Technology and Skill Mismatch

Ashwini K. Agrawal, Daniel Kim, Prasanna Tambe

September 4, 2025

Preliminary and Incomplete - Do not Circulate

Abstract

Firms increasingly invest in new technologies to boost productivity, yet little is known about how well workers' skills align with evolving production systems. We develop a new empirical methodology—leveraging large language models (LLM's) with matched data from worker resumes and firm job postings—to construct novel measures of skill mismatch across firms that utilize different information technologies (IT). We document three main findings. First, skill mismatch exhibits a U-shaped pattern as IT evolves: mismatch is high when new technologies are deployed, declines over time as firms and workers adjust, and rises again as technologies become obsolete. Second, mismatch is substantial not only for technical skills but also for complementary non-technical skills. Third, firms facing greater mismatch exhibit higher levels of capital investment, particularly in intangible assets. These patterns are consistent with theories of technological change in which skill adjustment lags drive heterogeneity in firm-level productivity. Our results help explain why productivity dispersion rises during periods of rapid technological progress, and highlight the central role of worker-firm skill alignment in the diffusion of new technologies.

1 Introduction

Firms invest heavily in information technologies (IT) to enhance productivity. The *skill mismatch hypothesis* posits that the returns to these investments depend critically on the alignment between workers' skills and the requirements of new systems. Practitioners frequently cite skill mismatch as a major source of inefficiency in modern labor markets, and a growing literature documents its prevalence and consequences. However, evidence remains limited on how skill mismatch varies with firms' technology choices. In particular, we know little about

how skill mismatch evolves over the technology lifecycle, which skills are most or least scarce, and how firms' investment decisions respond to the degree of mismatch they encounter in the labor market. Filling this gap is crucial for understanding patterns of technology diffusion and the widening dispersion of productivity across firms.

Progress on this question has been hindered by three challenges: conceptual, observational, and computational. Conceptually, it is difficult to pin down which dimensions of human capital matter most for production, since skills are inherently multidimensional. 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 complementary social skills for teamwork. Observationally, there is a dearth of matched data that describe both firms' skill requirements and workers' actual skills. Computationally, even when such data are available, comparing thousands of distinct and inconsistently defined skills across firms and workers is non-trivial. Deming and Kahn (2018), for example, document significant within-occupation variation in skill demand across firms. These barriers have limited our ability to systematically measure skill mismatch in relation to firms' technology choices.

To address these challenges, we develop a new empirical methodology with three components. First, we build a theoretical framework that combines the task-based view of human capital (Acemoglu and Autor, 2011) with recent advances in job search theory (Lindenlaub and Postel-Vinay, 2023); the theoretical framework helps us derive an economically meaningful measure of skill mismatch that relates to firms' production technologies. In our framework, firms' labor demand reflects the production technologies they adopt, with job postings specifying the multidimensional skills required of workers to perform associated tasks. Skills are imperfectly substitutable forms of human capital, and workers—who differ in their skill portfolios—search and match with firms to maximize joint surplus. Because job search is frictional, multidimensional skill mismatch arises endogenously in equilibrium, even when firms and workers act optimally. This framework provides the foundation for our empirical measurement strategy.

Second, we construct a matched employer–employee dataset that links U.S. firms' online job postings with workers' online resumes. The job postings data allow us to observe the skills that firms demand and the information technologies they adopt; these data have been analyzed in prominent studies such as Hershbein and Kahn (2018). Workers' online resumes provide detailed information on workers' skill portfolios. Merging the two data sources enables us to track the timing and characteristics of new hires following firms' job advertisements.

Third, we apply large language models (LLMs) and natural language processing (NLP) methods to quantify mismatch between firms' required skills and workers' actual skills. Specifically, we use BERT (Bidirectional Encoder Representations from Transformers) to to classify job requirements and worker skill portfolios into vectors spanning 25 skill categories. These categories include skill labels such as "Management", "Finance", "Engineering", etc. We then compute distance metrics between the two vectors using standard techniques in the NLP literature. Our approach produces firm-year measures of skill mismatch that are consistent with our conceptual framework and scalable across a wide range of technologies and occupations.

Our first main finding is that skill mismatch follows a U-shaped pattern over the technology lifecycle. Mismatch is high when firms initially adopt new technologies, declines as firms and workers gradually adjust, and rises again as technologies become obsolete. This pattern emerges consistently across both cross-sectional and within-firm analyses, and is especially pronounced among younger, smaller, and financially constrained firms—those that prior research has identified as struggling most with technology implementation. These results are robust to a wide range of specifications, including alternative LLMs, skill categorizations, and hiring windows around job postings.

Our second main finding concerns which skills are scarce and which are abundant as firms' IT systems evolve. We find persistent shortages in certain technical skills—such as advanced manufacturing and network security—as well as in complementary non-technical skills like management and financial analysis. In both cases, the associated gaps follow the

same U-shaped pattern over the technology lifecycle. By contrast, skills tied to older or more routine tasks (e.g., hospitality, sales, or legacy programming) show little or no mismatch, and in some cases appear oversupplied.

These patterns indicate that mismatch is not confined to technical skills, but reflects a broader scarcity of capabilities that complement modern production systems. The evidence is consistent with recent observations that firms struggle to hire workers who combine managerial or financial expertise with sufficient technological knowledge to meet evolving job requirements.

Our third main finding is that firms respond to higher skill mismatch by increasing capital investment, particularly in intangible assets. Tangible capital investments associated with IT include expenditures in hardware, software, and other physical assets that complement IT-based production systems. Intangible investments include expenditures for training, software customization, marketing and sales. This result aligns with recent arguments that general-purpose technologies require substantial complementary investments before yielding productivity gains (Brynjolfsson et al., 2021). Our evidence suggests that part of this investment reflects efforts to mitigate mismatch—for example, through worker training and other intangible assets that help firms adapt production when skill gaps are present.

Our paper relates to three strands of research: studies of technological change and productivity, work on skill mismatch and labor market adjustment, and the growing use of natural language processing methods to measure economic activity. The skill mismatch hypothesis has been proposed as a critical mediating channel that explains the productivity effects of IT investments. Our empirical framework—combining matched job posting–resume data with large language models—allows us to measure skill mismatch at scale and provide some of the first evidence to characterize the skill mismatch hypothesis in the context of firms' production technologies. The findings that we document are consistent with theories of technological change in which skill adjustment lags drive heterogeneity in firm-level productivity, and they can help explain why productivity dispersion rises during periods of rapid techno-

logical progress. Our study thus highlights the central role of worker–firm skill alignment in the diffusion of new technologies and the aggregate returns to technology innovation.

The rest of the paper proceeds as follows. Section 2 describes our conceptual framework, Section 3 describes our data, Section 4 presents our empirical findings, and Section 5 concludes.

2 Related Literature

There is a growing literature that attempts to measure skill gaps faced by firms and identify the causes and consequences of skill mismatch (Coraggio et al., 2025; Şahin et al., 2014; Fredriksson et al., 2018). These papers study the impact of mismatch on firm productivity, wages, and unemployment. [Insert description of methods used by these papers].

Surveys of employers likewise provide supporting evidence of pervasive skill gaps. A recent Congressional Research Service review notes that in a 2017 survey of U.S. small businesses with hiring difficulties, 36% cited a "lack of soft skills" in applicants as a key obstacle, second only to lack of work experience. "Soft skills" include communication, teamwork, and problem-solving – competencies that firms increasingly demand but often find missing. Large corporations echo these concerns: in a 2022 global survey, 74% of hiring managers agreed there is a skills gap in the labor market, with nearly half saying candidates lack necessary technical skills and a third citing insufficient workplace readiness or soft skills. These reports underscore that skills mismatches are not confined to niche fields; they span many occupations from advanced manufacturing and IT to healthcare and business services.

There is debate over whether skill gaps tend to be persistent rather than transitory. Even as labor market conditions shift, many firms chronically find certain skills in short supply. For instance, throughout the late 2010s and into the 2020s, the National Federation of Independent Business (NFIB) surveys show "quality of labor" has remained the top problem cited by U.S. small businesses, above even taxes or regulation (NFIB, 2025). Similarly,

studies find that shortages of workers in STEM fields have endured over time despite rising wages, because the pipeline of trained workers adjusts only with long lags. In fast-evolving occupations (e.g. data science, cybersecurity), skill requirements can change faster than education/training systems adapt, leading firms to face a continuous recruitment challenge to replace or upskill workers. In short, both real-time data and employer surveys confirm that skills gaps are a real and sustained phenomenon across U.S. firms.

2.1 Drivers of Skill Gaps in Organizations

Technological Change and Innovation: Rapid technology adoption is a double-edged sword for skill gaps. On one hand, adopting new technologies can boost productivity; on the other, it creates demand for new skills that may be scarce. Research shows firms at the forefront of innovation tend to report more skill shortages (McGuinness and Ortiz, 2016). For example, high-end product and high-tech firms are more likely to have positions unfilled due to skill deficits, as they require cutting-edge technical skills and continuous skill updating (McGuinness and Ortiz, 2016). Haskel and Martin (2011) argue that technological progress can create persistent skill shortages, since innovative firms constantly need workers proficient in the latest tools and methods. A case in point is the digital sector: as companies rapidly adopt AI, cloud computing, and data analytics, the workforce skilled in these areas has lagged. Burning Glass Institute reports that the average U.S. job has seen roughly 37% of its skills requirements change in just five years, due to emerging technologies and evolving work practices. This pace of change leaves many incumbent workers' skills partly obsolete and forces firms into a continual hunt for new competencies. If firms cannot reskill their existing workforce fast enough, a skills gap emerges. Thus, faster tech adoption often correlates with larger skill gaps in the short run, especially for SMEs that lack capacity to retrain staff.

Firm Size and Resources: SMEs vs. Large Firms. Smaller firms are thought to generally experience skill gaps more acutely than large corporations. SMEs have fewer financial and human resources to attract, develop, and retain talent. Many cannot offer the salaries or ben-

efits that large firms use to recruit highly skilled workers, nor do they have dedicated training programs to upskill employees. Limited access to finance plays a role – cash-constrained businesses invest less in worker training and may be outbid for top talent (OECD, 2019). SMEs also report fear of investing in training only to have employees poached by larger firms, which discourages skill development initiatives (OECD, 2019). The result is often a capability gap: for example, only about half as many U.S. small businesses adopt advanced technologies (like CRM systems or AI) compared to large firms, due in part to shortages of digital skills and capital (McKinsey Global Institute, 2024).

This contributes to productivity gaps – McKinsey estimates U.S. micro, small, and mid-size enterprises are only 50% as productive as large firms, a wider gap than in other advanced economies. In contrast, large firms typically have more resources to train workers, leverage networks to find skilled candidates, and attract talent with higher pay. However, large firms are not immune to skill gaps: they often have more specialized skill needs (e.g. cutting-edge technical roles) that even broad labor markets struggle to supply. A study of 11,000 roles at major companies found many have begun dropping strict degree requirements and embracing skills-based hiring to expand talent pools, implying that even big employers felt constrained by traditional skill pipelines.

2.2 Impact of Skill Gaps on Productivity and Performance

There is a strong consensus that skill gaps can hurt firm-level productivity and overall performance. When a company cannot find workers with the requisite skills, several negative outcomes can result. First, unfilled positions or under-skilled hires reduce operational efficiency and output. If key roles stay vacant or are filled by less qualified personnel, work may be done more slowly or with lower quality, directly dragging down productivity. Empirical studies have linked skills deficits to delays in product development and adoption of new processes. In a U.K. survey, over one-fifth of firms reported that internal skill gaps delayed the introduction of new products, and one-third said skill deficiencies were a barrier to rolling

out new efficient work practices (McGuinness and Ortiz, 2016).

Although that study is U.K.-based, U.S. firms face analogous issues – for example, a lack of IT specialists might delay a firm's implementation of a productivity-enhancing software system. Skill gaps also lead to quality problems and missed opportunities: case studies note that companies with workforce skill deficiencies suffer more errors, cannot meet project deadlines, and sometimes must forgo business opportunities (McGuinness and Ortiz, 2016). The American Productivity & Quality Center finds that nearly one in four U.S. employers has lost or been unable to pursue a business opportunity due to inadequate skills (e.g. lack of foreign-language ability or technical know-how in their team) (ACTFL, 2019; Andreason, 2015).

A critical mechanism by which skill gaps reduce productivity is through their effect on innovation and technology use. Firms with a strong talent base can better exploit new technologies and innovate in products or processes. Conversely, if workers lack necessary skills, firms may under-utilize advanced equipment or software, yielding lower productivity gains. An ICT (information and communication technology) skills gap, for instance, has been shown to negatively impact company sales growth in firms that rely on digital tools (McGuinness and Ortiz, 2016). Likewise, a shortage of data analysts or engineers may prevent a firm from adopting data-driven decision-making or optimizing its supply chain, keeping productivity below potential. At the macro level, widespread skill mismatches can slow the diffusion of innovations across the economy – only the few firms that have skilled workers adopt new productive technologies, while others lag behind, contributing to productivity dispersion between leading and lagging firms. Over time, these firm-level performance hits aggregate to a meaningful macro impact.

Quantitatively, several studies try to estimate the cost of skills mismatches. A review in IZA World of Labor summarizes evidence suggesting that productivity would be much higher and unemployment much lower if skill supply and demand were better matched (Rathelot and van Rens, 2020). By one estimate, eliminating skill mismatches could reduce unemploy-

ment spells by one-third during recessions (Rathelot and van Rens, 2020), as workers would more readily fill open jobs. The Boston Consulting Group (BCG) calculates that the global skills mismatch effectively imposes a "tax" of about 6% of world GDP in lost productivity (Boston Consulting Group, 2023). For the U.S. economy (roughly $25 trillion GDP in 2022), this would translate into several hundred billion dollars of foregone output annually due to unutilized or underutilized skills. While such figures are approximate, they underscore a significant drag on economic performance. At the firm level, a recent survey found 92% of U.S. employers believe the skills shortage is lowering their productivity and even contributing to higher employee stress and turnover as existing staff must pick up the slack. Companies that cannot find the skills they need may also experience slower revenue growth and lower competitiveness. In manufacturing, plants with a persistent skills gap show lower output per worker and weaker quality metrics compared to plants in the same industry that are fully staffed with qualified workers (McGuinness and Ortiz, 2016). All told, the literature strongly indicates that skill gaps are not just a hiring nuisance but a tangible performance issue: they can curtail efficiency, growth, and profit in individual firms, and when prevalent across many firms, they weigh on aggregate productivity.

The consequences of skill gaps can differ between SMEs and large firms. For SMEs, a single critical vacancy or skills deficit can be especially damaging. Small businesses operate with lean teams, so lacking expertise in key areas (finance, marketing, IT, etc.) has an outsized impact. An SME that cannot hire a proficient IT manager, for instance, might struggle to maintain cybersecurity or e-commerce operations, directly affecting its performance. Research finds that SMEs suffering skills shortages tend to report lower sales and difficulty expanding (McGuinness and Ortiz, 2016). In extreme cases, chronic skill gaps can stunt a small firm's growth or even lead to business failure if they cannot execute their business plan. Large firms, with more redundancy in their workforce, may be able to buffer the impact of a few skill gaps by redistributing work or investing in training. However, for specialized roles, even big companies feel the pinch: when leading tech companies vie for a limited pool

of AI engineers or data scientists, those unfilled roles can slow a strategic initiative. Large firms often respond by reallocating more resources to recruitment or contracting out work, options that small firms might not afford. Thus, while the productivity loss from each unfilled position is significant for any firm, SMEs have fewer ways to mitigate it. This helps explain why narrowing the SME skill gap could yield substantial productivity gains. Indeed, analysts argue that if U.S. small and mid-sized businesses improved their access to skilled labor (through better training, hiring, or partnerships), it could close part of the roughly 50% productivity gap with larger firms and boost overall GDP by over 5%.

2.3 Further Implications

The research paints a clear picture: skill gaps are a consequential issue for firm-level outcomes and the broader economy. At the firm level, having the right human capital is as vital as having physical capital or finance – when skills are lacking, productivity and performance suffer. At the macro level, pervasive skills mismatches constrain the economy's ability to grow and innovate. Labor shortages and skill gaps are now seen as a structural challenge, not a temporary fluctuation, and could act as a brake on U.S. economic growth for the rest of the decade. This has placed skills at the center of policy debates on productivity. Economists note that the post-2005 productivity slowdown coincided with rapid technological change and globalization, which may have outpaced the workforce's skills in many areas (Boston Consulting Group, 2023). If firms cannot find workers proficient in new technologies, the technologies themselves will not translate into higher output – a dynamic some have called the "skills paradox."

Addressing skill gaps thus emerges as a leverage point for improving productivity. The literature suggests two broad approaches: boosting the supply of in-demand skills (through education, training, re-skilling programs) and adjusting firms' demand-side practices. Most attention traditionally goes to the supply side – e.g. expanding STEM education, vocational training, or credential programs targeted at skills shortages (Rathelot and van Rens, 2020).

However, research also highlights the role of firms themselves in managing skill gaps. Employers can invest in training current workers, redesign jobs to be more accessible (for instance, breaking extremely specialized roles into more standard positions), and adopt skills-based hiring to recognize unconventional candidates (Rathelot and van Rens, 2020).

In conclusion, skill gaps between workers' abilities and firms' requirements have been documented as a significant drag on firm performance and productivity in the U.S. SMEs and large firms alike face these challenges, though smaller firms often struggle the most with limited resources. The drivers of skill gaps are multi-faceted – spanning firm size, finance, technology, location, and industry dynamics – but all point to the difficulty of matching a fast-changing demand for skills with a slower adapting supply **?**. Bridging these gaps carries high stakes: evidence suggests that better skill matching could substantially raise productivity, enhance business performance, and even reduce unemployment (Rathelot and van Rens, 2020).

3 Conceptual Framework

The central research problem of this paper is to empirically characterize skill mismatch in the context of firms' information technologies. To tackle this problem, we develop a conceptual framework that has three components. [Note: In this preliminary draft, we explain our methodology in words only; in later versions, we will present our methodology more carefully with mathematical notation to distill the key ideas behind our approach.]

3.1 Theoretical Model

The starting point for our approach is to provide a theoretical model that motivates our notion of skill mismatch and how it relates to firms' technology choices. We begin by assuming that a profit-maximizing firm adopts a system of production that entails various tasks that need to be completed. For example, a firm implementing new technologies might

need workers to complete tasks such as programming new software to manage inventories, selling customized products and services to consumers, managing teams of workers, etc. The skills demanded by the firm to complete these tasks will be multidimensional and reflect the firm's production function parameters and the relative wages of skills in the labor market. For example, firms that deploy new IT systems may require workers with proficiency in programming and management, while firms that rely on older technologies may demand workers who possess potentially different skill sets. Our formulation of skills is based on the task-based approach to human capital, a powerful framework that has been used extensively in the technical change literature (Acemoglu and Autor, 2011). The unique feature of the task-based approach to human capital, relative to other human capital frameworks, is distinguishing between the tasks that firms need completed and the skills that workers need to possess to perform these tasks.

The manner by which firms find workers- who themselves possess multidimensional skill portfolios- to fulfill their production requirements is in accordance with a job search model. Namely, we rely on the seminal work of Lindenlaub and Postel-Vinay (2023), who provide the first generalized model of job search in which firms and workers are characterized by multidimensional attributes. Lindenlaub and Postel-Vinay (2023) represents a significant advancement of the job search literature, as much of the prior theoretical literature on job search studies unidimensional firms and workers.

Following their model, we assume that firms and workers engage in random job search in a frictional labor market so as to maximize joint matching surplus. Job offers arrive stochastically from an exogenous sampling distribution. Matches between multidimensional firms and workers generate scalar surplus that is jointly shared by both parties. Lindenlaub and Postel-Vinay (2023) derive a steady state equilibrium that is characterized by equal flows of workers entering and leaving employment (and unemployment). No worker can be made better off by changing their decision to accept or reject a given job offer, and no firm can be made better off by changing their decision to match or reject a worker. Skill mismatch

arises as an endogenous equilibrium outcome.

The theoretical framework allows us to view skill mismatch between multidimensional firms and workers as an equilibrium outcome of the job search and matching process. Firms' IT adoption plays a role in driving skill mismatch by specifying the tasks, and thus the types of skills, that firms demand in the labor market. The question that we answer in this paper is: how does equilibrium skill mismatch look empirically for firms that use different information technologies?

3.2 Empirical Methodology

To motivate our empirical measure of skill mismatch, it is helpful to first illustrate the ideal measure that our theory prescribes. Ideally, we would like to be able to empirically identify the specific skills that firms seek and the specific skills that workers possess. We would then be able to compute the distance between the skill requirements of firms and the skill portfolios of workers to estimate skill mismatch. We could then relate observed levels of skill mismatch with firms' underlying production technologies.

There are numerous problems with implementing this procedure in practice, however. First, it is difficult to ascertain the specific skills that firms truly demand for production, as these skills are fundamentally unobservable. 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 complementary social skills for teamwork. Similarly, when a worker lists that they are able to do Java programming, are they signaling their ability to perform specific coding tasks in Java, solve general problems, and work in teams?

Second, even if we did know the specific skills that firms truly demand, it is hard to know how well the observable skills that are specified in job ads actually entail the unobservable skills that firms actually want. In the example above, it is hard to know to what extent the demanded skill listing of Java programming implies that the firm wants a worker who is able to do specific coding tasks, solve general problems, and work in teams. Similarly, when a

worker lists Java programming abilities on her resume, to what extent does that mean that the worker can perform different types of tasks such as coding, problem solving, and working in teams?

Third, there is a problem of computational feasibility. Even if one were to observe the skills that workers possess and the skills that firms demand, it is hard to harmonize these skills into a manageable list. There are typically thousands of distinct and inconsistently defined skills across firms and workers. If one were to come up with a uniform list of skills, it is difficult to know how those skills map into the actual skill listings that appear in job ads and worker resumes. Recent work in fact, shows that firms differ systematically in the skills they demand. Using Burning Glass data on U.S. job postings, Deming and Kahn (2018) illustrate that some firms consistently include higher skill requirements (e.g. advanced cognitive or social skills) in their job ads than others do. They find that firm-specific factors account for roughly 30% of the variation in posted skill requirements across companies.

To overcome these challenges, the innovation of this paper is to employ recent advances in large language models and classification algorithms to empirically identify the skills that firms seek and the skills that workers possess, to estimate consistent measures of skill mismatch across firms. We use zero shot classification (Yin et al., 2019) to classify the set of observed skills in job postings and worker resumes to a harmonized set of 25 skill groups. The skill groups that we employ are defined by Revelio, who claim that these skill categories are statistically meaningful categories that span the entire Revelio dataset and represent the most efficient cluster labels that predict the skills that appear in worker resumes. Zero shot classification is an algorithm that works by first taking skill attributes as vector inputs of varying lengths and then representing these vectors by embeddings (numerical representations) that are determined by a large language model (we use BERT, an untrained LLM). In other words, we transform the string of skill requirements that we see in a firm's job ads into a machine readable vector of high dimensionality that represents the contextual meaning of the vector in accordance with the LLM.

The zero shot classification algorithm then takes the list of 25 skill groups (each of which is also represented by an embedding vector assigned by the LLM), and returns numerical scores for each of the 25 skill groups, where the numerical score for a given skill group represents the degree to which the skill requirements in the job posting entails the skill group label. Likewise, we repeat the same exercise for the list of raw skills that appear in worker resumes to produce numerical scores that represent the extent to which the list of skills on a worker's resume entails the list of 25 skill groups that we specify.

The interpretation of the numerical scores from the zero shot classification can be understood in the following way. The numerical scores produced by zero shot classification reflect entailment logits that result from the following hypothesis test for each job attribute vector Yi and skill label Si: is the list of input skills Yi entailed by the job attribute Si? The confidence that the hypothesis is true is called the entailment logit.

Zero shot classification returns the entailment logits for each attribute hypothesis test. It is important to note that logits are not traditional logits as we are accustomed to seeing in statistics, as the logits produced by the LLM are deterministic and not probabilistic. Zero shot classification then performs the softmax transformation to the entire vector of 25 entailment logits to normalize the weights on each attribute and ensure that they sum to 1. Softmax allows us to have the following interpretation for skill data from job postings: what is the relative confidence that the set of skill attributes observed for a firm's skill requirements is entailed by the specific skill label Si?

Once we get the classified skill labels for each firm, we repeat the classification process for the skill portfolios that belong to the employees who join the firm within one year of the job postings (we later show that the results are invariant to the length of the time windows that we consider). For a given firm-worker match, this process yields a comparable set of skill attributes for the firm and the worker that can be used to characterize skill mismatch.

Armed with skill attributes for firms and workers, we are able to estimate measures of skill mismatch by employing commonly used distance measures from the machine learning

literature. For example, in our main specifications, we define skill mismatch as the Euclidean distance between the vectors Yi and Si. The Euclidean distance between two vectors is the square root of the sum of the squared differences between each of the values that appear for each coordinate of the vectors being compared. We also examine skill mismatch using alternative distance measures that are commonly used in the literature, such as cosine similarity and Manhattan distance. Our results are robust to all of these choice.

Finally, we 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 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 signal the types of production systems that the firm is looking to utilize.

4 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.

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,

likely 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.

Figure 1 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.

Table 2 presents summary statistics that describe our central measure of skill mismatch, across each of the 25 skill groups that we use as skill labels in our main analysis. The skill labels are provided by Revelio. 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.

[Still to be added: discussion of sample selection, population vs. sample, interpretation of skill mismatch scores and technology vintage measures]

5 Empirical Findings

Table 3 and Figure 2 depict our first main finding. Skill mismatch follows a pronounced U-shape over the technology lifecycle: it is high when firms adopt very new systems, declines as firms and workers adjust, and rises again as systems become obsolete. This U-shape lines up with a profit-maximizing benchmark where firms demand a vector of skills that best fits the current technology (task weights) and relative skill prices. With very new IT, technology weights tilt toward frontier tasks faster than the workforce can recompose or

retrain, so observed skill shares lag the desired mix (high mismatch). With mature/medium-age IT, task weights are closer to the market modal technology and firms have had time to reallocate workers and invest in complements (low mismatch). With very old IT, required tasks tilt back toward legacy capabilities that are increasingly scarce in the labor market, generating mismatch again.

Table 4 shows the U-shaped pattern further appears in both cross-sectional and within-firm variation and is strongest for younger, smaller, and financially constrained firms—those with fewer resources to smooth adjustment. The result is robust across specifications, alternative LLMs for text parsing, skill categorizations, and hiring windows around postings. The stronger U-shape in financially constrained and small firms is consistent with adjustment frictions (training, hiring, and organizational change costs) that delay convergence to the desired skill vector.

The results support task-based views with imperfect substitution across skills and complementarities (mismatch is costly when σ is not too large). It also fits vintage/adoption models where technology changes the task weights over time and frictional labor markets where reallocation is gradual. It challenges frictionless models with instant costless re-optimization and one-dimensional skill indices (multi-skill evidence implies richer, multidimensional sorting/mismatch).

Our second set of findings describe the types of skills that are relatively scare vs. abundant supply. Table 5 and Figures **??** and Figure 6 shows that shortages persist in specific technical skills (e.g., advanced manufacturing, network security) and in complementary non-technical skills (management, financial analysis). Both follow the same U-shape over the lifecycle. By contrast, skills tied to older, more routine tasks (e.g., hospitality, sales, legacy programming) show little or no mismatch and are sometimes oversupplied.

The scarcity of complementary non-technical capabilities indicates that productivity from new IT depends on bundles of skills (technical + managerial/financial) that enable process redesign, coordination, and investment governance. In production function terms, these bun-

dles likely have low substitutability ($\sigma < 1$) with pure technical labor, so missing complements can generate large efficiency losses. The oversupply of legacy/routine skills suggests that, outside legacy systems, their task weights have fallen; where firms still run very old IT, these skills can be scarce relative to need, contributing to the right-hand side of the U-shape.

The evidence supports O-ring/coordination ideas and organizational capital views where non-technical complements are essential to realize IT returns, and skill-biased and task-biased technological change frameworks emphasizing complementarities rather than pure displacement. It challenges narratives in which "only coders are scarce" or where routine skills uniformly decline in value; these results show complementary scarcity and vintage-contingent scarcity.

Our third set of findings illustrate how firms invest in capital around skill mismatch. In Table 6, we see that firms facing higher mismatch increase capital investment, with a disproportionate rise in intangibles (training, software customization, organizational processes, marketing/sales), alongside tangible IT spending (hardware, software, equipment). This is consistent with the view that general-purpose technologies require sizable complementary investments before productivity gains materialize (Brynjolfsson et al., 2021). Our evidence suggests part of this response targets mismatch directly—e.g., worker training and process customization to align actual with desired skill inputs.

When the observed skill vector deviates from the desired vector implied by technology and prices, firms can (i) recompose labor through hiring/separation, or (ii) upgrade efficiency units of existing workers via training and organizational change. The tilt toward intangibles indicates firms are endogenously raising the efficiency weights of scarce skills and reshaping tasks to increase substitutability where possible—precisely the margins predicted by a CES-with-complements framework (need to flesh this out!). The investment response is also stronger where the U-shape is steeper (young/small/constrained firms), pointing to adjustment costs and the need to build organizational capital to unlock IT value.

The findings support complementarity between IT and intangibles, J-curve dynamics of

general purpose technology adoption, and models where productivity payoffs are realized only after organizational adaptation. It challenges "plug-and-play" views of technology and models with very high cross-skill substitutability, under which mismatch would be cheaply arbitraged by wages alone without needing intangible build-out.

[Add discussion of TFP findings, wage results, etc., theoretical models and cite relevant literature!]

[Add substantive section to discuss the various sources of measurement error and the ways that we address it in Table 7].

6 Conclusion

This paper presents new empirical findings that characterize the skill mismatch hypothesis in the context of firms' information technologies. Our conceptual framework uses a job search theoretic framework as a lens through which one can examine differences between firms' skill requirements and workers' skill portfolios. The empirical approach that we propose – using large language models and classification algorithms – to harmonize skill requirements across firms and produce measures of skill mismatch with newly hired employees, enables us to produce some of the first estimates of skill mismatch across companies that use different types of information technologies. Our results help support the view that skill adjustment lags can explain heterogeneity in productivity gains to information technology investments across firms.

References

Acemoglu, D. and Autor, D. (2011). *Chapter 12 - Skills, Tasks and Technologies: Implications for Employment and Earnings*, volume 4, Part B.

ACTFL (2019). Making languages our business: Addressing foreign language demand among U.S. employers.

Andreason, S. (2015). The soft skills gap. *Partners Update*.

Boston Consulting Group (2023). The global skills mismatch: Lost productivity and what to do about it. Technical report.

Brynjolfsson, E., Rock, D., and Syverson, C. (2021). The productivity j-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics*, 13(1).

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).

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

Fredriksson, P., Hensvik, L., and Skans, O. N. (2018). Mismatch of talent: Evidence on match quality, entry wages, and job mobility. *American Economic Review*, 108(11):3303–3338.

Hadlock, C. and Pierce, J. (2010). New evidence on measuring financial constraints: Moving beyond the kz index. *Review of Financial Studies*, 23(5).

Haskel, J. and Martin, C. (2011). Technology, wages, and skills.

Hershbein, B. and Kahn, L. (2018). Do recessions accelerate routine-biased technological change? evidence from vacancy postings. *American Economic Review*, 108(7):1732–1772.

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

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

McGuinness, S. and Ortiz, L. (2016). Skill gaps in the workplace: measurement, determinants and impacts. *Industrial Relations Journal*, 47(3):253–278.

McKinsey Global Institute (2024). America's small businesses: Time to think big. Technical report.

NFIB (2025). Small business economic trends report. https://www.nfib.com/surveys/small-business-economic-trends/. Monthly survey data on small business sentiment and hiring.

OECD (2019). *OECD Skills Outlook 2019: Thriving in a Digital World*. OECD Publishing,

Paris.

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

Rathelot, R. and van Rens, T. (2020). Rethinking the skills gap. *IZA World of Labor*.

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

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.

Şahin, A., Song, J., Topa, G., and Violante, G. L. (2014). Mismatch unemployment. *American Economic Review*, 104(11):3529–3564.

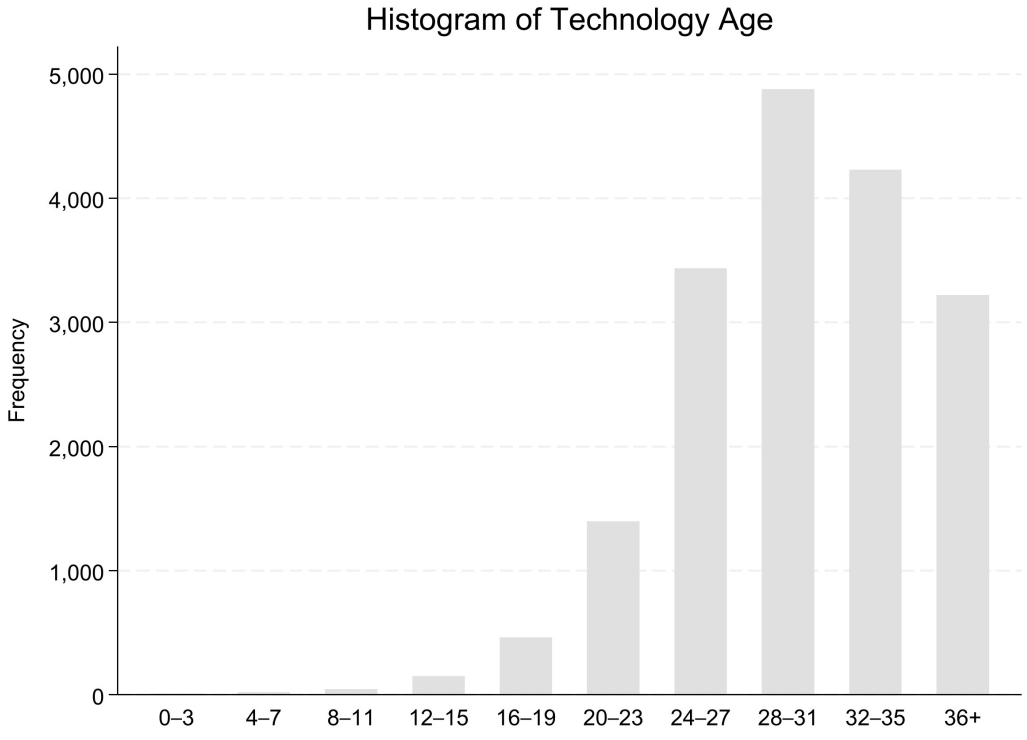


Figure 1: Skill Gaps by Firm Technology Age

Notes: This figure shows the histogram

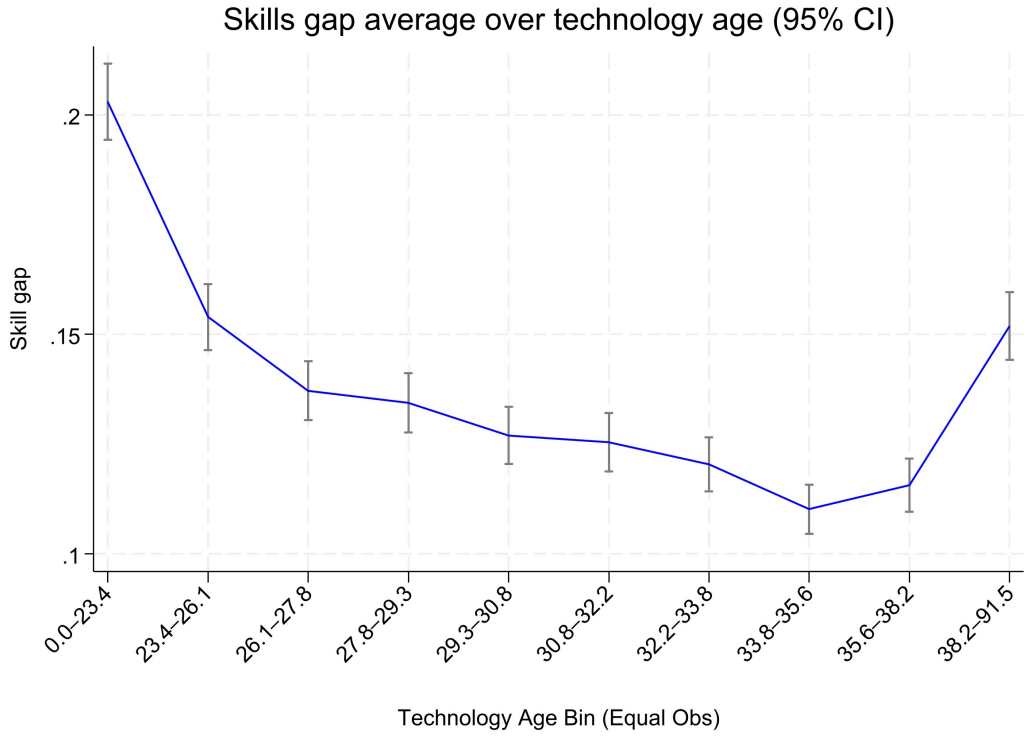


Figure 2: Skill Gaps by Firm Technology Age

Notes: This figure shows the relationship between firm technology age and average skill gaps. Technology age is measured as the vintage of the primary technologies used by the firm, with newer technologies corresponding to lower technology age values. The figure demonstrates that firms using newer technologies tend to experience larger skill gaps, consistent with the rapid evolution of skill requirements in technology-intensive industries.

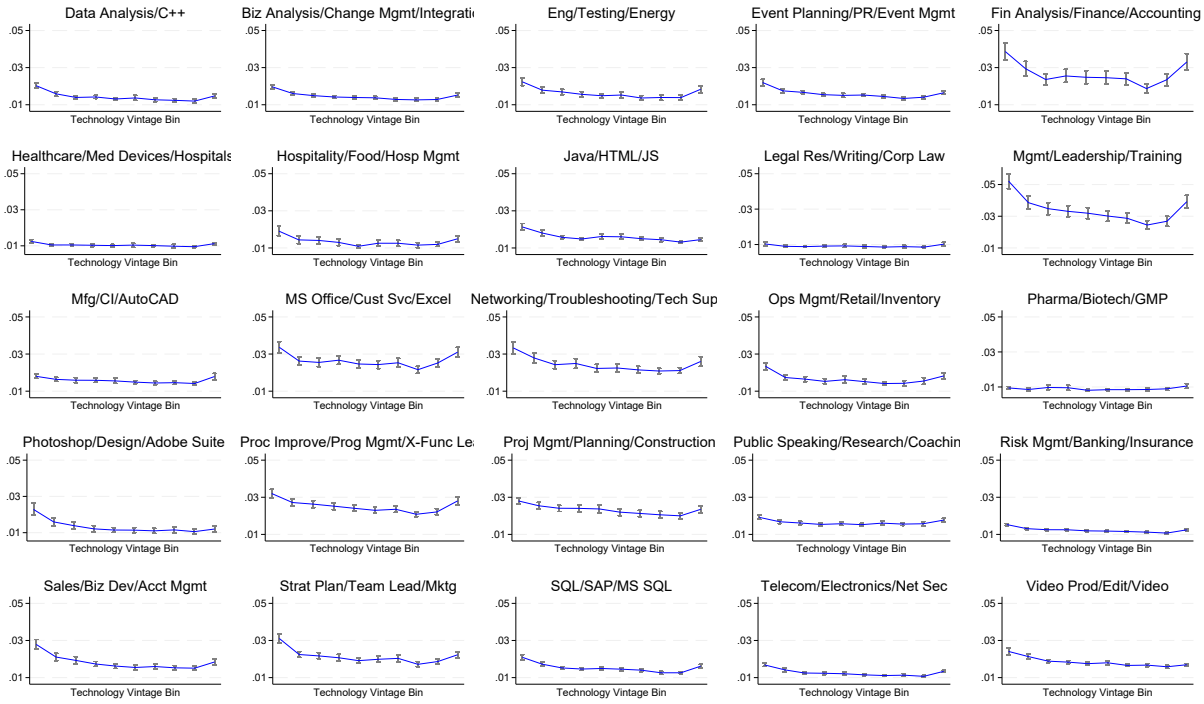


Figure 3: Distribution of Skill Gaps by Skill Category

Notes: This figure presents the distribution of skill gaps across different skill categories. Technical skills, particularly those related to data science, artificial intelligence, and advanced computing, show the largest average gaps. This pattern reflects the high demand for technical expertise coupled with limited supply of workers with these specialized skills.

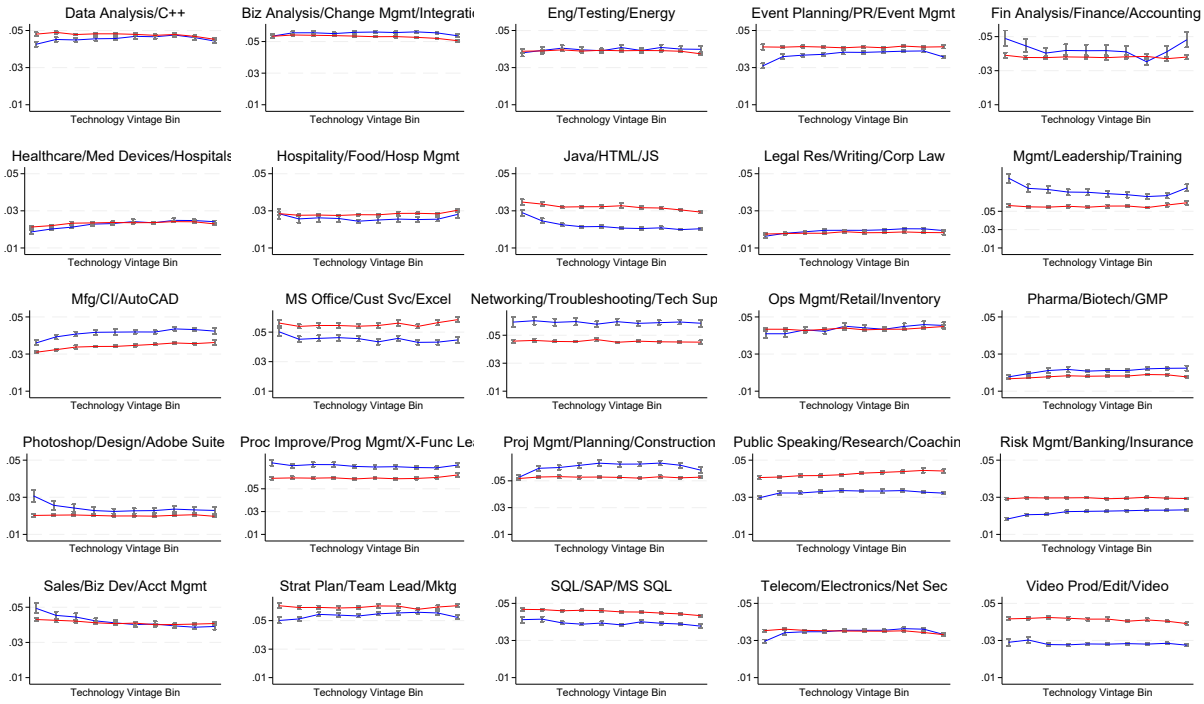


Figure 4: Distribution of Skill Gaps by Skill Category: Demand vs. Supply
Notes: This figure presents the distribution of skill demand (blue) and skill supply (red) across different skill categories. XXX

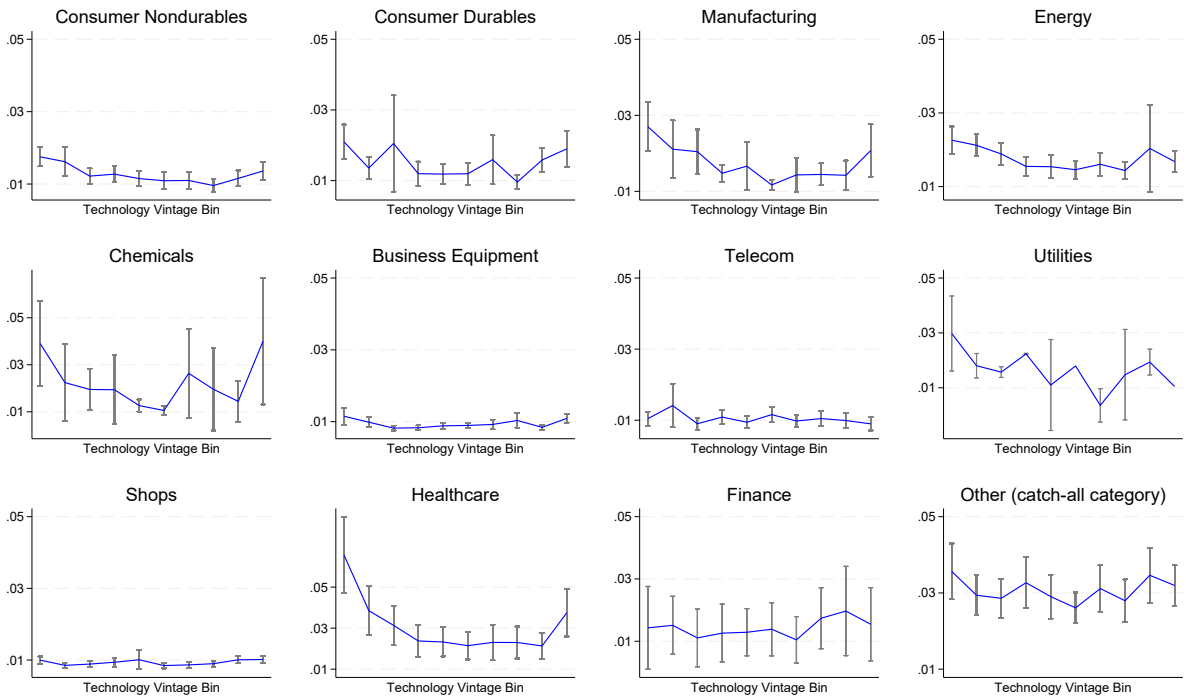


Figure 5: Distribution of Skill Gaps by Industries

Notes: This figure presents the distribution of skill gaps across different 12 Fama-French-defined industries. XXX

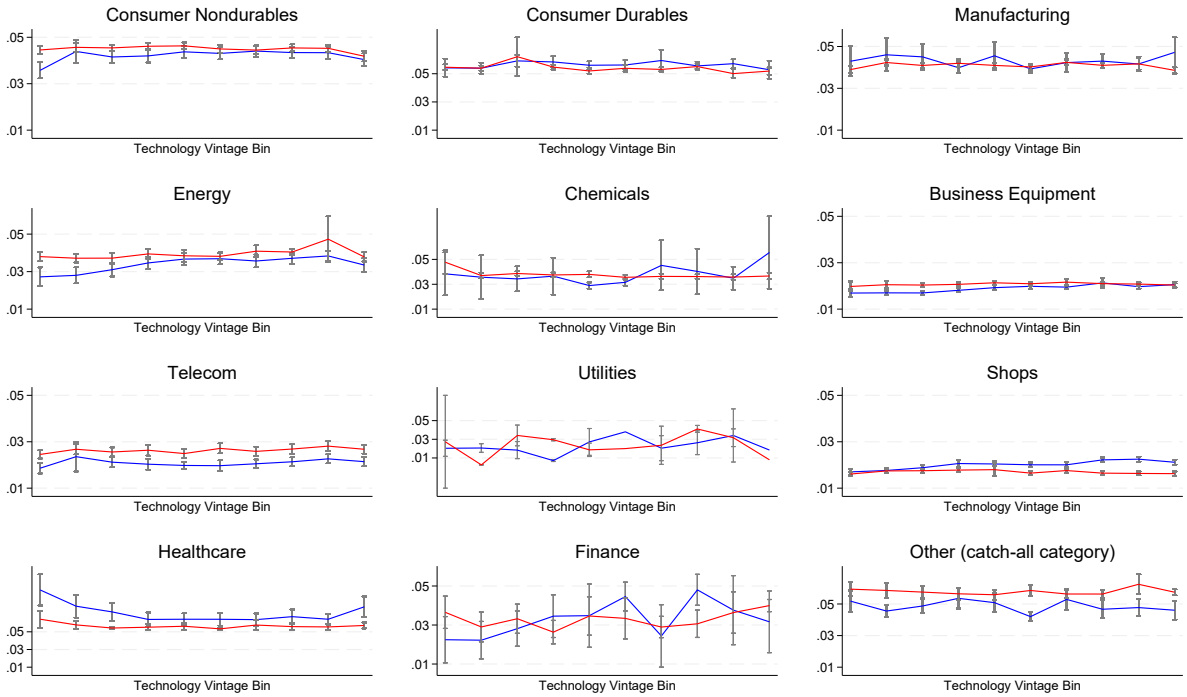


Figure 6: Distribution of Skill Gaps by Industries: Demand vs. Supply
Notes: This figure presents the distribution of skill demand (blue) and skill supply (red) across 12 Fama-French-defined industries. XXX

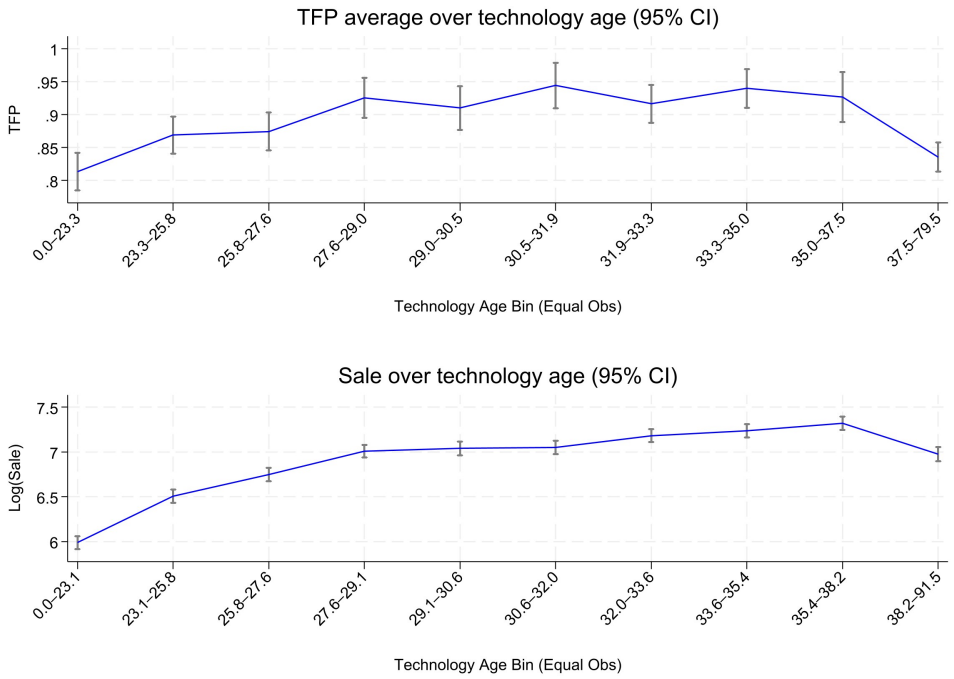


Figure 7: Relationship Between Skill Gaps and Firm Performance

Notes: This figure illustrates the negative relationship between skill gaps and two key measures of firm performance: sales growth (left panel) and total factor productivity (right panel). Firms with larger skill gaps tend to exhibit lower sales growth and reduced productivity, highlighting the economic consequences of skill mismatches.

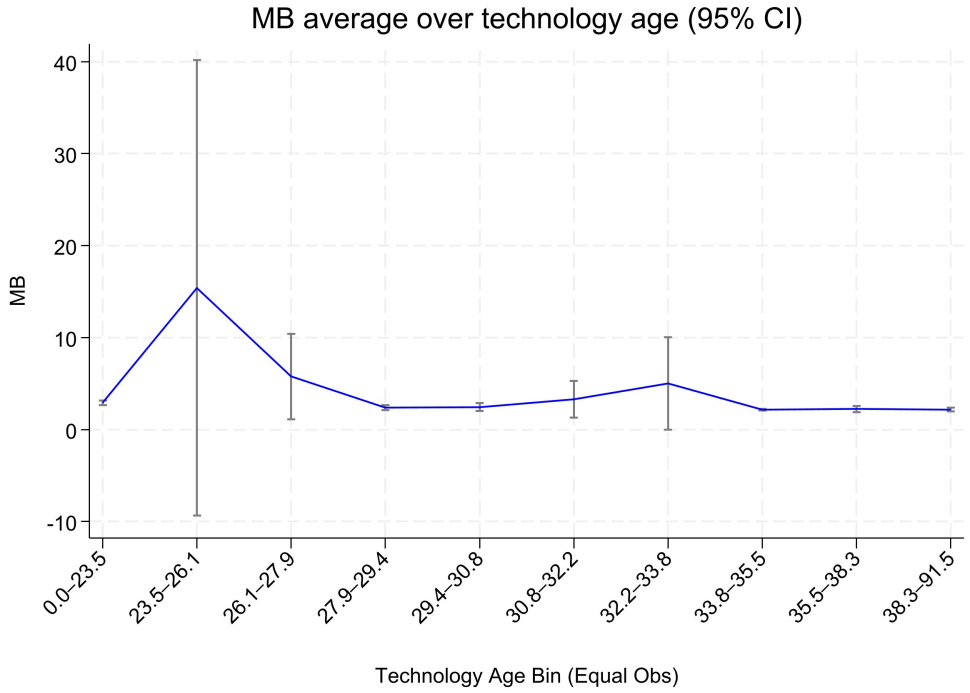


Figure 8: Market-to-Book Ratios by Technology Age and Skill Gaps

Notes: This figure shows how the relationship between technology age and market-to-book ratios varies by the magnitude of skill gaps. Firms with smaller skill gaps (blue line) are better able to capture the market value benefits of using newer technologies, while firms with larger skill gaps (red line) show weaker relationships between technology adoption and market valuation.

Table 1: Summary Statistics: Sample vs Population

Variable	N	Mean	Std Dev	p25	Median	p75
Panel A: Our Sample						
Skill gaps	22,467	0.159	0.166	0.0624	0.0762	0.201
Technology age	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
SA index	19,351	-3.858	0.603	-4.370	-3.904	-3.444
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
Total investment rate	18,990	0.149	0.126	0.0735	0.114	0.176
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
SA index	124,932	-2.900	1.521	-3.844	-3.231	-2.392
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
Total investment rate	95,830	0.225	0.355	0.0659	0.123	0.235

Notes: This table compares summary statistics between our analysis sample and the broader Compustat population. Sample period runs from year 2010 through year 2024. Skill Gap is our measure of firm-level skill mismatches. Technology age is XXX. 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. Our sample firms are generally larger and more productive than the average Compustat firm, reflecting the selection toward technology-intensive companies that are more likely to post jobs online and have employees with LinkedIn profiles. All dollar amounts are inflation-adjusted to 2010 dollars. All variables are winsorized at the 1st and 99th percentiles.

Table 2: Summary Statistics: Skill Gaps

#	Skill group	Variable	N	Mean	Std Dev	Min	Median	Max
1	Data Analysis / C++	Demand	22,467	0.0442	0.0250	0.0367	0.0458	0.0524
		Supply	22,467	0.0470	0.0132	0.0430	0.0478	0.0528
		Gap	22,467	0.0157	0.0230	0.00436	0.00979	0.0208
2	Biz Analysis / Change Mgmt / Integration	Demand	22,467	0.0543	0.0216	0.0469	0.0551	0.0628
		Supply	22,467	0.0524	0.0138	0.0471	0.0534	0.0591
		Gap	22,467	0.0158	0.0193	0.00493	0.0109	0.0207
3	Eng / Testing / Energy	Demand	22,467	0.0388	0.0389	0.0276	0.0374	0.0452
		Supply	22,467	0.0383	0.0169	0.0316	0.0380	0.0451
		Gap	22,467	0.0181	0.0372	0.00507	0.0112	0.0216
4	Event Planning / PR / Event Mgmt	Demand	22,467	0.0351	0.0253	0.0181	0.0400	0.0467
		Supply	22,467	0.0409	0.0183	0.0334	0.0409	0.0483
		Gap	22,467	0.0178	0.0256	0.00569	0.0127	0.0250
5	Fin Analysis / Finance / Accounting	Demand	22,467	0.0441	0.0861	0.0218	0.0296	0.0376
		Supply	22,467	0.0378	0.0279	0.0306	0.0368	0.0425
		Gap	22,467	0.0299	0.0850	0.00565	0.0123	0.0226
6	Healthcare / Med Devices / Hospitals	Demand	22,467	0.0225	0.0200	0.0132	0.0207	0.0290
		Supply	22,467	0.0232	0.0136	0.0164	0.0213	0.0283
		Gap	22,467	0.0114	0.0194	0.00385	0.00837	0.0146
7	Hospitality / Food / Hosp Mgmt	Demand	22,467	0.0294	0.0596	0.0165	0.0219	0.0284
		Supply	22,467	0.0287	0.0157	0.0218	0.0266	0.0331
		Gap	22,467	0.0174	0.0560	0.00403	0.00901	0.0166
8	Java / HTML / JS	Demand	22,467	0.0227	0.0217	0.0148	0.0193	0.0253
		Supply	22,467	0.0317	0.0212	0.0248	0.0310	0.0375
		Gap	22,467	0.0165	0.0266	0.00679	0.0131	0.0204
9	Legal Res / Writing / Corp Law	Demand	22,467	0.0185	0.0121	0.0121	0.0183	0.0241
		Supply	22,467	0.0179	0.0166	0.0128	0.0168	0.0217
		Gap	22,467	0.00956	0.0180	0.00348	0.00732	0.0127
10	Mgmt / Leadership / Training	Demand	22,467	0.0766	0.0865	0.0449	0.0543	0.0664
		Supply	22,467	0.0570	0.0374	0.0472	0.0520	0.0573
		Gap	22,467	0.0400	0.0872	0.00571	0.0128	0.0274
11	Mfg / CI / AutoCAD	Demand	22,467	0.0407	0.0299	0.0304	0.0394	0.0477
		Supply	22,467	0.0338	0.0163	0.0268	0.0335	0.0404

Continued on next page

Summary Statistics: Skill Gaps (continued)

#	Skill group	Variable	N	Mean	Std Dev	Min	Median	Max
		Gap	22,467	0.0170	0.0285	0.00567	0.0119	0.0207
12	MS Office / Cust Svc / Excel	Demand	22,467	0.0468	0.0476	0.0291	0.0381	0.0485
		Supply	22,467	0.0565	0.0413	0.0461	0.0512	0.0572
		Gap	22,467	0.0296	0.0560	0.00837	0.0175	0.0300
13	Networking / Troubleshooting / Tech Support	Demand	22,467	0.0583	0.0559	0.0428	0.0544	0.0649
		Supply	22,467	0.0452	0.0204	0.0399	0.0451	0.0507
		Gap	22,467	0.0263	0.0543	0.00768	0.0164	0.0284
14	Ops Mgmt / Retail / Inventory	Demand	22,467	0.0441	0.0427	0.0314	0.0412	0.0496
		Supply	22,467	0.0436	0.0153	0.0376	0.0434	0.0498
		Gap	22,467	0.0193	0.0398	0.00512	0.0113	0.0222
15	Pharma / Biotech / GMP	Demand	22,467	0.0206	0.0224	0.0140	0.0198	0.0249
		Supply	22,467	0.0178	0.0121	0.0135	0.0164	0.0203
		Gap	22,467	0.00963	0.0221	0.00331	0.00703	0.0118
16	Photoshop / Design / Adobe Suite	Demand	22,467	0.0244	0.0476	0.0134	0.0202	0.0259
		Supply	22,467	0.0203	0.0148	0.0136	0.0192	0.0249
		Gap	22,467	0.0147	0.0474	0.00395	0.00828	0.0144
17	Proc Improve / Prog Mgmt / X-Func Lead	Demand	22,467	0.0720	0.0440	0.0520	0.0634	0.0787
		Supply	22,467	0.0602	0.0279	0.0502	0.0575	0.0654
		Gap	22,467	0.0283	0.0447	0.00750	0.0163	0.0313
18	Proj Mgmt / Planning / Construction	Demand	22,467	0.0581	0.0447	0.0445	0.0608	0.0703
		Supply	22,467	0.0527	0.0210	0.0478	0.0525	0.0576
		Gap	22,467	0.0255	0.0425	0.00866	0.0178	0.0321
19	Public Speaking / Research / Coaching	Demand	22,467	0.0319	0.0191	0.0232	0.0320	0.0393
		Supply	22,467	0.0426	0.0192	0.0354	0.0430	0.0494
		Gap	22,467	0.0176	0.0228	0.00647	0.0136	0.0236
20	Risk Mgmt / Banking / Insurance	Demand	22,467	0.0211	0.0115	0.0138	0.0216	0.0277
		Supply	22,467	0.0295	0.0119	0.0242	0.0293	0.0350
		Gap	22,467	0.0132	0.0128	0.00498	0.0108	0.0192
21	Sales / Biz Dev / Acct Mgmt	Demand	22,467	0.0434	0.0460	0.0265	0.0377	0.0486

Continued on next page

Summary Statistics: Skill Gaps (continued)

#	Skill group	Variable	N	Mean	Std Dev	Min	Median	Max
		Supply	22,467	0.0416	0.0199	0.0341	0.0422	0.0485
		Gap	22,467	0.0211	0.0442	0.00561	0.0121	0.0225
22	Strat Plan / Team Lead / Mktg	Demand	22,467	0.0524	0.0356	0.0390	0.0530	0.0630
		Supply	22,467	0.0606	0.0314	0.0522	0.0576	0.0633
		Gap	22,467	0.0248	0.0416	0.00623	0.0140	0.0300
23	SQL / SAP / MS SQL	Demand	22,467	0.0394	0.0245	0.0292	0.0386	0.0468
		Supply	22,467	0.0449	0.0139	0.0390	0.0448	0.0513
		Gap	22,467	0.0166	0.0227	0.00545	0.0119	0.0221
24	Telecom / Electronics / Net Sec	Demand	22,467	0.0329	0.0196	0.0223	0.0367	0.0423
		Supply	22,467	0.0345	0.0113	0.0305	0.0350	0.0398
		Gap	22,467	0.0138	0.0169	0.00424	0.00974	0.0200
25	Video Prod / Edit / Video	Demand	22,467	0.0277	0.0229	0.0192	0.0268	0.0337
		Supply	22,467	0.0412	0.0205	0.0343	0.0401	0.0470
		Gap	22,467	0.0197	0.0264	0.00790	0.0159	0.0266

Table 3: Main Result: Skill Gaps vs Technology Vintage

	(1)	(2)	(3)	(4)	(5)	(6)
TechAge	-2.292***		-2.317***		-0.811***	
	(0.173)		(0.169)		(0.165)	
$TechAge^2$	3.464***		3.479***		1.241***	
	(0.271)		(0.262)		(0.254)	
TechAge2		-0.0445***		-0.0441***		-0.0120**
		(0.00650)		(0.00638)		(0.00573)
TechAge3		-0.0617***		-0.0621***		-0.0248***
		(0.00641)		(0.00629)		(0.00557)
TechAge4		-0.0608***		-0.0616***		-0.0220***
		(0.00654)		(0.00642)		(0.00585)
TechAge5		-0.0632***		-0.0652***		-0.0239***
		(0.00670)		(0.00659)		(0.00591)
TechAge6		-0.0625***		-0.0648***		-0.0208***
		(0.00700)		(0.00706)		(0.00636)
TechAge7		-0.0637***		-0.0654***		-0.0263***
		(0.00687)		(0.00687)		(0.00630)
TechAge8		-0.0713***		-0.0735***		-0.0246***
		(0.00707)		(0.00721)		(0.00651)
TechAge9		-0.0637***		-0.0660***		-0.0207***
		(0.00743)		(0.00766)		(0.00693)
TechAge10		-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	Industry	Industry	Firm	Firm

Notes: This table investigates how skill gaps vary across different technology vintage. TechAge 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 gaps first decrease with technology age (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 4: Firm Characteristics Analysis: Age, Size, and Financial Constraints - Industry FE

	(1)	(2)	(3)	(4)	(5)	(6)
	Firm Age		Size		SA Index	
	Young	Old	Small	Large	Sound	Constraint
TechAge2	-0.0209*	-0.0610***	-0.0262**	-0.0385***	-0.0504***	-0.0234*
	(0.0123)	(0.0161)	(0.0120)	(0.0117)	(0.0117)	(0.0127)
TechAge3	-0.0525***	-0.0997***	-0.0413***	-0.0389***	-0.0363***	-0.0489***
	(0.0123)	(0.0153)	(0.0132)	(0.0108)	(0.0118)	(0.0130)
TechAge4	-0.0422***	-0.0752***	-0.0482***	-0.0432***	-0.0569***	-0.0429***
	(0.0132)	(0.0160)	(0.0134)	(0.0125)	(0.0128)	(0.0133)
TechAge5	-0.0500***	-0.0837***	-0.0421***	-0.0547***	-0.0506***	-0.0404***
	(0.0139)	(0.0162)	(0.0134)	(0.0129)	(0.0136)	(0.0142)
TechAge6	-0.0584***	-0.102***	-0.0475***	-0.0475***	-0.0412***	-0.0453***
	(0.0137)	(0.0164)	(0.0144)	(0.0134)	(0.0137)	(0.0141)
TechAge7	-0.0548***	-0.0782***	-0.0583***	-0.0498***	-0.0512***	-0.0443***
	(0.0140)	(0.0178)	(0.0135)	(0.0131)	(0.0133)	(0.0151)
TechAge8	-0.0444***	-0.0875***	-0.0443***	-0.0500***	-0.0553***	-0.0288*
	(0.0145)	(0.0173)	(0.0149)	(0.0138)	(0.0138)	(0.0151)
TechAge9	-0.0629***	-0.0976***	-0.0438***	-0.0570***	-0.0487***	-0.0392**
	(0.0153)	(0.0178)	(0.0157)	(0.0143)	(0.0146)	(0.0164)
TechAge10	-0.0252	-0.0576***	-0.0138	-0.00533	-0.0124	0.000705
	(0.0163)	(0.0191)	(0.0166)	(0.0170)	(0.0158)	(0.0179)
Observations	4,619	2,899	4,296	4,525	4,567	4,328
R-squared	0.083	0.114	0.079	0.104	0.097	0.071
Year FE	YES	YES	YES	YES	YES	YES
Industry/Firm FE	Industry	Industry	Industry	Industry	Industry	Industry

Notes: This table investigates how skill gaps vary across different firm characteristics. TechAge is technology vintage, normalized by 100. Columns (1) and (2) splits by firm age. Columns (3) and (4) splits by size (total assets). Columns (5) and (6) splits by financial constraints using the SA index (Hadlock and Pierce, 2010), with low SA indicating financially sound firms and high SA indicating constrained firms. The results show that the U-shaped technology-skill gap relationship is strongest for financially constrained, smaller, and older firms, reflecting their greater difficulty in adapting to new technologies and acquiring appropriate skills. 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: Skill Gaps vs Technology Age by Skill Groups - Firm FE

	Skill #1	Skill #2	Skill #3	Skill #4	Skill #5	Skill #6	Skill #7
TechAge	-0.0692**	-0.0515*	-0.139***	-0.0237	-0.200**	-0.0185	-0.0187
	(0.0344)	(0.0264)	(0.0465)	(0.0264)	(0.0917)	(0.0168)	(0.0533)
TechAge^2	0.114**	0.0805**	0.221***	0.0339	0.331**	0.0349	0.0144
	(0.0553)	(0.0381)	(0.0684)	(0.0344)	(0.145)	(0.0240)	(0.0820)
Observations	17,800	17,800	17,800	17,800	17,800	17,800	17,800
R-squared	0.246	0.249	0.235	0.250	0.258	0.244	0.345
	Skill #8	Skill #9	Skill #10	Skill #11	Skill #12	Skill #13	
TechAge	-0.00813	-0.0108	-0.335***	0.0278	-0.0791	-0.161**	
	(0.0214)	(0.0141)	(0.111)	(0.0294)	(0.0571)	(0.0651)	
TechAge^2	0.0160	0.0111	0.497***	-0.0482	0.107	0.254***	
	(0.0303)	(0.0206)	(0.170)	(0.0475)	(0.0837)	(0.0967)	
Observations	17,800	17,800	17,800	17,800	17,800	17,800	
R-squared	0.337	0.198	0.280	0.249	0.302	0.255	
	Skill #14	Skill #15	Skill #16	Skill #17	Skill #18	Skill #19	
TechAge	-0.0981***	-0.0320**	-0.0303	-0.120**	-0.0217	-0.0343	
	(0.0372)	(0.0163)	(0.0518)	(0.0512)	(0.0344)	(0.0237)	
TechAge^2	0.136**	0.0633**	0.0568	0.190**	0.0461	0.0570	
	(0.0556)	(0.0285)	(0.0743)	(0.0785)	(0.0550)	(0.0359)	
Observations	17,800	17,800	17,800	17,800	17,800	17,800	
R-squared	0.243	0.320	0.230	0.226	0.276	0.210	
	Skill #20	Skill #21	Skill #22	Skill #23	Skill #24	Skill #25	
TechAge	-0.0282***	-0.152***	-0.0817**	-0.0709***	-0.0490***	-0.0216	
	(0.0102)	(0.0437)	(0.0394)	(0.0237)	(0.0150)	(0.0281)	
TechAge^2	0.0408**	0.217***	0.124**	0.116***	0.0726***	0.0253	
	(0.0158)	(0.0654)	(0.0582)	(0.0343)	(0.0218)	(0.0384)	
Observations	17,800	17,800	17,800	17,800	17,800	17,800	
R-squared	0.276	0.252	0.304	0.257	0.245	0.281	

Notes: This table investigates how skill gaps vary across technology vintage for each of the 25 skill groups individually. TechAge is technology vintage, normalized by 100. Each cell shows results from a separate regression with quadratic specification. The U-shaped relationship between technology vintage and skill gaps is present across most skill categories, but is strongest for technical skills (Skills #5, #10) related to finance, and management, and weakest for more traditional skills. The magnitude of coefficients indicates which skill areas face the most severe technology-driven mismatches. Table 2 in the appendix provides detailed definitions of each skill group. 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 6: Firm Investment vs Technology Vintages

	(1) Total Inv.	(2) Intangible Inv.	(3) Tangible Inv.	(4) Total Inv.	(5) Intangible Inv.	(6) Tangible Inv.
TechAge2	-0.0289***	-0.0246***	-0.00321	-0.0157***	-0.0105***	-0.00451***
	(0.00752)	(0.00646)	(0.00210)	(0.00417)	(0.00324)	(0.00160)
TechAge3	-0.0427***	-0.0378***	-0.00562**	-0.0192***	-0.0147***	-0.00519***
	(0.00780)	(0.00664)	(0.00222)	(0.00423)	(0.00318)	(0.00167)
TechAge4	-0.0530***	-0.0464***	-0.00559**	-0.0159***	-0.0113***	-0.00412**
	(0.00801)	(0.00694)	(0.00229)	(0.00387)	(0.00288)	(0.00168)
TechAge5	-0.0575***	-0.0501***	-0.00645***	-0.0145***	-0.0101***	-0.00376**
	(0.00779)	(0.00682)	(0.00222)	(0.00378)	(0.00285)	(0.00164)
TechAge6	-0.0603***	-0.0526***	-0.00708***	-0.0191***	-0.0125***	-0.00604***
	(0.00786)	(0.00689)	(0.00221)	(0.00383)	(0.00286)	(0.00166)
TechAge7	-0.0608***	-0.0551***	-0.00545**	-0.0137***	-0.00840***	-0.00503***
	(0.00803)	(0.00711)	(0.00232)	(0.00373)	(0.00276)	(0.00162)
TechAge8	-0.0652***	-0.0580***	-0.00622***	-0.0109***	-0.00718**	-0.00299*
	(0.00790)	(0.00703)	(0.00226)	(0.00387)	(0.00284)	(0.00172)
TechAge9	-0.0680***	-0.0622***	-0.00474**	-0.00691*	-0.00313	-0.00330*
	(0.00803)	(0.00717)	(0.00240)	(0.00377)	(0.00278)	(0.00175)
TechAge10	-0.0709***	-0.0660***	-0.00410	-1.05e-05	0.00109	-0.00131
	(0.00819)	(0.00721)	(0.00264)	(0.00389)	(0.00287)	(0.00182)
Observations	17,549	17,567	17,549	17,374	17,391	17,374
R-squared	0.187	0.275	0.173	0.772	0.851	0.638
Year FE	YES	YES	YES	YES	YES	YES
Ind/Firm FE	Ind	Ind	Ind	Firm	Firm	Firm

Notes: This table investigates how firm investment varies across technology vintage. TechAge is technology vintage normalized by 100. Column (2) shows intangible investment normalized by lagged total capital (intangible + tangible as defined by Peters and Taylor (2017). Column (3) shows tangible investment (CAPX) normalized by lagged tota capital. Column (1) shows total investment (intangible investment plus tangible investment). The results reveal negativ relationship between technology vintage and firm investment. Two-digit SIC industry fixed effects included. Standar errors are heteroskedasticity consistent and clustered by firm.

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

Table 7: Alternative Skill Gap Measure

	(1)	(2)	(3)	(4)	(5)	(6)
TechAge2	-0.0107	0.00357	0.0124	-0.00780	0.0148	-0.0164
	(0.0166)	(0.0161)	(0.0160)	(0.0106)	(0.0210)	(0.0161)
TechAge3	-0.0252	-0.0120	-0.0180	-0.0142	0.0351*	-0.0284*
	(0.0164)	(0.0159)	(0.0158)	(0.0105)	(0.0208)	(0.0160)
TechAge4	-0.0189	0.000330	-0.00633	-0.0118	0.0293	-0.0240
	(0.0168)	(0.0163)	(0.0162)	(0.0108)	(0.0213)	(0.0164)
TechAge5	-0.0357**	-0.00636	-0.0296*	-0.0285***	0.0559***	-0.0428***
	(0.0164)	(0.0159)	(0.0158)	(0.0105)	(0.0208)	(0.0160)
TechAge6	-0.0334**	-0.0260*	-0.0260*	-0.0268***	0.0492**	-0.0417***
	(0.0162)	(0.0157)	(0.0156)	(0.0104)	(0.0205)	(0.0158)
TechAge7	-0.0315*	-0.0260*	-0.0213	-0.0202*	0.0479**	-0.0386**
	(0.0162)	(0.0156)	(0.0156)	(0.0104)	(0.0205)	(0.0157)
TechAge8	-0.0387**	-0.0388**	-0.0423***	-0.0316***	0.0602***	-0.0512***
	(0.0160)	(0.0155)	(0.0154)	(0.0102)	(0.0203)	(0.0156)
TechAge9	-0.0279*	-0.0237	-0.0142	-0.0268***	0.0380*	-0.0345**
	(0.0160)	(0.0156)	(0.0154)	(0.0102)	(0.0202)	(0.0155)
TechAge10	-0.00519	0.0164	-0.000590	-0.00955	0.0137	-0.0133
	(0.0162)	(0.0157)	(0.0156)	(0.0104)	(0.0205)	(0.0158)
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 gap measures for year 2020. Column (1) shows our benchmark result. Column (2) uses skill gap 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 simiarlity. 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.

Appendix for "Skill Gaps and Technology Adoption"

by Ashwini Agrawal, Daniel Kim, and Prasanna Tambe

A Variable definitions

- *Skill gaps*: XXX
- *Technology vintage*: As in Tambe (2014)
- 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: Skill Gap and Firm Performance

	(1) TFP	(2) Log(Sales)	(3) Profitability
Skill gap	-0.150***	-2.182***	-0.0404***
	(0.0450)	(0.148)	(0.00826)
Observations	14,038	19,350	19,461
R-squared	0.036	0.199	0.056
Year FE	YES	YES	YES
Industry FE	YES	YES	YES

Notes: This table studies whether skill gap negatively affect performance. This table uses three measures for firm performance. Column (1) uses TFP, as constructed by Imrohoroglu and Tuzel (2014). Column (2) uses Log of sale. Column (3) uses profitability. Standard errors are clustered by firm. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A2: Skill Gap and Wage

	(1) Log(Salary)	(2) Log(1+Salary range)
Skill gap	-0.118***	0.404
	(0.0421)	(0.382)
Observations	3,482	3,822
R-squared	0.571	0.418
Year FE	YES	YES
Firm FE	YES	YES
Occupation FE	YES	YES

Notes: This table examines whether skill gaps negatively affect wages. The unit of observation is firm–year–occupation, using data from 2020. Occupations are defined at the 2-digit ONET code level. Salary refers to the wage posted in job postings. Salary range is measured as the difference between the posted upper and lower bounds, averaged at the firm–year–occupation level. Standard errors are clustered by firm. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A3: Skill Gaps vs Technology Vintage by Skill Groups: #1 − #7

	Skill #1	Skill #2	Skill #3	Skill #4	Skill #5	Skill #6	Skill #7
TechAge2	-0.00131	-0.000680	-0.00257*	-0.000688	-0.00393	-0.000773	0.00044
	(0.000837)	(0.000763)	(0.00140)	(0.00106)	(0.00327)	(0.000642)	(0.00175
TechAge3	-0.00263***	-0.000971	-0.00304**	-0.00106	-0.00907***	-0.000668	0.00088
	(0.000766)	(0.000719)	(0.00154)	(0.00112)	(0.00302)	(0.000740)	(0.00166
TechAge4	-0.00196**	-0.00156**	-0.00412***	-0.00162	-0.00632*	-0.000144	-0.00010
	(0.000821)	(0.000767)	(0.00156)	(0.00116)	(0.00337)	(0.000702)	(0.00177
TechAge5	-0.00207**	-0.000586	-0.00409***	-0.00258**	-0.00627*	-0.000240	-0.00239
	(0.000844)	(0.000758)	(0.00153)	(0.00122)	(0.00329)	(0.000701)	(0.00165
TechAge6	-0.000918	-0.000354	-0.00314*	-0.000742	-0.00559	-7.31e-05	-0.00037
	(0.00107)	(0.000809)	(0.00181)	(0.00144)	(0.00352)	(0.000903)	(0.00197
TechAge7	-0.00184*	-0.00147*	-0.00460***	-0.00184	-0.00804**	-3.04e-05	-0.00128
	(0.00106)	(0.000754)	(0.00174)	(0.00140)	(0.00348)	(0.000690)	(0.00204
TechAge8	-0.00196*	-0.000842	-0.00291	-0.00214	-0.00790**	0.000154	-0.00204
	(0.00107)	(0.000891)	(0.00187)	(0.00152)	(0.00355)	(0.00107)	(0.00209
TechAge9	-0.00119	-0.000466	-0.00266	-0.00136	-0.00481	-6.45e-05	-0.00086
	(0.00116)	(0.000870)	(0.00190)	(0.00158)	(0.00378)	(0.000848)	(0.00215
TechAge10	-0.000510	-0.000282	-0.000683	-0.00155	-0.00248	0.000696	-0.00137
	(0.00112)	(0.000880)	(0.00212)	(0.00172)	(0.00415)	(0.000855)	(0.00249
Observations	17,800	17,800	17,800	17,800	17,800	17,800	17,800
R-squared	0.246	0.250	0.235	0.251	0.259	0.244	0.346
Year FE	YES	YES	YES	YES	YES	YES	YES
Ind/Firm FE	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Notes: This table investigates how skill gaps vary across technology vintage for each of the 25 skill groups individual TechAge is technology vintage, normalized by 100. Each cell shows results from a separate regression with quadratic sp ification. The U-shaped relationship between technology vintage and skill gaps is present across most skill categories, b is strongest for technical skills (Skills #1, #5, #10) related to data analytics, finance, and management, and weakest more traditional skills. The magnitude of coefficients indicates which skill areas face the most severe technology-driven m matches. Table 2 provides detailed definitions of each skill group. Two-digit SIC industry fixed effects included. Standa errors are heteroskedasticity consistent and clustered by firm.

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

Table A4: Skill Gaps vs Technology Vintage by Skill Groups: #8 – #13

	Skill #8	Skill #9	Skill #10	Skill #11	Skill #12	Skill #13
TechAge2	-0.000105	-0.000680	-0.00338	0.000413	-0.00255	-0.000658
	(0.00110)	(0.000674)	(0.00353)	(0.000843)	(0.00205)	(0.00225)
TechAge3	-0.00120	-0.00104	-0.00715**	0.000640	-0.00241	-0.00421*
	(0.000942)	(0.000790)	(0.00354)	(0.00106)	(0.00196)	(0.00238)
TechAge4	-0.00218**	-0.000636	-0.00769**	0.000650	-0.00108	-0.00211
	(0.00100)	(0.000822)	(0.00353)	(0.00103)	(0.00220)	(0.00238)
TechAge5	-8.93e-06	-0.000840	-0.00762**	0.000240	-0.00245	-0.00395
	(0.00106)	(0.000985)	(0.00363)	(0.00103)	(0.00219)	(0.00247)
TechAge6	0.000339	-0.00128	-0.00819**	-0.000357	-0.00273	-0.00277
	(0.00122)	(0.00104)	(0.00367)	(0.00104)	(0.00230)	(0.00269)
TechAge7	-0.000877	-0.00162	-0.00926**	-0.00114	-0.00266	-0.00351
	(0.000993)	(0.000986)	(0.00373)	(0.00106)	(0.00230)	(0.00252)
TechAge8	-0.000350	-0.00122	-0.0102***	9.42e-05	-0.00432*	-0.00227
	(0.00111)	(0.00108)	(0.00385)	(0.00123)	(0.00233)	(0.00257)
TechAge9	-0.00109	-0.00165	-0.00894**	-0.00157	-0.00296	-0.00151
	(0.00104)	(0.00116)	(0.00413)	(0.00139)	(0.00256)	(0.00263)
TechAge10	2.38e-05	-0.00151	-0.00769*	-0.000164	-0.00258	0.000764
	(0.00115)	(0.00131)	(0.00431)	(0.00173)	(0.00286)	(0.00295)
Observations	17,800	17,800	17,800	17,800	17,800	17,800
R-squared	0.337	0.198	0.280	0.250	0.302	0.255
Year FE	YES	YES	YES	YES	YES	YES
Ind/Firm FE	Firm	Firm	Firm	Firm	Firm	Firm

Notes: This table investigates how skill gaps vary across technology vintage for each of the 25 skill groups individually. TechAge is technology vintage, normalized by 100. Each cell shows results from a separate regression with quadratic specification. The U-shaped relationship between technology vintage and skill gaps is present across most skill categories, but is strongest for technical skills (Skills #1, #5, #10) related to data analytics, finance, and management, and weakest for more traditional skills. The magnitude of coefficients indicates which skill areas face the most severe technology-driven mismatches. Table 2 provides detailed definitions of each skill group. 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: Skill Gaps vs Technology Vintage by Skill Groups: #14 – #19

	Skill #14	Skill #15	Skill #16	Skill #17	Skill #18	Skill #19
TechAge2	-0.00273**	-0.000498	-0.00117	-0.000957	0.00153	-0.000654
	(0.00135)	(0.000579)	(0.00206)	(0.00164)	(0.00134)	(0.000771)
TechAge3	-0.00337**	0.000218	-0.00246	-0.000584	0.000626	-0.00107
	(0.00135)	(0.000771)	(0.00204)	(0.00160)	(0.00127)	(0.000859)
TechAge4	-0.00452***	0.000560	-0.00200	-0.000683	0.00101	-0.00137
	(0.00139)	(0.000858)	(0.00222)	(0.00167)	(0.00145)	(0.000912)
TechAge5	-0.00369**	-0.000600	-0.00242	-0.00234	0.00151	-0.00132
	(0.00168)	(0.000658)	(0.00207)	(0.00166)	(0.00166)	(0.000998)
TechAge6	-0.00395**	1.01e-05	-0.00229	-0.00274*	0.000700	-0.00228**
	(0.00160)	(0.000689)	(0.00210)	(0.00165)	(0.00155)	(0.00101)
TechAge7	-0.00517***	-0.000238	-0.00150	-0.00114	3.91e-05	-0.000708
	(0.00163)	(0.000679)	(0.00228)	(0.00182)	(0.00167)	(0.00115)
TechAge8	-0.00381**	-0.000496	-1.60e-05	-0.00239	-8.06e-05	-0.000894
	(0.00176)	(0.000806)	(0.00225)	(0.00177)	(0.00161)	(0.00107)
TechAge9	-0.00314	-0.000210	-0.000811	-0.00201	-0.000349	-0.00112
	(0.00194)	(0.000726)	(0.00240)	(0.00190)	(0.00179)	(0.00107)
TechAge10	-0.00379**	0.00149	5.38e-05	0.000399	0.00230	-0.000798
	(0.00193)	(0.000907)	(0.00252)	(0.00216)	(0.00222)	(0.00125)
Observations	17,800	17,800	17,800	17,800	17,800	17,800
R-squared	0.244	0.320	0.230	0.226	0.276	0.210
Year FE	YES	YES	YES	YES	YES	YES
Ind/Firm FE	Firm	Firm	Firm	Firm	Firm	Firm

Notes: This table investigates how skill gaps vary across technology vintage for each of the 25 skill groups individually. TechAge is technology vintage, normalized by 100. Each cell shows results from a separate regression with quadratic specification. The U-shaped relationship between technology vintage and skill gaps is present across most skill categories, but is strongest for technical skills (Skills #1, #5, #10) related to data analytics, finance, and management, and weakest for more traditional skills. The magnitude of coefficients indicates which skill areas face the most severe technology-driven mismatches. Table 2 provides detailed definitions of each skill group. 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 A6: Skill Gaps vs Technology Vintage by Skill Groups: #20 – #25

	Skill #20	Skill #21	Skill #22	Skill #23	Skill #24	Skill #25
TechAge2	-0.000659*	-0.00240	-0.00173	-0.00134	-0.000350	-0.000142
	(0.000396)	(0.00195)	(0.00150)	(0.00101)	(0.000761)	(0.00112)
TechAge3	-0.000794**	-0.00388**	-0.00259*	-0.00245***	-0.00153***	-0.00181
	(0.000381)	(0.00179)	(0.00141)	(0.000912)	(0.000585)	(0.00117)
TechAge4	-0.000683	-0.00502***	-0.00235	-0.00246**	-0.00100	-0.00163
	(0.000481)	(0.00170)	(0.00158)	(0.000967)	(0.000618)	(0.00135)
TechAge5	-0.000999**	-0.00484***	-0.00286*	-0.00151	-0.000853	-0.00196
	(0.000406)	(0.00176)	(0.00152)	(0.00101)	(0.000727)	(0.00123)
TechAge6	-0.000822**	-0.00466***	-0.00207	-0.00133	-0.00137**	-0.00169
	(0.000419)	(0.00180)	(0.00158)	(0.00103)	(0.000621)	(0.00134)
TechAge7	-0.00101**	-0.00474**	-0.00148	-0.00130	-0.00156**	-0.00227*
	(0.000427)	(0.00191)	(0.00190)	(0.00109)	(0.000665)	(0.00128)
TechAge8	-0.000710	-0.00416**	-0.00274	-0.00196*	-0.00125*	-0.00121
	(0.000452)	(0.00187)	(0.00173)	(0.00113)	(0.000667)	(0.00129)
TechAge9	-0.00114**	-0.00432**	-0.00117	-0.00143	-0.00141**	-0.00204
	(0.000475)	(0.00204)	(0.00176)	(0.00114)	(0.000703)	(0.00139)
TechAge10	-0.000851	-0.00345	-0.00128	0.000244	-0.000724	-0.00230*
	(0.000529)	(0.00219)	(0.00183)	(0.00136)	(0.000674)	(0.00131)
Observations	17,800	17,800	17,800	17,800	17,800	17,800
R-squared	0.276	0.252	0.304	0.257	0.245	0.281
Year FE	YES	YES	YES	YES	YES	YES
Ind/Firm FE	Firm	Firm	Firm	Firm	Firm	Firm

Notes: This table investigates how skill gaps vary across technology vintage for each of the 25 skill groups individually. TechAge is technology vintage, normalized by 100. Each cell shows results from a separate regression with quadratic specification. The U-shaped relationship between technology vintage and skill gaps is present across most skill categories, but is strongest for technical skills (Skills #1, #5, #10) related to data analytics, finance, and management, and weakest for more traditional skills. The magnitude of coefficients indicates which skill areas face the most severe technology-driven mismatches. Table 2 provides detailed definitions of each skill group. 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 A7: Top 7 Software Used in Each TechAge Bins

Rank	TechAge1: less than 23.4	TechAge2: (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	TechAge3: (26.1, 27.8)	TechAge4: (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	TechAge5: (29.3, 30.8)	TechAge6: (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	TechAge7: (32.2, 33.8)	TechAge8: (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	TechAge9: (35.6, 38.2)	TechAge10: 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)