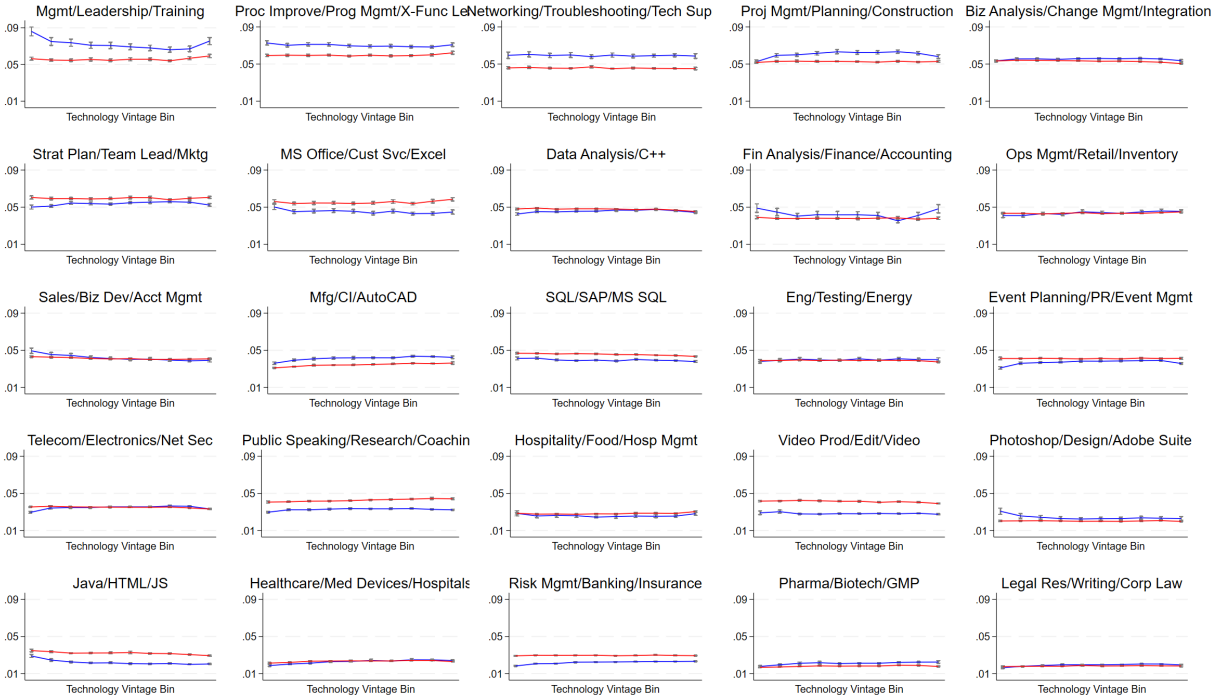


Figure 4: Distribution of Skill Mismatch by Skill Category: Demand vs. Supply
This figure presents the distribution of skill demand weights for job requirements (blue) and skill supply weights for workers (red) across each of the 25 skill categories used in our analysis (defined by Revelio Labs). The Y-axis depicts the average weight score for each skill group, the X-axis depicts technology vintage bins as defined in Figure 3.

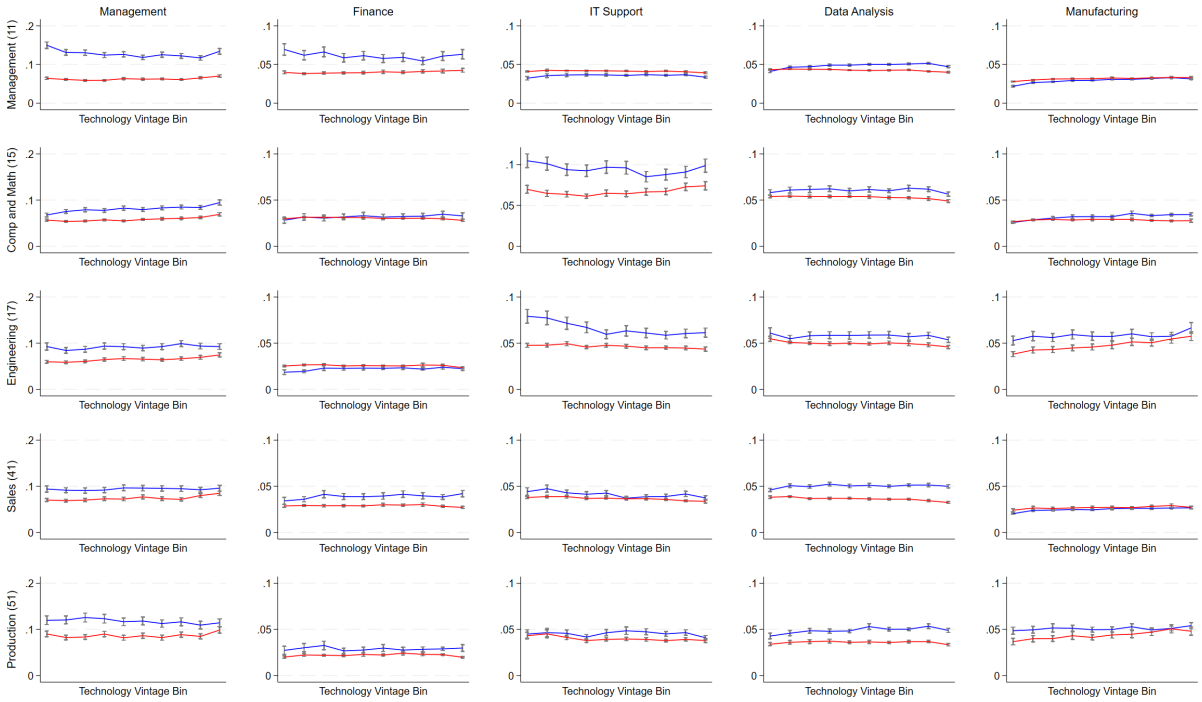


Figure 5: Distribution of Skill Mismatch by Skill Category: Demand vs. Supply
XXX This figure presents the distribution of skill demand weights for job requirements (blue) and skill supply weights for workers (red) across each of the five skill categories used in our analysis (defined by Revelio Labs) across different occupations. The Y-axis depicts the average weight score for each skill group, the X-axis depicts technology vintage bins as defined in Figure 3.

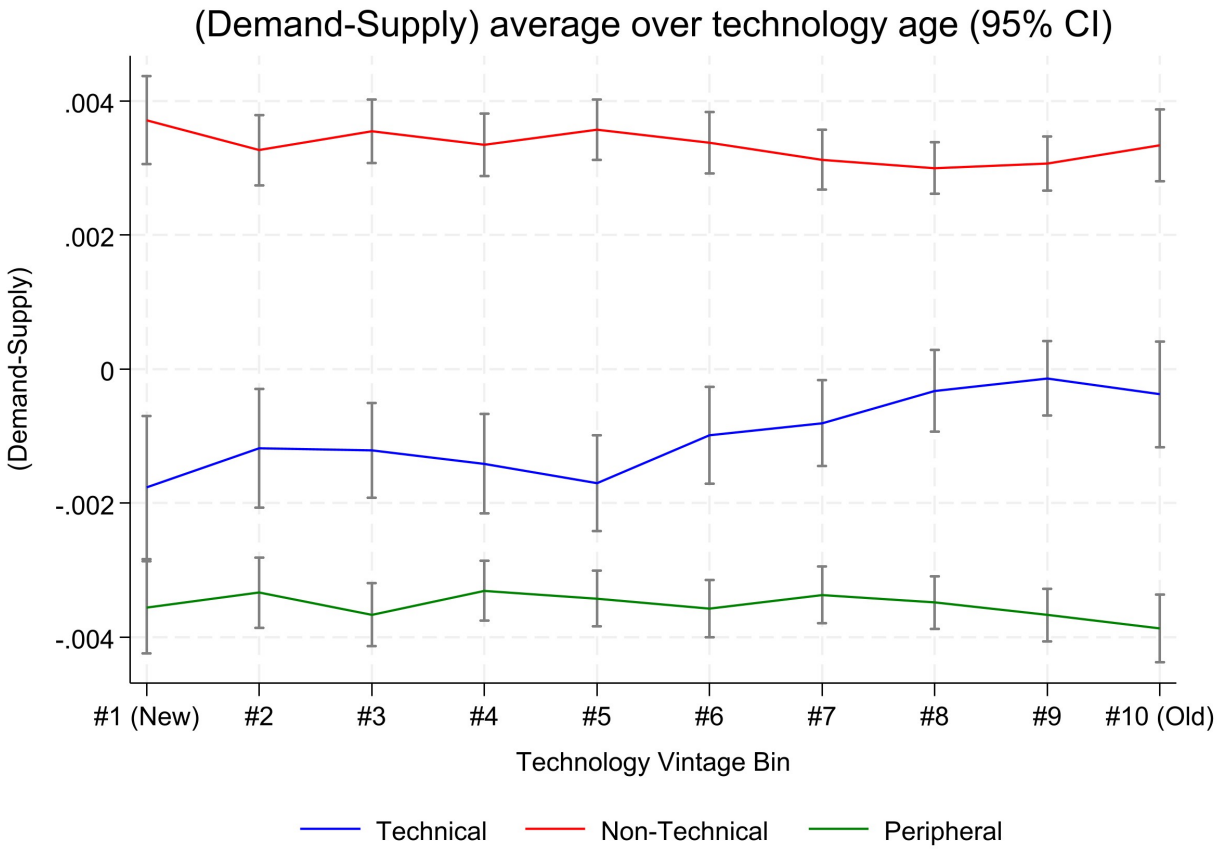


Figure 6: XXX

This figure presents differences between firm skill requirements and worker skill attributes for three groups of skills: IT-complementary technical, IT-complementary nontechnical, and IT-neutral skills. The Y-axis depicts the average score for each skill group, the X-axis depicts technology vintage bins as defined in Figure 3.

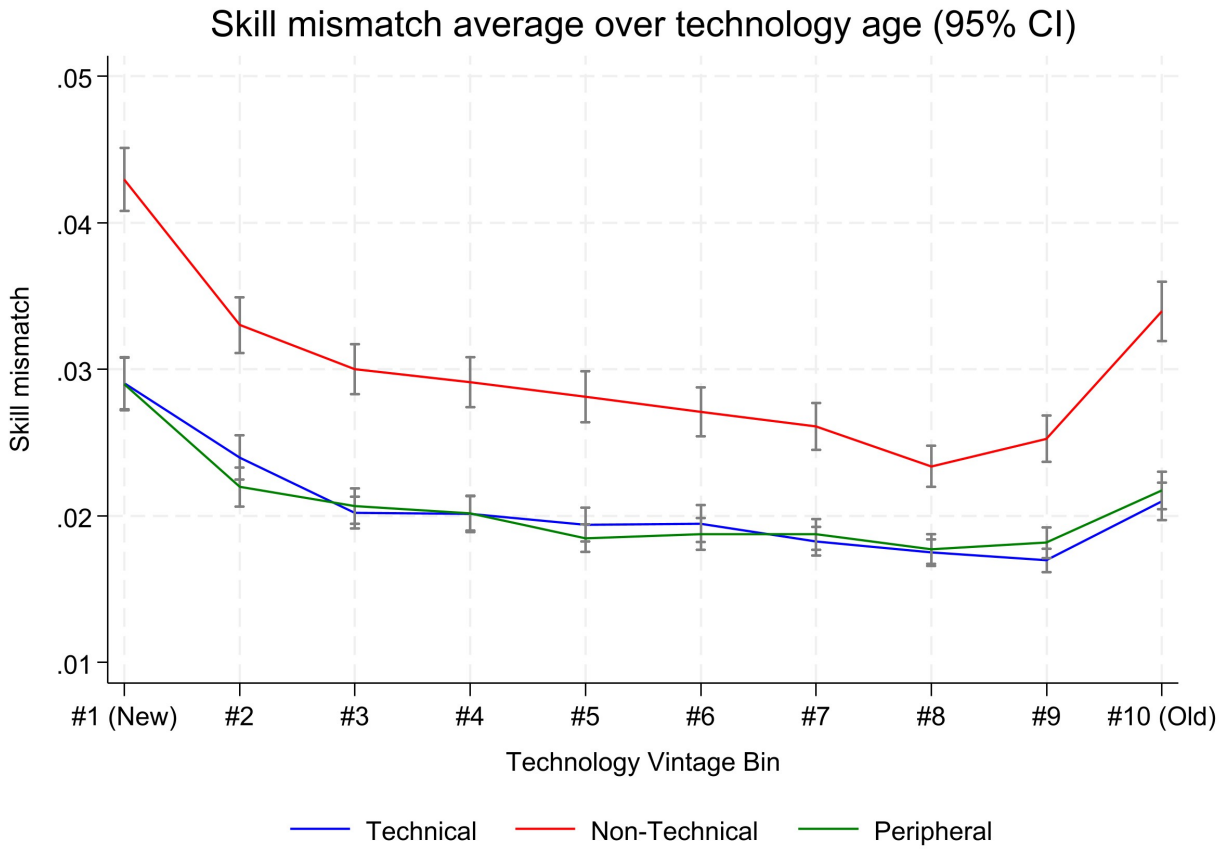


Figure 7: XXX

This figure presents skill mismatch (Euclidean distance measures) between firm skill requirements and worker skill attributes for three groups of skills: IT-complementary technical, IT-complementary nontechnical, and IT-neutral skills. The Y-axis depicts the average mismatch for each skill group, the X-axis depicts technology vintage bins as defined in Figure 3.

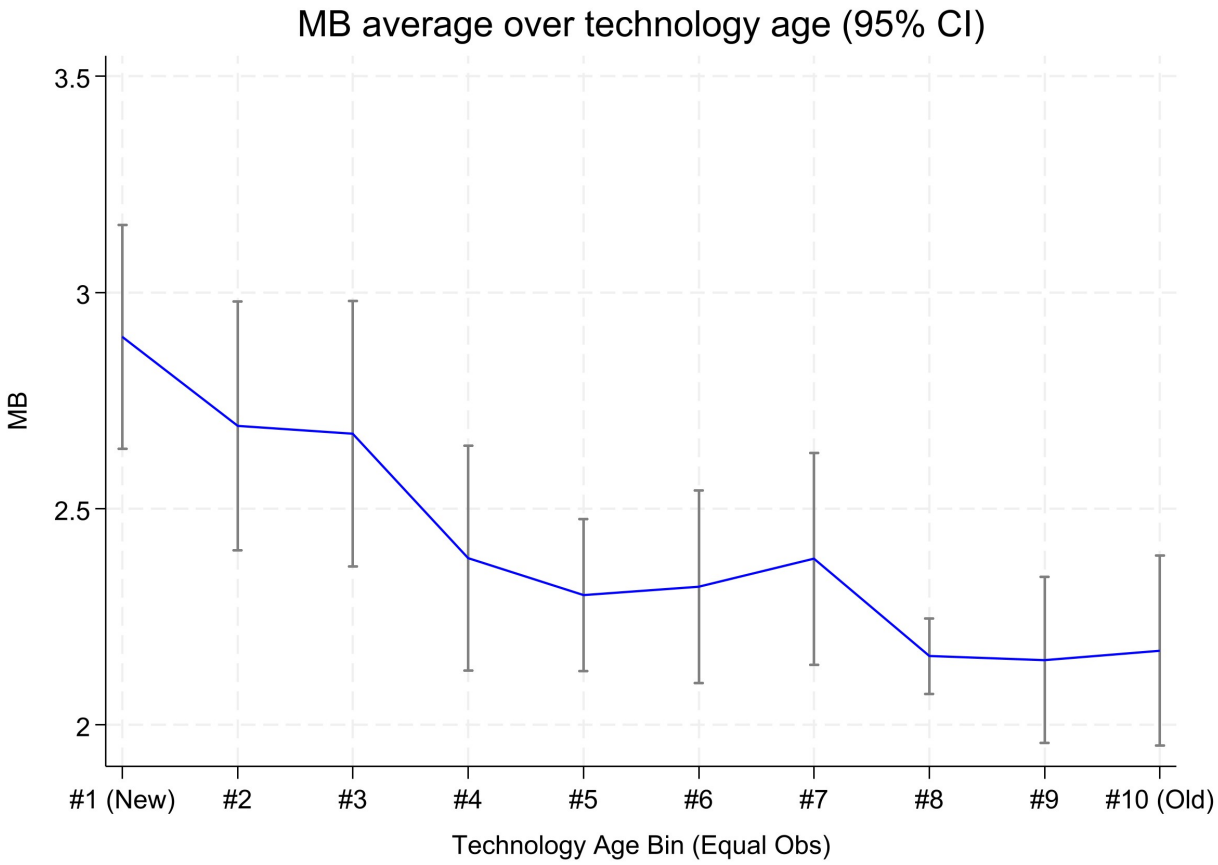


Figure 8: Market-to-Book Ratios over The Technology life cycle

This figure depicts firm market-to-book ratios across technology vintages. The Y-axis depicts the average market-to-book ratio for sample firms; the X-axis depicts technology vintage bins as defined in Figure 3.

Table 1: Summary Statistics: Sample vs Population

Variable	N	Mean	Std Dev	p25	Median	p75
Panel A: Our Sample						
Skill mismatch	22,467	0.159	0.166	0.0624	0.0762	0.201
Technology vintage	17,998	30.85	6.195	26.94	30.75	34.64
TFP	14,039	-0.242	0.507	-0.486	-0.246	0.0204
Sale (millions)	19,350	6,408	16,166	416.8	1,395	4,620
Profitability	19,461	0.105	0.114	0.0659	0.111	0.159
Firm Age	19,461	22.72	11.33	14	23	35
Total asset (millions)	19,351	8,665	22,677	497.6	1,678	6,000
Intangible investment rate	19,011	0.104	0.112	0.0318	0.0743	0.132
Tangible investment rate	18,990	0.0439	0.0479	0.0156	0.0292	0.0527
Panel B: Compustat Population						
TFP	33,953	-0.317	0.576	-0.580	-0.296	-0.0113
Sale (millions)	124,905	2,630	8,451	6.367	126.9	1,089
Profitability	175,342	-0.238	1.347	-0.00332	0	0.0797
Firm Age	175,342	12.87	11.35	3	9	20
Total asset (millions)	125,471	7,435	28,560	35.36	376.0	2,475
Intangible investment rate	96,436	0.157	0.274	0.0187	0.0747	0.174
Tangible investment rate	95,830	0.0598	0.127	0.00622	0.0233	0.0576

This table compares summary statistics between our analysis sample and the broader Compustat population. The sample period runs from year 2010 through year 2024. Skill mismatch is our measure of firm-level skill mismatch. Technology vintage is defined as per Figure 3. Panel A shows statistics for firms in our sample with both job posting and employee skill data. Panel B shows statistics for all Compustat firms during the same time period. All dollar amounts are inflation-adjusted to 2010 dollars. All variables are winsorized at the 1st and 99th percentiles.

Table 2: Main Result: Skill Mismatch vs Technology Vintage

	(1)	(2)	(3)	(4)	(5)	(6)
TechVint	-2.292***		-2.317***		-0.811***	
	(0.173)		(0.169)		(0.165)	
TechVint^2	3.464***		3.479***		1.241***	
	(0.271)		(0.262)		(0.254)	
TechVint2		-0.0445***		-0.0441***		-0.0120**
		(0.00650)		(0.00638)		(0.00573)
TechVint3		-0.0617***		-0.0621***		-0.0248***
		(0.00641)		(0.00629)		(0.00557)
TechVint4		-0.0608***		-0.0616***		-0.0220***
		(0.00654)		(0.00642)		(0.00585)
TechVint5		-0.0632***		-0.0652***		-0.0239***
		(0.00670)		(0.00659)		(0.00591)
TechVint6		-0.0625***		-0.0648***		-0.0208***
		(0.00700)		(0.00706)		(0.00636)
TechVint7		-0.0637***		-0.0654***		-0.0263***
		(0.00687)		(0.00687)		(0.00630)
TechVint8		-0.0713***		-0.0735***		-0.0246***
		(0.00707)		(0.00721)		(0.00651)
TechVint9		-0.0637***		-0.0660***		-0.0207***
		(0.00743)		(0.00766)		(0.00693)
TechVint10		-0.0298***		-0.0335***		-0.0126*
		(0.00812)		(0.00830)		(0.00732)
Observations	17,978	17,978	17,978	17,978	17,800	17,800
R-squared	0.045	0.040	0.062	0.056	0.439	0.439
Year FE	YES	YES	YES	YES	YES	YES
Industry/Firm FE	NO	NO	Ind(2-digit)	Ind(2-digit)	Firm	Firm

Notes: This table investigates how skill mismatch vary across different technology vintage. TechVint is technology vintage, normalized by 100. Columns (1) and (4) show linear regression. Columns (2) and (5) show regression with linear and quadratic terms, revealing a U-shaped relationship. Columns (3) and (6) show piece-wise linear regression. The results consistently show that skill mismatch first decrease with technology vintage (as firms adopt newer technologies) but then increase again for the newest technologies, reflecting the particularly challenging skill requirements of cutting-edge innovations. Two-digit SIC industry fixed effects included. Standard errors are heteroskedasticity consistent and clustered by firm.

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

Table 3: Summary Statistics: Skill Mismatch

#	Skill group	Variable	N	Mean	Std Dev
#1	Mgmt / Leadership / Training	Demand	22,467	0.0766	0.0865
		Supply	22,467	0.0570	0.0374
		Mismatch	22,467	0.0400	0.0872
#2	Proc Improve / Prog Mgmt / X-Func Lead	Demand	22,467	0.0720	0.0440
		Supply	22,467	0.0602	0.0279
		Mismatch	22,467	0.0283	0.0447
#3	Networking / Troubleshooting / Tech Support	Demand	22,467	0.0583	0.0559
		Supply	22,467	0.0452	0.0204
		Mismatch	22,467	0.0263	0.0543
#4	Proj Mgmt / Planning / Construction	Demand	22,467	0.0581	0.0447
		Supply	22,467	0.0527	0.0210
		Mismatch	22,467	0.0255	0.0425
#5	Biz Analysis / Change Mgmt / Integration	Demand	22,467	0.0543	0.0216
		Supply	22,467	0.0524	0.0138
		Mismatch	22,467	0.0158	0.0193
#6	Strat Plan / Team Lead / Mktg	Demand	22,467	0.0524	0.0356
		Supply	22,467	0.0606	0.0314
		Mismatch	22,467	0.0248	0.0416
#7	MS Office / Cust Svc / Excel	Demand	22,467	0.0468	0.0476
		Supply	22,467	0.0565	0.0413
		Mismatch	22,467	0.0296	0.0560
#8	Data Analysis / C++	Demand	22,467	0.0442	0.0250
		Supply	22,467	0.0470	0.0132
		Mismatch	22,467	0.0157	0.0230
#9	Fin Analysis / Finance / Accounting	Demand	22,467	0.0441	0.0861
		Supply	22,467	0.0378	0.0279
		Mismatch	22,467	0.0299	0.0850
#10	Ops Mgmt / Retail / Inventory	Demand	22,467	0.0441	0.0427
		Supply	22,467	0.0436	0.0153
		Mismatch	22,467	0.0193	0.0398
#11	Sales / Biz Dev / Acct Mgmt	Demand	22,467	0.0434	0.0460
		Supply	22,467	0.0416	0.0199
		Mismatch	22,467	0.0211	0.0442
#12	Mfg / CI / AutoCAD	Demand	22,467	0.0407	0.0299
		Supply	22,467	0.0338	0.0163
		Mismatch	22,467	0.0170	0.0285
#13	SQL / SAP / MS SQL	Demand	22,467	0.0394	0.0245
		Supply	22,467	0.0449	0.0139
		Mismatch	22,467	0.0166	0.0227

Continued on next page

Summary Statistics: Skill Mismatch (continued)

#	Skill group	Variable	N	Mean	Std Dev
#14	Eng / Testing / Energy	Demand	22,467	0.0388	0.0389
		Supply	22,467	0.0383	0.0169
		Mismatch	22,467	0.0181	0.0372
#15	Event Planning / PR / Event Mgmt	Demand	22,467	0.0351	0.0253
		Supply	22,467	0.0409	0.0183
		Mismatch	22,467	0.0178	0.0256
#16	Telecom / Electronics / Net Sec	Demand	22,467	0.0329	0.0196
		Supply	22,467	0.0345	0.0113
		Mismatch	22,467	0.0138	0.0169
#17	Public Speaking / Research / Coaching	Demand	22,467	0.0319	0.0191
		Supply	22,467	0.0426	0.0192
		Mismatch	22,467	0.0176	0.0228
#18	Hospitality / Food / Hosp Mgmt	Demand	22,467	0.0294	0.0596
		Supply	22,467	0.0287	0.0157
		Mismatch	22,467	0.0174	0.0560
#19	Video Prod / Edit / Video	Demand	22,467	0.0277	0.0229
		Supply	22,467	0.0412	0.0205
		Mismatch	22,467	0.0197	0.0264
#20	Photoshop / Design / Adobe Suite	Demand	22,467	0.0244	0.0476
		Supply	22,467	0.0203	0.0148
		Mismatch	22,467	0.0147	0.0474
#21	Java / HTML / JS	Demand	22,467	0.0227	0.0217
		Supply	22,467	0.0317	0.0212
		Mismatch	22,467	0.0165	0.0266
#22	Healthcare / Med Devices / Hospitals	Demand	22,467	0.0225	0.0200
		Supply	22,467	0.0232	0.0136
		Mismatch	22,467	0.0114	0.0194
#23	Risk Mgmt / Banking / Insurance	Demand	22,467	0.0211	0.0115
		Supply	22,467	0.0295	0.0119
		Mismatch	22,467	0.0132	0.0128
#24	Pharma / Biotech / GMP	Demand	22,467	0.0206	0.0224
		Supply	22,467	0.0178	0.0121
		Mismatch	22,467	0.00963	0.0221
#25	Legal Res / Writing / Corp Law	Demand	22,467	0.0185	0.0121
		Supply	22,467	0.0179	0.0166
		Mismatch	22,467	0.00956	0.0180

Table 4: MB ratio vs. vs Technology Vintage

	(1)	(2)	(3)	(4)	(5)	(6)
TechVint	-2.800***		-1.717***		-1.236***	
	(0.508)		(0.435)		(0.404)	
TechVint2		-0.0237		0.00456		0.000222
		(0.0871)		(0.0794)		(0.0790)
TechVint3		-0.220**		-0.105		-0.0677
		(0.0863)		(0.0768)		(0.0752)
TechVint4		-0.249***		-0.129		-0.0987
		(0.0958)		(0.0868)		(0.0825)
TechVint5		-0.339***		-0.190**		-0.139*
		(0.0978)		(0.0863)		(0.0816)
TechVint6		-0.316***		-0.130		-0.118
		(0.103)		(0.0901)		(0.0869)
TechVint7		-0.374***		-0.198**		-0.154*
		(0.107)		(0.0922)		(0.0876)
TechVint8		-0.346***		-0.163*		-0.135
		(0.112)		(0.0963)		(0.0926)
TechVint9		-0.492***		-0.249**		-0.166*
		(0.118)		(0.0994)		(0.0930)
TechVint10		-0.619***		-0.365***		-0.237**
		(0.117)		(0.103)		(0.0949)
Constant	3.018***	2.452***	2.682***	2.304***	2.533***	2.262***
	(0.167)	(0.0900)	(0.139)	(0.0745)	(0.129)	(0.0713)
Observations	16,337	16,337	16,337	16,337	16,333	16,333
R-squared	0.021	0.022	0.144	0.144	0.244	0.244
Year FE	YES	YES	YES	YES	YES	YES
Industry/Firm FE	NO	NO	Ind(2-digit)	Ind(2-digit)	Ind(4-digit)	Ind(4-digit)

Notes: This table investigates how skill mismatch varies across different technology vintage. TechVint is technology vintage, normalized by 100. Columns (1) and (4) show linear regression. Columns (2) and (5) show regression with linear and quadratic terms, revealing a U-shaped relationship. Columns (3) and (6) show piece-wise linear regression. The results consistently show that skill mismatch first decreases with technology vintage (as firms adopt newer technologies) but then increase again for the newest technologies, reflecting the particularly challenging skill requirements of cutting-edge innovations. Two-digit SIC industry fixed effects included. Standard errors are heteroskedasticity consistent and clustered by firm.

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

Table 5: Alternative Skill Mismatch Measure

	(1)	(2)	(3)	(4)	(5)	(6)
TechVint2	-0.0107	0.00357	0.0124	-0.00780	0.0148	-0.0164
	(0.0166)	(0.0161)	(0.0160)	(0.0106)	(0.0210)	(0.0161)
TechVint3	-0.0252	-0.0120	-0.0180	-0.0142	0.0351*	-0.0284*
	(0.0164)	(0.0159)	(0.0158)	(0.0105)	(0.0208)	(0.0160)
TechVint4	-0.0189	0.000330	-0.00633	-0.0118	0.0293	-0.0240
	(0.0168)	(0.0163)	(0.0162)	(0.0108)	(0.0213)	(0.0164)
TechVint5	-0.0357**	-0.00636	-0.0296*	-0.0285***	0.0559***	-0.0428***
	(0.0164)	(0.0159)	(0.0158)	(0.0105)	(0.0208)	(0.0160)
TechVint6	-0.0334**	-0.0260*	-0.0260*	-0.0268***	0.0492**	-0.0417***
	(0.0162)	(0.0157)	(0.0156)	(0.0104)	(0.0205)	(0.0158)
TechVint7	-0.0315*	-0.0260*	-0.0213	-0.0202*	0.0479**	-0.0386**
	(0.0162)	(0.0156)	(0.0156)	(0.0104)	(0.0205)	(0.0157)
TechVint8	-0.0387**	-0.0388**	-0.0423***	-0.0316***	0.0602***	-0.0512***
	(0.0160)	(0.0155)	(0.0154)	(0.0102)	(0.0203)	(0.0156)
TechVint9	-0.0279*	-0.0237	-0.0142	-0.0268***	0.0380*	-0.0345**
	(0.0160)	(0.0156)	(0.0154)	(0.0102)	(0.0202)	(0.0155)
TechVint10	-0.00519	0.0164	-0.000590	-0.00955	0.0137	-0.0133
	(0.0162)	(0.0157)	(0.0156)	(0.0104)	(0.0205)	(0.0158)
Constant	0.140***	0.335***	0.180***	0.275***	0.847***	0.202***
	(0.0123)	(0.0119)	(0.0118)	(0.00785)	(0.0155)	(0.0119)
Observations	1,417	1,431	1,417	1,417	1,417	1,417
R-squared	0.009	0.017	0.015	0.014	0.013	0.013

Notes: This table uses five alternative skill mismatch measures for year 2020. Column (1) shows our benchmark result. Column (2) uses skill mismatch measure constructed by aggregating over occupation. Column (3) uses 10 skill classifications used by Deming and Kahn (2018). Column (4) uses Modern Bert. Column (5) uses Cosine similarity. Column (6) uses Hellinger. The results are qualitatively similar to our main findings, confirming that skill mismatches negatively affect firm performance. Standard errors are clustered by firm. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 6: Skill Mismatch vs Technology Vintage By Occupation

ONET	Constant	SE	TechVint	SE	TechVint^2	SE	Observations	R-squared
Panel A: Occupations with pronounced hump shape								
11	0.442***	0.044	-1.417***	0.270	2.127***	0.412	15221	0.454
13	0.461***	0.049	-1.434***	0.302	2.229***	0.464	14403	0.456
15	0.362***	0.046	-0.876***	0.279	1.271***	0.426	13752	0.487
17	0.420***	0.065	-0.897**	0.393	1.177**	0.593	10397	0.512
31	0.640***	0.151	-1.669*	0.872	2.438*	1.283	1597	0.565
37	0.673***	0.122	-1.474**	0.741	2.070*	1.132	2491	0.501
41	0.370***	0.047	-0.797***	0.282	1.198***	0.423	12184	0.505
43	0.411***	0.048	-0.992***	0.291	1.512***	0.435	13788	0.461
51	0.425***	0.062	-0.780**	0.362	1.008*	0.533	9651	0.511
Panel B: Other occupations								
19	0.399***	0.084	-0.368	0.490	0.357	0.717	7506	0.463
21	0.435***	0.119	-0.490	0.706	1.003	1.054	3212	0.499
23	0.535***	0.119	-0.903	0.716	1.447	1.074	5152	0.482
25	0.341**	0.141	0.121	0.851	0.003	1.271	4410	0.423
27	0.471***	0.081	-0.804	0.495	1.011	0.754	9699	0.453
29	0.331***	0.090	-0.016	0.536	0.061	0.801	5209	0.553
33	0.405***	0.111	-0.373	0.642	0.658	0.924	3359	0.512
35	0.498***	0.124	-0.709	0.688	1.159	0.945	3658	0.492
39	0.356***	0.117	-0.045	0.654	0.151	0.913	2376	0.492
45	0.100	0.326	1.326	1.799	-1.074	2.492	527	0.521
47	0.167	0.110	1.153*	0.645	-1.892**	0.950	4792	0.474
49	0.299***	0.072	-0.045	0.413	0.141	0.593	8154	0.528
53	0.328***	0.066	-0.241	0.383	0.332	0.559	8462	0.539

Notes: XXX Standard errors are clustered by firm. *** p $<$ 0.01, ** p $<$ 0.05, * p $<$ 0.10.

Appendix for "Skill Mismatch Over The Technology life cycle"

A Variable definitions

- *Skill mismatch*: As described in Section 4.2
- *Technology vintage*: Following the literature (eg. Tambe (2014)), we compute the average (and median) vintage year of all the technologies that appear in the firms' job postings. This measure captures the stage of the technology cycle that corresponds to the information technologies that are being adopted by firms and listed in job postings to convey worker skill requirements.
- Market-to-book ratio: (AT+PRCC*CSHO-CEQ-TXDB)/AT
- Total asset: AT in 2010 dollar
- Sale: SALE in 2010 dollar
- Profitability: Operating Income Before Depreciation (OIBDP) scaled by total asset (AT)
- TFP: TFP, as explained in Imrohoroglu and Tuzel (2014). The extended sample for TFP is provided https://sites.google.com/usc.edu/selale-tuzel/home?authuser=2

B Additional Tables

Table A1: Top 7 Software Used in Each TechVint Bins

Rank	TechVint1: less than 23.4	TechVint2: (23.4, 26.1)
1	Microsoft Outlook	JavaScript (Programming Language)
2	Java (Programming Language)	Microsoft Access
3	Salesforce	HyperText Markup Language (HTML)
4	Amazon Web Services	Windows Servers
5	Microsoft Azure	PostgreSQL
6	C# (Programming Language)	Visual Basic (Programming Language)
7	Microsoft SharePoint	SolidWorks (CAD)
Rank	TechVint3: (26.1, 27.8)	TechVint4: (27.8, 29.3)
1	Linux	Python (Programming Language)
2	Microsoft Visio	Microsoft SQL Servers
3	R (Programming Language)	Information Technology Infrastructure Library
4	PL/SQL	Learning Management Systems
5	Applicant Tracking Systems	Business Intelligence Tools
6	SAP ERP	Operational Data Store
7	Web Servers	Web Browsers
Rank	TechVint5: (29.3, 30.8)	TechVint6: (30.8, 32.2)
1	Microsoft Office	Microsoft PowerPoint
2	Dashboard	Adobe Illustrator
3	Perl (Programming Language)	Transact-SQL
4	Firewall	LabVIEW
5	Adobe Photoshop	MicroStation (CAD Design Software)
6	PeopleSoft Applications	Information Technology Architecture
7	Bash (Scripting Language)	Presentation Software
Rank	TechVint7: (32.2, 33.8)	TechVint8: (33.8, 35.6)
1	Microsoft Excel	Microsoft Word
2	C++ (Programming Language)	Microsoft Project
3	Microsoft Windows	MATLAB
4	Field-Programmable Gate Array (FPGA)	IBM DB2
5	Customer Relationship Management (CRM) Software	Verilog
6	IBM Maximo	Primavera (Software)
7	Objective-C (Programming Language)	OSI Models
Rank	TechVint9: (35.6, 38.2)	TechVint10: greater than 38.2
1	AutoCAD	SQL (Programming Language)
2	TurboTax	SAP Applications
3	Oracle Databases	Operating Systems
4	Mac OS	Application Programming Interface (API)
5	Bug Tracking And Management	Spreadsheets
6	Oracle Hyperion	Unix
7	QuickBooks (Accounting Software)	C (Programming Language)

Table A2: 25 skills into three groups

Skill groups	25 Skill categories
Technical	java / html / javascript
	structured query language / sap / microsoft sql server
	analysis / data analysis / c++
	networking / troubleshooting / technical support
	telecommunications / electronics / network security
Non-technical	business analysis / change management / integration
	process improvement / program management / cross-functional team leadership
	management / leadership / training
	project management / project planning / construction
	strategic planning / team leadership / marketing
	manufacturing / continuous improvement / autocad
	financial analysis / finance / accounting
	operations management / retail / inventory management
	risk management / banking / insurance
	engineering / testing / energy
	sales / business development / account management
Peripheral	microsoft office / customer service / microsoft excel
	healthcare / medical devices / hospitals
	pharmaceutical industry / biotechnology / GMP
	public speaking / research / coaching
	photoshop / graphic design / adobe creative suite
	hospitality / food / hospitality management
	video production / video editing / video
	event planning / public relations / event management
	legal research / legal writing / corporate law

Table A3: Non-Technical Skills: Skill Mismatch vs Technology Vintage

	(1)	(2)	(3)	(4)	(5)	(6)
TechVint	-0.496***		-0.518***		-0.497***	
	(0.0417)		(0.0409)		(0.0407)	
TechVint^2	0.766***		0.790***		0.757***	
	(0.0663)		(0.0644)		(0.0639)	
TechVint2		-0.00899***		-0.00908***		-0.00862***
		(0.00154)		(0.00151)		(0.00146)
TechVint3		-0.0121***		-0.0126***		-0.0120***
		(0.00147)		(0.00145)		(0.00143)
TechVint4		-0.0120***		-0.0126***		-0.0125***
		(0.00151)		(0.00148)		(0.00145)
TechVint5		-0.0119***		-0.0129***		-0.0122***
		(0.00153)		(0.00152)		(0.00150)
TechVint6		-0.0124***		-0.0136***		-0.0133***
		(0.00159)		(0.00160)		(0.00156)
TechVint7		-0.0123***		-0.0135***		-0.0132***
		(0.00155)		(0.00156)		(0.00153)
TechVint8		-0.0143***		-0.0156***		-0.0145***
		(0.00158)		(0.00161)		(0.00159)
TechVint9		-0.0118***		-0.0133***		-0.0127***
		(0.00169)		(0.00174)		(0.00170)
TechVint10		-0.00385**		-0.00550***		-0.00527***
		(0.00190)		(0.00193)		(0.00190)
Observations	17,978	17,978	17,978	17,978	17,975	17,975
R-squared	0.037	0.032	0.053	0.047	0.103	0.099
Year FE	YES	YES	YES	YES	YES	YES
Industry/Firm FE	NO	NO	Ind(2-digit)	Ind(2-digit)	Ind(4-digit)	Ind(4-digit)

Notes: This table investigates how skill mismatch vary across different technology vintage. TechVint is technology vintage, normalized by 100. Columns (1) and (4) show linear regression. Columns (2) and (5) show regression with linear and quadratic terms, revealing a U-shaped relationship. Columns (3) and (6) show piece-wise linear regression. The results consistently show that skill mismatch first decrease with technology vintage (as firms adopt newer technologies) but then increase again for the newest technologies, reflecting the particularly challenging skill requirements of cutting-edge innovations. Two-digit SIC industry fixed effects included. Standard errors are heteroskedasticity consistent and clustered by firm.

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

Table A4: Technical Skills: Skill Mismatch vs Technology Vintage

	(1)	(2)	(3)	(4)	(5)	(6)
TechVint	-0.231***		-0.220***		-0.209***	
	(0.0253)		(0.0253)		(0.0255)	
TechVint^2	0.335***		0.327***		0.314***	
	(0.0370)		(0.0365)		(0.0365)	
TechVint2		-0.00414***		-0.00380***		-0.00335***
		(0.00102)		(0.00100)		(0.000983)
TechVint3		-0.00714***		-0.00669***		-0.00601***
		(0.000978)		(0.000970)		(0.000958)
TechVint4		-0.00733***		-0.00670***		-0.00617***
		(0.000995)		(0.000998)		(0.000987)
TechVint5		-0.00729***		-0.00663***		-0.00607***
		(0.00102)		(0.00102)		(0.00101)
TechVint6		-0.00707***		-0.00630***		-0.00564***
		(0.00105)		(0.00106)		(0.00106)
TechVint7		-0.00735***		-0.00642***		-0.00580***
		(0.00102)		(0.00103)		(0.00102)
TechVint8		-0.00751***		-0.00648***		-0.00563***
		(0.00105)		(0.00110)		(0.00110)
TechVint9		-0.00765***		-0.00636***		-0.00544***
		(0.00102)		(0.00106)		(0.00105)
TechVint10		-0.00458***		-0.00330***		-0.00241**
		(0.00107)		(0.00112)		(0.00112)
Observations	17,978	17,978	17,978	17,978	17,975	17,975
R-squared	0.031	0.030	0.046	0.045	0.082	0.080
Year FE	YES	YES	YES	YES	YES	YES
Industry/Firm FE	NO	NO	Ind(2-digit)	Ind(2-digit)	Ind(4-digit)	Ind(4-digit)

Notes: This table investigates how skill mismatch vary across different technology vintage. TechVint is technology vintage, normalized by 100. Columns (1) and (4) show linear regression. Columns (2) and (5) show regression with linear and quadratic terms, revealing a U-shaped relationship. Columns (3) and (6) show piece-wise linear regression. The results consistently show that skill mismatch first decrease with technology vintage (as firms adopt newer technologies) but then increase again for the newest technologies, reflecting the particularly challenging skill requirements of cutting-edge innovations. Two-digit SIC industry fixed effects included. Standard errors are heteroskedasticity consistent and clustered by firm.

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

Table A5: Peripheral Skills: Skill Mismatch vs Technology Vintage

	(1)	(2)	(3)	(4)	(5)	(6)
TechVint	-0.252***		-0.242***		-0.232***	
	(0.0260)		(0.0258)		(0.0257)	
TechVint^2	0.366***		0.347***		0.332***	
	(0.0391)		(0.0383)		(0.0381)	
TechVint2		-0.00605***		-0.00601***		-0.00559***
		(0.00110)		(0.00108)		(0.00107)
TechVint3		-0.00753***		-0.00746***		-0.00732***
		(0.00109)		(0.00106)		(0.00105)
TechVint4		-0.00762***		-0.00763***		-0.00760***
		(0.00110)		(0.00109)		(0.00108)
TechVint5		-0.00869***		-0.00881***		-0.00854***
		(0.00111)		(0.00108)		(0.00109)
TechVint6		-0.00861***		-0.00867***		-0.00864***
		(0.00112)		(0.00113)		(0.00114)
TechVint7		-0.00814***		-0.00810***		-0.00794***
		(0.00116)		(0.00116)		(0.00117)
TechVint8		-0.00923***		-0.00925***		-0.00880***
		(0.00119)		(0.00120)		(0.00122)
TechVint9		-0.00897***		-0.00897***		-0.00870***
		(0.00123)		(0.00126)		(0.00128)
TechVint10		-0.00568***		-0.00617***		-0.00593***
		(0.00131)		(0.00135)		(0.00137)
Observations	17,978	17,978	17,978	17,978	17,975	17,975
R-squared	0.018	0.018	0.039	0.039	0.083	0.083
Year FE	YES	YES	YES	YES	YES	YES
Industry/Firm FE	NO	NO	Ind(2-digit)	Ind(2-digit)	Ind(4-digit)	Ind(4-digit)

Notes: This table investigates how skill mismatch vary across different technology vintage. TechVint is technology vintage, normalized by 100. Columns (1) and (4) show linear regression. Columns (2) and (5) show regression with linear and quadratic terms, revealing a U-shaped relationship. Columns (3) and (6) show piece-wise linear regression. The results consistently show that skill mismatch first decrease with technology vintage (as firms adopt newer technologies) but then increase again for the newest technologies, reflecting the particularly challenging skill requirements of cutting-edge innovations. Two-digit SIC industry fixed effects included. Standard errors are heteroskedasticity consistent and clustered by firm.

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

A Skill Adjustment and Mismatch Dynamics

A.1 Skill Vectors and Adding-Up Constraints

There are $N = 25$ skill dimensions indexed by $i = 1, \ldots, N$.

Firm f at time t has a vector of skill requirements

$$F_t = (F_{1,t}, \ldots, F_{N,t}),$$

and workers hired at time t have skill endowments

$$W_t = (W_{1,t}, \ldots, W_{N,t}).$$

Both vectors are normalized and consist of skill weights that sum to one:

$$\sum_{i=1}^{N} F_{i,t} = 1, \tag{1}$$

$$\sum_{i=1}^{N} W_{i,t} = 1. \tag{2}$$

All components are nonnegative; i.e. all elements satisfy $F_{i,t} \geq 0$ and $W_{i,t} \geq 0$.

A.2 Mismatch Measure

Skill mismatch is defined as the Euclidean distance:

$$\widetilde{M}_t = \left(\sum_{i=1}^{N} (F_{i,t} - W_{i,t})^2 \right)^{1/2}.$$

For analytical convenience, we work with squared mismatch:

$$\mathcal{M}_t \equiv \sum_{i=1}^{N} (F_{i,t} - W_{i,t})^2. \tag{3}$$

Since the square root is monotone, minimizing $\mathcal{M}_t$ is equivalent to minimizing $\widetilde{M}_t$.

A.3 Firm Adjustment Problem

Between t and $t+1$, firms adjust skill requirements. Let $S_t > 0$ denote the number of skilled workers employed by the firm and let κ represent an adjustment efficiency parameter .

The firm chooses $\{F_{i,t+1}\}_{i=1}^{N}$ to solve:

$$\min_{\{F_{i,t+1}\}} \quad \underbrace{\sum_{i=1}^{N}(F_{i,t+1}-W_{i,t+1})^2}_{\text{mismatch}} + \frac{1}{2\kappa S_t}\underbrace{\sum_{i=1}^{N}(F_{i,t+1}-F_{i,t})^2}_{\text{adjustment costs}} \tag{4}$$

$$\text{s.t.} \ \sum_{i=1}^{N} F_{i,t+1} = 1.$$

Adjustment costs decline in S_t, reflecting greater internal capacity to reorganize skill requirements.

A.4 Lagrangian

The Lagrangian is:

$$\mathcal{L} = \sum_{i=1}^{N}(F_{i,t+1}-W_{i,t+1})^2 + \frac{1}{2\kappa S_t}\sum_{i=1}^{N}(F_{i,t+1}-F_{i,t})^2 + \lambda\left(\sum_{i=1}^{N} F_{i,t+1} - 1\right). \tag{5}$$

A.5 First-Order Conditions

For each i:

$$\frac{\partial \mathcal{L}}{\partial F_{i,t+1}} = 2(F_{i,t+1}-W_{i,t+1}) + \frac{1}{\kappa S_t}(F_{i,t+1}-F_{i,t}) + \lambda = 0. \tag{6}$$

Rearranging:

$$\left(2+\frac{1}{\kappa S_t}\right)F_{i,t+1} = 2W_{i,t+1} + \frac{1}{\kappa S_t}F_{i,t} - \lambda. \tag{7}$$

A.6 Solving for the Multiplier

Summing (7) over i and using $\sum_i F_{i,t+1} = 1$, $\sum_i F_{i,t} = 1$, and $\sum_i W_{i,t+1} = 1$:

$$\left(2+\frac{1}{\kappa S_t}\right) = 2 + \frac{1}{\kappa S_t} - N\lambda,$$

which implies

$$\lambda = 0.$$

A.7 Adjustment Rule

Substituting $\lambda = 0$:

$$F_{i,t+1} = \frac{2}{2+\frac{1}{\kappa S_t}}W_{i,t+1} + \frac{\frac{1}{\kappa S_t}}{2+\frac{1}{\kappa S_t}}F_{i,t}.$$

Define

$$\alpha(S_t) = \frac{2\kappa S_t}{1 + 2\kappa S_t}, \quad 1 - \alpha(S_t) = \frac{1}{1 + 2\kappa S_t}.$$

Then

$$F_{i,t+1} = (1 - \alpha(S_t))F_{i,t} + \alpha(S_t)W_{i,t+1}. \tag{8}$$

A.8 Mismatch After Adjustment

Subtracting $W_{i,t+1}$:

$$F_{i,t+1} - W_{i,t+1} = (1 - \alpha(S_t))(F_{i,t} - W_{i,t+1}).$$

Squaring and summing across skills:

$$\mathcal{M}_{t+1} = \sum_{i=1}^{N}(F_{i,t+1} - W_{i,t+1})^2 \tag{9}$$

$$= \sum_{i=1}^{N}(1 - \alpha(S_t))^2(F_{i,t} - W_{i,t+1})^2 \tag{10}$$

$$= (1 - \alpha(S_t))^2 \sum_{i=1}^{N}(F_{i,t} - W_{i,t+1})^2. \tag{11}$$

The inner summation is strictly positive unless skill requirements exactly match worker skills.

A.9 Comparative Statics with Respect to Skilled Workers

Using $1 - \alpha(S_t) = \frac{1}{1+2\kappa S_t}$, rewrite (11) as:

$$\mathcal{M}_{t+1} = \frac{1}{(1 + 2\kappa S_t)^2} \sum_{i=1}^{N}(F_{i,t} - W_{i,t+1})^2.$$

First derivative.

$$\frac{\partial \mathcal{M}_{t+1}}{\partial S_t} = -\frac{4\kappa}{(1 + 2\kappa S_t)^3} \sum_{i=1}^{N}(F_{i,t} - W_{i,t+1})^2 < 0, \tag{12}$$

since the summation term is strictly positive.

Thus mismatch between the firm and its unskilled workers is decreasing in the number of skilled workers S_t employed by the firm.

Second derivative.

$$\frac{\partial^2 \mathcal{M}_{t+1}}{\partial S_t^2} = \frac{24\kappa^2}{(1+2\kappa S_t)^4} \sum_{i=1}^{N} (F_{i,t} - W_{i,t+1})^2 > 0. \tag{13}$$

Thus mismatch decreases in S_t at a diminishing rate.

A.10 Comparative Statics with IT-Complementary and IT-Neutral Skills

We now provide a detailed comparative-statics analysis for the extension in which skill dimensions differ in their importance for information technology adoption.

A.10.1 Setup

Partition the set of skills into two disjoint subsets:

$$\mathcal{C} \cup \mathcal{N} = \{1, \ldots, N\}, \qquad \mathcal{C} \cap \mathcal{N} = \emptyset,$$

where:

- $\mathcal{C}$ denotes IT-complementary skills (e.g., managerial, organizational, system-integration skills);
- $\mathcal{N}$ denotes IT-neutral skills (e.g., legal research, event planning, public speaking).

Adjustment costs differ across these skill types. Let:

$$\kappa_C > \kappa_N > 0,$$

so that firms can more easily adjust IT-complementary skill requirements as the number of skilled workers increases. This formulation is essentially equivalent to assuming that adjustments to IT-complementary skill requirements generate larger marginal productivity effects than adjustments to IT-neutral skill requirements.

From the firm's optimization problem, the skill-adjustment rules are:

$$F_{i,t+1} = (1 - \alpha_C(S_t))F_{i,t} + \alpha_C(S_t)W_{i,t+1}, \quad i \in \mathcal{C}, \tag{14}$$
$$F_{i,t+1} = (1 - \alpha_N(S_t))F_{i,t} + \alpha_N(S_t)W_{i,t+1}, \quad i \in \mathcal{N}, \tag{15}$$

where

$$\alpha_j(S_t) = \frac{2\kappa_j S_t}{1 + 2\kappa_j S_t}, \qquad j \in \{C, N\}.$$

A.10.2 Post-Adjustment Mismatch

Subtracting worker skills from firm requirements yields:

$$F_{i,t+1} - W_{i,t+1} = (1 - \alpha_j(S_t))(F_{i,t} - W_{i,t+1}), \quad j \in \{C, N\}.$$

Squaring and summing over skill groups, post-adjustment mismatch is:

$$\mathcal{M}_{t+1} = \sum_{i \in \mathcal{C}} (1 - \alpha_C(S_t))^2 (F_{i,t} - W_{i,t+1})^2 + \sum_{i \in \mathcal{N}} (1 - \alpha_N(S_t))^2 (F_{i,t} - W_{i,t+1})^2. \tag{16}$$

Note that both summation terms are strictly positive unless skills perfectly align.

A.10.3 First Derivative with Respect to Skilled Workers

Using

$$1 - \alpha_j(S_t) = \frac{1}{1 + 2\kappa_j S_t},$$

rewrite (16) as:

$$\mathcal{M}_{t+1} = \sum_{i \in \mathcal{C}} \frac{(F_{i,t} - W_{i,t+1})^2}{(1 + 2\kappa_C S_t)^2} + \sum_{i \in \mathcal{N}} \frac{(F_{i,t} - W_{i,t+1})^2}{(1 + 2\kappa_N S_t)^2}. \tag{17}$$

Differentiate term by term with respect to S_t.

IT-complementary skills.

$$\frac{\partial}{\partial S_t} \left[\frac{(F_{i,t} - W_{i,t+1})^2}{(1 + 2\kappa_C S_t)^2} \right] = (F_{i,t} - W_{i,t+1})^2 \cdot \frac{\partial}{\partial S_t} (1 + 2\kappa_C S_t)^{-2} \tag{18}$$

$$= -4\kappa_C \frac{(F_{i,t} - W_{i,t+1})^2}{(1 + 2\kappa_C S_t)^3}. \tag{19}$$

Summing over $i \in \mathcal{C}$:

$$\frac{\partial \mathcal{M}^C_{t+1}}{\partial S_t} = -4\kappa_C \frac{\sum_{i \in \mathcal{C}} (F_{i,t} - W_{i,t+1})^2}{(1 + 2\kappa_C S_t)^3} < 0. \tag{20}$$

IT-neutral skills. By the same steps:

$$\frac{\partial \mathcal{M}^N_{t+1}}{\partial S_t} = -4\kappa_N \frac{\sum_{i \in \mathcal{N}} (F_{i,t} - W_{i,t+1})^2}{(1 + 2\kappa_N S_t)^3} < 0. \tag{21}$$

Comparison. Since $\kappa_C > \kappa_N$, it follows that:

$$\left| \frac{\partial \mathcal{M}^C_{t+1}}{\partial S_t} \right| > \left| \frac{\partial \mathcal{M}^N_{t+1}}{\partial S_t} \right| \quad \text{for all } S_t > 0.$$

Thus mismatch declines more rapidly along IT-complementary skill dimensions as the number of skilled workers increases.

A.10.4 Second Derivative and Convexity

We now show that mismatch declines at a decreasing rate.

IT-complementary skills. Differentiate (20) again:

$$\frac{\partial^2 \mathcal{M}_{t+1}^C}{\partial S_t^2} = -4\kappa_C \sum_{i \in \mathcal{C}} (F_{i,t} - W_{i,t+1})^2 \cdot \frac{\partial}{\partial S_t} (1 + 2\kappa_C S_t)^{-3} \tag{22}$$

$$= 24\kappa_C^2 \frac{\sum_{i \in \mathcal{C}} (F_{i,t} - W_{i,t+1})^2}{(1 + 2\kappa_C S_t)^4} > 0. \tag{23}$$

IT-neutral skills. Analogously:

$$\frac{\partial^2 \mathcal{M}_{t+1}^N}{\partial S_t^2} = 24\kappa_N^2 \frac{\sum_{i \in \mathcal{N}} (F_{i,t} - W_{i,t+1})^2}{(1 + 2\kappa_N S_t)^4} > 0. \tag{24}$$

Comparison of curvature. Since $\kappa_C > \kappa_N$:

$$\frac{\partial^2 \mathcal{M}_{t+1}^C}{\partial S_t^2} > \frac{\partial^2 \mathcal{M}_{t+1}^N}{\partial S_t^2}.$$

Thus mismatch along IT-complementary dimensions not only declines faster, but also exhibits stronger diminishing returns to additional skilled workers.

A.10.5 Interpretation

The comparative statics imply:

- Increasing the stock of skilled workers reduces overall mismatch between the firm and its unskilled workers;
- Adjustments are concentrated in IT-complementary skills, which firms prioritize because they are more important for effective technology adoption;
- As skilled labor becomes abundant, remaining mismatch increasingly reflects hard-to-adjust or low-return skill dimensions.