Intangible Capital Meets Skilled Labor: The Implications for Productivity Dynamics*

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Abstract

This paper empirically and theoretically studies the synergy between intangible capital and skilled labor and its relationship with increasing productivity dispersion across U.S. firms. Our empirical findings reveal that firms with higher intangible capital ratio and skill ratio achieve higher labor productivity. This relationship is further magnified by firm size, leading to increased productivity dispersion. To rationalize the reduced-form empirical evidence, we first outline a stylized model that explains the channels through which firms with higher intangible capital benefit from skilled labor. We then develop a firm-level general equilibrium model with non-homothetic constant elasticity of substitution production technology that integrates the complementarity between intangible capital and skilled labor, along with economies of scale. Our model elucidates how economies of scale enhance this complementarity within the firm-level production framework.

Keywords: Productivity Dispersion, Intangible Capital, Skilled Labor, Economies of Scale

JEL codes: D22, D24, E22, J24, O33

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1 Introduction

Recent literature highlights a significant increase in productivity dispersion among U.S. firms, with evidence showing that this growing disparity is primarily driven by the rising relative productivity of large firms (Andrews et al. (2016), Decker et al. (2018), Akcigit and Ates (2023)). This trend is often attributed to various factors. One perspective suggests that diminished competitiveness, due to stringent regulations, has empowered large incumbent firms with increased market power (Gutiérrez and Philippon (2017)). Conversely, another view posits that sectors experiencing stronger growth in productivity simultaneously witness higher concentration (Bessen (2017), Autor et al. (2020)). Despite these insights, the causes and mechanisms underlying the increasing productivity dispersion remain debated. Concurrently, the U.S. economy has been experiencing two other notable trends. First, there has been an increase in skill-biased technological change (Acemoglu (1998), Krusell et al. (2000), Violante (2008)). Second, there has been a dramatic rise in intangible capital, including information technology, knowledge, human, and organizational capital (Corrado et al. (2009), Haskel and Westlake (2017), among others). In this paper, we investigate the role of synergy between intangible capital and skilled labor in explaining the productivity dispersion observed across heterogeneous firms.

We argue that trends in intangible capital and skilled labor collectively shape firm-level productivity dynamics. Intangible capital, including intellectual property, brand value, and organizational knowledge, has become a crucial driver of economic growth. Skilled labor, with its specialized knowledge and capabilities, plays a pivotal role in managing and utilizing this intangible capital. Hence, we hypothesize and explore the existence of synergy between intangible capital and skilled labor, based on the premise that the effective utilization of intangible capital requires skilled labor. This synergy impacts firm-level productivity by enhancing the efficiency of converting inputs into outputs. In this context, we define the synergy (a term consistently used throughout the paper) between intangible capital and skilled labor as the positive and significant association of their joint presence with firm-level productivity.

Our approach examines how the association between synergy and productivity varies across the firm-size distribution, considering economies of scale as a crucial factor influencing this synergy. Our motivation is rooted in the scalability and non-rivalrous nature of intangible capital, which provides larger firms with a greater advantage in leveraging intangible assets across multiple business lines and units (see Crouzet et al. (2022a) for further discussion). In other words, large firms benefit disproportionately from rising intangible capital by combining it with skilled labor, enabling them to scale up and enhance their productivity.

We explore several questions: Through which channels do firms effectively leverage their intangible capital to achieve productivity gains? What role does skilled labor play in the relationship between intangible capital and productivity? How significant is firm-size heterogeneity for this synergy? To address these questions, we introduce a new channel of synergy between intangible capital and skilled labor, aiming to partially explain productivity dispersion in the U.S. economy. Although our study has some limitations, as discussed in Section 8, it represents one of the first attempts to investigate the role of synergy between rising intangible capital and the skill ratio on firm-level productivity, emphasizing its heterogeneous implications across different firm sizes.

We approach these questions based on our central argument that skilled labor is essential for implementing high-stakes intangible capital. Firms typically invest in intangible capital to enhance productivity, but this process involves more than just developing software or advertising goods and services. To effectively utilize high-stakes intangible capital and achieve optimal production capacity, firms need skilled workers, thereby establishing synergy between intangible capital and skilled labor. Additionally, we argue that the degree of synergy and its impact on productivity are amplified by firm size. This is due to the scalability and non-rivalrous nature of intangible capital, which highlights the importance of economies of scale. For instance, among large firms in the U.S. economy, Amazon employs numerous Ph.D. researchers to analyze and operationalize crucial consumer data, while Microsoft hires many IT engineers to leverage its extensive software investments. As anecdotal evidence, Table 1 reports the average intangible capital ratio and skill ratio for a selection of well-known large firms in the U.S. economy. We observe that these large firms exhibit both a high intangible capital ratio and a high skill ratio, surpassing the average for the economy.

Table 1: Anecdotal Evidence on the Intangible Capital Ratio and Skill Ratio

Firm Name	Intangible Capital Ratio	Skill Ratio	Intangible Capital	Skilled Labor
Amazon	0.73	0.46	Consumer data	Ph.D. researchers
Apple	0.77	0.47	Design	Product designer
Google	0.68	0.54	Branding	Data analytics
IBM	0.85	0.47	R&D	Inventors
Microsoft	0.85	0.72	Software	IT engineer
Economy Average	0.53	0.3		

Note: This table shows the average intangible capital ratio and skill ratio for selected well-known large firms in the U.S economy.

We examine the specific channel of intangible capital-skilled labor synergy using both empirical and theoretical frameworks. After documenting several motivating stylized facts from the data sample, our empirical analysis quantifies the association between intangible capital-skilled labor synergy and firm-level productivity. Next, we outline a stylized model and then develop a firm-level general equilibrium model that incorporates the role of synergy between intangible capital and skilled labor, along with economies of scale, on firm-level production dynamics.

Utilizing firm-level measures from Compustat and industry-level variables from Quarterly Workforce Indicators (QWI), we document four main stylized facts: (i) increasing productivity dispersion driven by large firms, (ii) rising intangible capital in large firms, (iii) higher skill ratio in large and intangible firms, and (iv) higher productivity in large firms with higher intangible capital ratio and skill ratio. We interpret these stylized facts as indicative of a potential synergy between intangible capital and skilled labor and emphasize the importance of economies of scale in influencing the degree of this synergy and its impact on productivity.

The next section of the empirical analysis develops a more systematic approach through reduced-form regression analysis, quantifying the main insights captured by the stylized data facts. First, we estimate the association between firm-level intangible capital and skill ratio. We find that a one-standard-deviation increase in the intangible capital ratio is associated with an increase of up to 0.60 standard deviations in the skill ratio, which translates to an increase of 0.11 in the skill ratio, depending on different fixed effects. This association is further amplified by firm size; in other words, larger firms with higher intangible capital ratio are more likely to exhibit higher skill ratio. Second, we quantify the association between the synergy of intangible capital and skilled labor and firm-level productivity. We demonstrate that firms with higher intangible capital ratio and skill ratio have higher productivity, and this association is magnified by firm size. A one-standard-deviation increase in the firm-level skill ratio is associated with up to a 3.4% increase in firm-level labor productivity, while a one-standard-deviation increase in the f

To empirically quantify the synergy between intangible capital and the skill ratio, we investigate how their joint interaction is associated with firm-level productivity. We find that the coefficient of the interaction term becomes positive and significant for larger firms. This indicates that a one-standard-deviation joint increase in the intangible capital ratio and skill ratio is associated with an approximate 2% increase in firm-level labor productivity for large firms.

This set of empirical results aligns with our hypothesis and provides several insights. Firstly, it indicates a significant synergy between intangible capital and skilled labor. Secondly, the association between the synergy and productivity varies across the firm-size distribution, with larger firms experiencing greater productivity gains. This suggests that larger firms are better positioned to leverage this synergy to enhance their productivity. Therefore, our findings highlight a specific channel through which the synergy between intangible capital and skilled labor contributes to the observed increase in productivity dispersion, particularly benefiting larger firms.

Since we are unable to measure skill composition precisely at the firm level, we take an additional step by providing a micro-founded approach and a more detailed measure of skill composition. We conduct supplementary analyses to complement our benchmark approach by examining the synergy between intangible capital and inventors in relation to productivity dynamics. This complementary approach utilizes individual-level disaggregated data to identify variations in skill components at both the firm and inventor levels, using USPTO patent and inventor data merged with Compustat. This methodology allows us to capture a more granular level of skill components and validate our benchmark mechanism. In this additional analysis, we investigate how the accumulation of intangible capital influences inventor reallocation across firms, focusing on inventor mobility. We find that while mobility to firms with lower intangible capital has declined, particularly after the 2000s when productivity dispersion increased, there has been no decline in mobility to firms with higher intangible capital during that period. This suggests a synergy between intangible capital and skilled inventors, aligning with our baseline evidence. Motivated by this finding, we further explore how intangible capital is associated with inventors' productivity across different firm sizes. Our results indicate that inventors produce more patents when they move to larger firms with higher intangible capital, suggesting that the synergy between intangible capital and skilled inventors is especially pronounced in large firms, thus confirming our benchmark empirical evidence.

To rationalize our reduced-form empirical evidence, we first present a simple industry-level model that provides a basic explanation for our findings, specifically detailing how firms with higher intangible capital benefit from skilled labor. Our aim is to develop a basic model that integrates intangible capital into the conventional production framework, reflecting its growing significance as a factor of production in the real economy. To achieve this, we adapt and simplify the model proposed by Acemoglu and Autor (2011). In our motivating model, the primary channel through which the accumulation of intangible capital attracts skilled labor is driven by changes in skill premia resulting from shifts in the relative demand for skilled labor due to increased intangible capital intensity in the economy. The model predicts that an increase in intangible capital intensity also raises the skill premium. We empirically test this basic model prediction using the NBER-CES database to measure industry-level skill premiums and unskilled-to-skilled labor ratio at the industry (4-digit *NAICS*) level. Our findings reveal that an increase in the intangible capital ratio is positively and significantly associated with the industry-level skill premium. Furthermore, our regression coefficients align with the elasticity of substitution parameter between skilled and unskilled workers at the industry level, as derived in existing related studies. This alignment suggests that our method of incorporating intangible capital into the standard production framework captures well-established parameters in the literature, supporting the plausibility of our motivating model framework. Additionally, our model provides an alternative approach for identifying unobserved skill-specific total factor productivity (TFP). While Acemoglu and Autor (2011) and many other standard approaches rely on proxies to measure unobserved skill-specific TFP, our approach addresses this by precisely measuring both intangible and tangible capital stocks, which are observable, and incorporating them into the industry-level skill-biased technical change framework developed by Acemoglu and Autor (2011).

Building on the insights and plausibility derived from the motivating model, we develop an extended version using a firm-level general equilibrium model that incorporates heterogeneous firms investing in intangible capital and hiring both skilled and unskilled labor. Our primary goal is to construct a model framework that elucidates how economies of scale shape the complementarity within the firm-level production framework, allowing us to align with our related empirical evidence. The model features a non-homothetic constant elasticity of substitution (CES) production technology to highlight the importance of intangible capital-skilled labor complementarity along with economies of scale. In this sense, our model heavily builds on the framework developed by Eckert et al. (2022), extending a neoclassical production function with capital-labor complementarity based on their insights.

The model comprises three main components: (i) A representative final goods producer who manufactures goods using a combination of varieties produced by intermediate input producers, (ii) Intermediate input producers who produce each variety by combining capital and labor, and (iii) A representative household that maximizes its utility by selecting consumption bundles. The model indicates that the marginal rate of substitution between intangible capital and high-skilled labor decreases with firm output, suggesting that intangible capital and high-skilled labor are more complementary in larger firms, a finding supported by our empirical analysis. Thus, the non-homothetic CES model, incorporating the scale elasticity parameter, allows us to capture the heterogeneous synergy that varies across different firm-size groups.

Although the general equilibrium model effectively integrates the complementarity channel and economies of scale in line with our empirical findings, the absence of data on specific firm-level variables (e.g., skilled labor) limits our ability to perform a comprehensive quantitative analysis. However, in the Online Appendix, we present a preliminary quantitative analysis using our available data, which demonstrates the significance and scope of the synergy within the firm-level production framework. Our results show that 80% of the complementarity between intangible capital and skilled labor over time is attributed to economies of scale. This finding further suggests that the distribution of firm size and the presence of scale elasticity are crucial factors in shaping the interaction between intangible capital and skilled labor in the economy.

We conduct our empirical and theoretical analysis within the context of the U.S. economy for several reasons. First, we have access to comprehensive U.S. databases that allow us to measure key variables for our study, including firm-level intangible capital, labor productivity, and industry-level skill composition. Second, our paper contributes to the ongoing discussion of declining U.S. business dynamism by proposing an alternative channel and explanation. While our findings are specifically based on the U.S. economy, they can be extended to other regions or countries. A key policy implication of our evidence, relevant across different economies, is that investment in intangible capital represents a critical form of technological change with significant implications for firm-level productivity dynamics, closely related to the skill composition within the economy. Moreover, various studies focusing on business dynamism and productivity dispersion in other economies reveal patterns similar to those observed in the U.S. economy (Van Ark et al. (2013), Andrews et al. (2016), Bartelsman and Wolf (2017), Adler and Siegel (2019)). Therefore, we argue that our paper provides general insights and context that are not specific to the U.S. but applicable to several countries experiencing similar trends in intangible capital, skill composition, and productivity dynamics.

Related Literature Our paper is related to several strands of literature. The first strand focuses on the declining business dynamism in the U.S. economy. Explanations for this decline include slowing technological diffusion (Akcigit and Ates (2023)), reallocation of factors toward superstar firms (Autor et al. (2020)), implementation and restructuring lags of breakthrough technology (Brynjolfsson et al. (2018)), structural changes in the cost structure due to intangible capital (De Ridder (2019)), and increased market power driven by intangible capital (Crouzet and Eberly (2019)), among others. Our contribution to this strand is to emphasize an additional channel: how the synergy between intangible capital and skilled labor benefits large firms, leading to increased productivity dispersion.

The second strand examines the secular rise of corporate intangible capital over the last five decades (Corrado et al. (2009); Corrado and Hulten (2010); McGrattan and Prescott (2010); Eisfeldt and Papanikolaou (2014); Corrado et al. (2016); Haskel and Westlake (2017); McGrattan (2020)). This literature documents that the accumulation of intangible capital affects several dimensions of firm dynamics, including productivity growth (Corrado et al. (2017), McGrattan (2020)), competition (Ayyagari et al. (2019)), market power (Crouzet and Eberly (2019), De Ridder (2019), Zhang (2019)), markup (Altomonte et al. (2021)), rents (Crouzet and Eberly (2020)), and factor inputs (Chiavari and Goraya (2021)). Our contribution is to argue that, along with the rising share of intangible capital in the U.S. economy, the heterogeneity of intangible capital across different firm sizes can partially explain the increasing productivity dispersion.

The third strand highlights the role of skilled workers in the production and enhancement of intangible assets. Crouzet et al. (2022b) argue that firms investing heavily in intangible assets, such as R&D and technological innovations, rely on a workforce with specialized skills and knowledge. Döttling et al. (2020) focus on the dynamic interplay between intangible capital and skilled workers, showing that intangible assets result from joint investments by firms and skilled labor. Sun and Xiaolan (2019) propose a dynamic model where investments in intangible capital to boost labor productivity lead to increased deferred wage obligations, reducing the firm's ability to secure debt financing due to employees' limited commitment and potential departure for better opportunities. Our contribution is to highlight the role of the synergy between intangible capital and skilled labor in the firm-level production framework and its impact on productivity dispersion across firms.

The fourth strand investigates the impact of technical change on labor market dynamics. Several papers explore wage dynamics (Katz and Murphy (1992), Acemoglu (1998), Katz et al. (1999), Autor et al. (2008), Violante (2008)), skill-biased technological change (Solow (1957), Greenwood et al. (1997), Krusell et al. (2000), Acemoglu (2002a), Acemoglu (2002b), Aghion et al. (2002), Bresnahan et al. (2002), Hornstein et al. (2005)), and capital-skill complementarity (Griliches (1969), Greenwood and Yorukoglu (1997), Goldin and Katz (1998b), Bresnahan et al. (2002), Autor et al. (2003)). Most of these studies focus on the aggregate economy and labor market. However, data limitations often lead to attributing technical change to specific technological trends (e.g., computers, robots, or IT revolution) or unobservable TFP components. Instead, we consider the role of intangible capital in technological change and the structural transformation of the economy. Rather than focusing on specific technological inventions or relying on unobservable TFP components, we observe and quantify the overall trend in intangible capital, emphasizing its role as a new form of technical change in the U.S. economy and its strong association with skilled labor and firm-level productivity.

The final strand explores the driving forces behind increasing skill premiums. This includes studies on skill-biased technical change (Autor et al. (1998), Acemoglu (2002a), Acemoglu (2002b), Haskel and Slaughter (2002), Violante (2008)), capital-skill complementarity (Goldin and Katz (1998b), Krusell et al. (2000), Lindquist (2004), Parro (2013)), human capital accumulation (Katz and Murphy (1992), Acemoglu (1996), Goldin and Katz (1998a), Dix-Carneiro and Kovak (2015), Lucas Jr (2015), Murphy and Topel (2016)), and trade-induced changes (Pissarides (1997), Parro (2013), Caselli (2014), Harrigan and Reshef (2015), Burstein and Vogel (2017)). Our contribution is to examine how the synergy between intangible capital and skilled labor affects productivity and raises the demand for skilled labor, particularly in an environment with increasing intangible capital, leading to higher skill premiums. Additionally, we highlight that this synergy, related to firm size, drives the increasing skill premium observed in large, intangible-intensive firms.

Layout The paper is organized as follows. Section 2 describes the data and the measurement of key variables, such as intangible capital and skill ratio. Section 3 documents stylized facts on the association between productivity dynamics, intangible capital, and skilled labor. Section 4 develops an empirical framework to quantify the association between intangible capital-skilled labor synergy and firm-level productivity across different firm sizes. Section 5 presents an empirical robustness check. Section 6 outlines a motivating model that provides a basic explanation for the empirical evidence on why and through which channels the synergy between intangible capital and skilled labor occurs. Section 7 extends the motivating model and develops a firm-level general equilibrium model to investigate the role of synergy along with economies of scale in the firm-level production function. Section 8 discusses the main limitations of our study and elaborates on how we aim to address these in future projects. Finally, Section 9 concludes by discussing policy implications and future extensions.

2 Data

We use the U.S. Compustat database to measure firm-level financial balance sheet variables on an annual basis. We employ the Total Q database from Peters and Taylor (2017) to measure firm-level intangible capital. Additionally, we use the Quarterly Workforce Indicators (QWI) from the Longitudinal Employer-Household Dynamics (LEHD) program of the U.S. Census Bureau to measure industry-level and firm-level skill ratio.

Our Compustat sample data covers the period from 1985 to 2015. In line with standard procedures in the literature, we exclude financial firms (SIC codes 4900-4999), utilities (SIC codes 6000-6999), and government entities (SIC code 9000 and above). We also exclude firms with missing or negative values for assets or sales, as well as those with negative CAPX, R&D, or SG&A (Selling, general, and administrative) expenditures. Additionally, we exclude very small firms with physical capital under $5 million and drop firm observations where acquisitions exceed 5% of total assets. Firms with less than 5 years of presence in the sample are also excluded. The variables are deflated by the CPI and trimmed by industry and year. Table A.1 presents the firm-level constructed data variables and their descriptions in the Compustat sample. Table A.2 shows the summary statistics for our key variables in the Compustat data.

Measurement of Labor Productivity We measure firm-level labor productivity as the ratio of sales revenue per employee, as commonly used in the standard macroeconomics literature (see Comin and Philippon (2005), Gutiérrez and Philippon (2016), Autor et al. (2020)).

Measurement of Intangible Capital We use the Total Q database from Peters and Taylor (2017) to measure intangible capital at the firm level. Intangible capital consists of external and internal components. External intangibles are those acquired from another firm during mergers and acquisitions.[1] Internal intangibles refer to knowledge and organizational capital, which are not capitalized on balance sheets. To account for these off-balance-sheet internal intangible expenses, we use the perpetual inventory method, consistent with other studies on measuring intangible capital (Lev and Radhakrishnan (2005), Eisfeldt and Papanikolaou (2014), Ewens et al. (2019)).

In that regard, the perpetual inventory method constructs the stock of knowledge capital from past R&D expenses as follows:

$$A_{it} = (1 - \delta_{R\&D})A_{it-1} + R\&D_{it} \tag{1}$$

where A_{it} is the end-of-period stock of knowledge capital, $R\&D_{it}$ is the Research and Development expenditures during the year, and $\delta_{R\&D}$ is the industry-specific $R\&D$ depreciation rates based on the estimates from Ewens et al. (2020). We assume that starting

[1] The intangible capital stock of an acquired or merged company is reported in Compustat as the "*intan*" variable.

A_{i0} is zero.

Similarly, the perpetual inventory method measures the stock of organizational capital from past SG&A expenses as follows:

$$B_{it} = (1 - \delta_{SG\&A})B_{it-1} + \gamma \times SG\&A_{it} \tag{2}$$

where B_{it} is the end-of-period stock of organizational capital, $SG\&A_{it}$ is the selling, general, and administrative during the year, and $\delta_{SG\&A}$ is the SG&A depreciation rates. Based on the estimates from Ewens et al. (2020), $\delta_{SG\&A}$ is 0.2 and γ represents industry-specific values for the percent of SG&A spending. We assume that starting B_{i0} is zero.

Finally, we include the reported external intangible (G_{it}) in the balance sheet to the measured stock of knowledge and organizational capital and construct a measure of intangible capital for each firm-year level as follows:

$$INT_{it} = G_{it} + A_{it} + B_{it} \tag{3}$$

Table A.3 shows the summary statistics for intangible capital ratio. Table A.4 documents the median of some selected variables for firms with different quintiles of intangible capital ratio. Figure B.1 shows the histogram of the measured intangible capital ratio, in which we see a sufficient degree of heterogeneity across firms. Figure B.2 documents the histogram of intangible capital ratio for different selected sectors. We see that there is a striking heterogeneity in the intangible capital ratio across different sectors. Hence, we confirm a significant variation in intangible capital ratio across firms and sectors, which enables us to implement our empirical specification.

Measurement of Skill Ratio Access to databases that include firm-level skill components is challenging, which limits the variation in skill ratio at the firm level. To address this issue, we use the Quarterly Workforce Indicators (QWI) from the Longitudinal Employer-Household Dynamics (LEHD) of the U.S. Census Bureau. This local labor market database reports various economic indicators, such as employment, earnings, job creation and destruction, and worker turnover, categorized by geography, industry, worker, and firm characteristics.[2] The data begins in the early 1990s and covers nearly all states and industries in the U.S. economy.

To measure skill ratio, in line with the related literature, we use the education characteristics variable in QWI and compute the share of workers with a "Bachelor's degree or

[2]For details on the database construction, see Abowd et al. (2009).

advanced degree" (labelled as *E4* in the database) within each state, year, industry (4-digit *NAICS*), and firm size. This allows us to capture a disaggregated and detailed measure of skill ratio that vary across industries, states, firm size categories, and years.

To create a proxy for firm-level skill ratio, we merge our skill ratio measurements with the Compustat firm sample using a crosswalk by state, year, industry (4-digit *NAICS*), and firm size. We determine the state information of a particular firm based on the location of its headquarters in Compustat. To match the two databases, we categorize Compustat firms by size (total assets) using the same categorization rules applied in the QWI database to determine firm size groups.

Table 2: Example - Skill Ratio Variation across Industry, State, Firm Size and Year

Firm Name	Industry (4-digit *NAICS*)	State	Firm Size	Year	Skill Ratio
MORNINGSTAR INC	Other Information Services	IL	Large	2008	0.57
SABA SOFTWARE INC	Other Information Services	CA	Large	2008	0.7
ROCK ENERGY RESOURCES INC	Metal Ore Mining	TX	Small	1996	0.15
MIND TECHNOLOGY INC	Electronic Instrument Manufacturing	TX	Small	1996	0.24

Note: This table shows shows an example in the sample of how we capture the variation in skill ratio across the industry, state, firm size, and year.

Matching the two databases by state, year, industry (4-digit *NAICS*), and firm size helps us capture detailed variation in skill ratio across firms. For instance, consider two similar firms operating in different states and industries. Even if these firms have similar production scales, they will end up with different measurements of skill ratio based on our matching algorithm, providing sufficient variation for our empirical analysis. Table 2 provides an example of how we capture variation in skill ratio across industries, states, firm sizes, and years.

Throughout the paper, we use the terms "skill ratio" and "skill intensity" interchangeably. Table A.5 reports the summary statistics for skill ratio, and Figure B.3 displays the histogram of skill ratio in our sample. Figure B.4 shows the histogram of skill ratio for selected industries. We observe that intangible-intensive industries, such as Healthcare and High Tech, have higher skill ratio compared to tangible-intensive industries, such as Consumer Goods and Manufacturing. Additionally, there is significant variation in skill ratio across firms and industries. Figure B.5 plots the kernel density of skill ratio across several years, revealing that variation changes over time, with an increase in the density of skill ratio over time. Figures B.6 and B.7 show the histograms of skill ratio for small versus large firms and low versus high intangible firms, respectively. We observe that large and high intangible-intensive firms have higher skill ratio compared to small and low intangible-intensive firms.

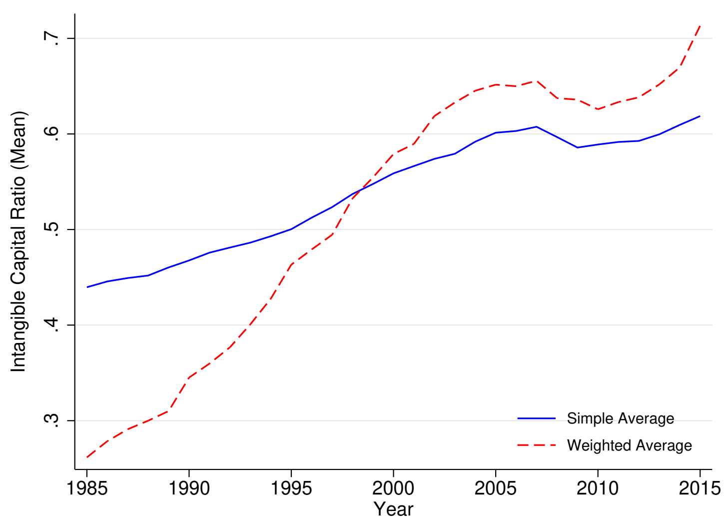
3 Stylized Facts

In this section, we document several stylized facts from the data sample which show the association between productivity dispersion, intangible capital, and skilled labor.

Fact 1: Intangible capital rises in the U.S. economy, which has a heterogeneous pattern across firm size distribution.

Figure 1 show the simple and sales-weighted average of intangible capital ratio across industries over the last three decades, respectively. Both figures suggest an increasing pattern in the intangible capital ratio and more precisely the simple (sales-weighted) average intangible capital ratio has risen from about 43% (25%) in the 1985s to about 61% (71%) in the 2015s. This fact suggests that the composition of the corporate capital structure becomes more intangible capital heavy on average over time in the U.S. economy.

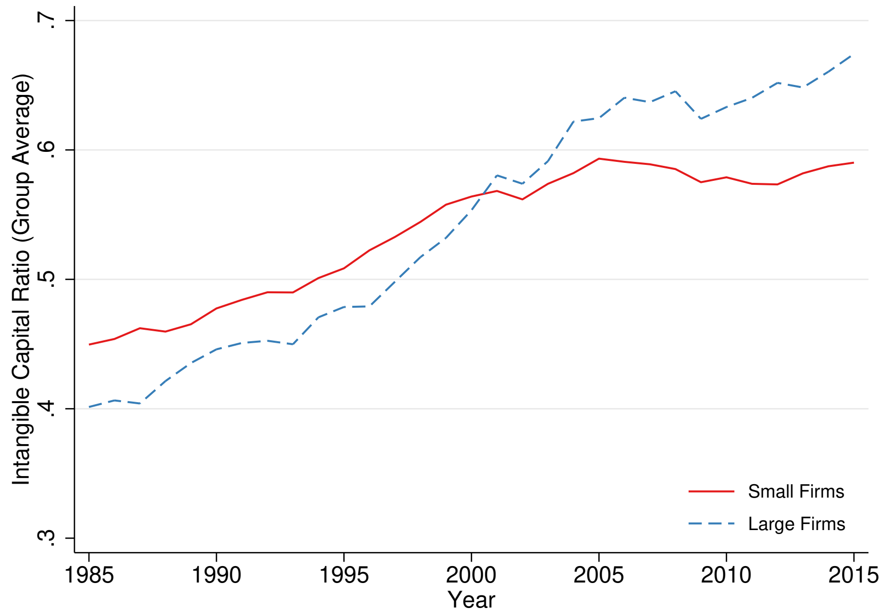
Figure 1: Intangible Capital Ratio



Note: This figure shows the simple and the sales-weighted annual averages of intangible capital ratio in the Compustat. Intangible capital ratio is defined as $\frac{\text{Intangible capital stock}}{\text{Intangible capital stock + Tangible capital stock}}$. Intangible capital stock is based on the perpetual inventory method of Peters and Taylor (2017). Tangible capital stock is the gross plant, property and equipment. Sales weights are calculated within each industry (*NAICS*).

Figure B.8 plots the simple median of intangible capital and tangible capital per book value over time respectively and shows that the median share of tangible assets displayed a pronounced downward trend, declining from about 30% during 1985s to about 10% during 2015s. Also, the secular declining trend in tangible capital per book value was steady and not concentrated in any particular decade. However, the median of intangible capital per book value has an increasing pattern, from about 40% during 1985s to 70% during 2015s, especially with a dramatic increase during the early 2000s.

Figure 2: Intangible Capital Ratio by Firm Size Group



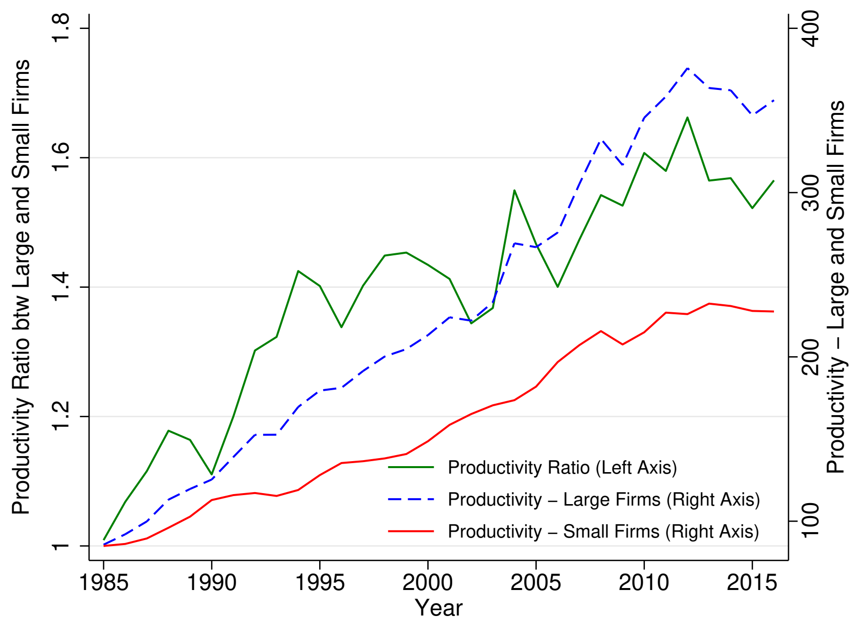
Note: This figure shows the annual average of intangible capital ratio over time for small and large firms. Small firms are the ones that are within Quantile 1, where quantiles are constructed based on the firm-level total asset within industry (*NAICS*) and year. Large firms are the ones that are within Quantile 10.

Figure 2 documents the quantile-level annual average of intangible capital ratio for small and large firms. We observe that even though small firms have relatively higher intangible capital ratio on average during 1985s, large firms close the gap fast until 2000s and even head off after 2000s. It also indicates that large firms disproportinately accumulate more intangible capital compared to small firms during the last two decades, which remarks the importance of heterogeneity in intangible capital accumulation across firm size distribution.

Fact 2: Labor productivity gap between large and small firms widens over time in favor of large firms.

Figure 3 shows the average labor productivity ratio between large firms (90th percentile) and small firms (10th percentile) of firm size distribution within each industry and year.[3]

Figure 3: Labor Productivity Ratio Between Large and Small Firms



Note: The left axis of the figure shows an average labor productivity ratio between large firms and small firms. The right axis of the figure shows the average productivity of large and small firms. Firm size is captured by firm-level total assets. Small firms are the ones which are at the 10th percentile and large firms are the ones which are at the 90th percentile within each year and industry (*NAICS*).

We see in the figure that the the productivity gap between large and small firms widens over time. We also see from the right axis of the figure that large firms have an overall higher increasing trend in labor productivity over time compared to small firms. It implies that large firms in their industry seem to be main drivers of productivity gains, but small firms are not able to catch them up.

Fact 3: Intangible intensive firms have higher skill ratio.

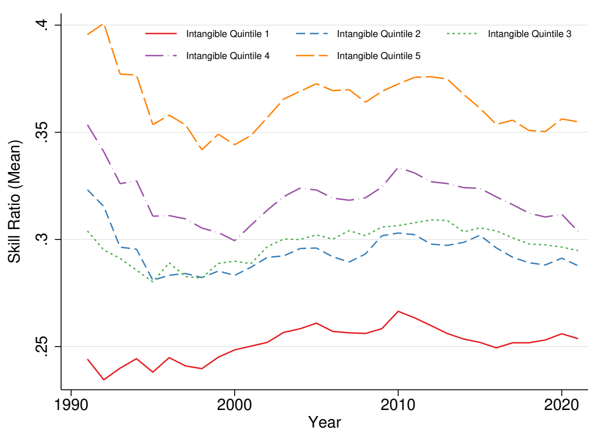
Now, we show some stylized facts to document the linkage between intangible capital and skill components. Our underlying conjecture is that firms need to develop some alternative ways to attract skilled labor. We show that one of the alternative ways how

[3]The Online Appendix provides a descriptive analysis of the productivity slowdown in the U.S. economy.

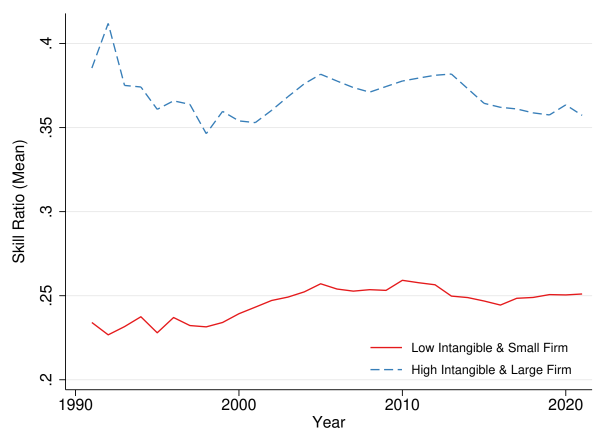
firms attract skilled labor is their effective intangible capital. We can think of firm-level intangible capital as R&D expenditures, organizational capital including employee training, organizational structure, and business culture. Given that intangible capital can be potentially used to enhance skilled labor's personal and career development, firms with more effective intangible capital would be more likely to have skilled labor.

Figure 4a shows a supporting evidence for our hypothesis. We see that firms with higher intangible capital also have higher skill ratio, which is persistent over time. To understand the role of firm size in the relationship between intangible capital and skill ratio, Figure 4b plots an annual average of skill ratio for low intangible and small firms, and high intangible and large firms. We find that the skill ratio is always higher for high intangible and large firms compared to the one for low intangible and small firms. The persistency in the pattern is also a suggestive evidence that large firms with high intangibles also have higher skill ratio on average over time.[4]

Figure 4: Intangible Capital and Skill Ratio



(a) Skill Ratio by Intangible Quintile



(b) Skill Ratio by Intangible and Firm Size

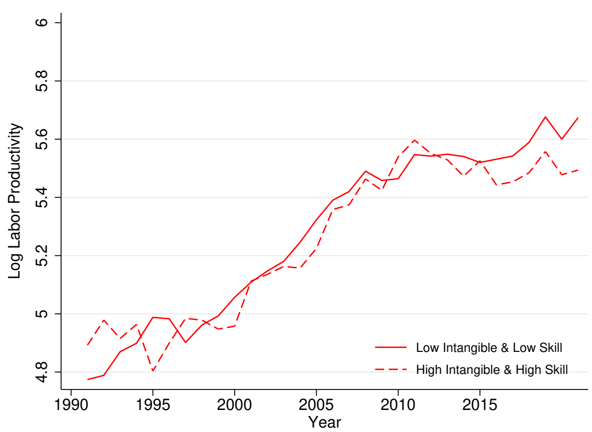
Note: Panel (a) displays the annual average skill ratio, categorized by quintiles of intangible capital, which are constructed within each year and industry. Panel (b) compares the skill ratio for low intangible small firms (quintile 1 for each intangible capital and firm size within each year and industry) with high intangible large firms (quintile 5 for each intangible capital and firm size within each year and industry).

[4]The Online Appendix provides a descriptive analysis of industry-level intangible capital, productivity dispersion, and skill ratio.

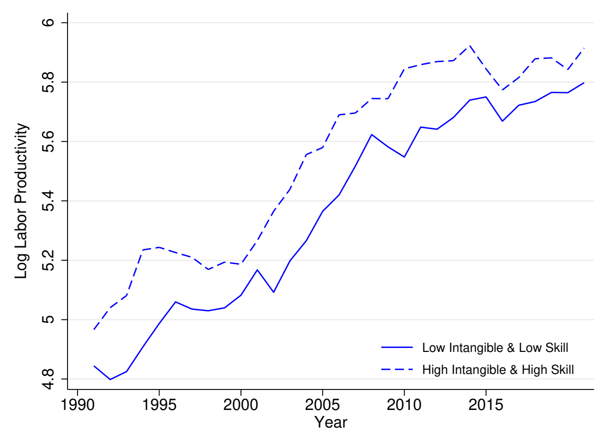
Fact 4: Large firms with high intangible capital ratio and skill ratio have higher labor productivity.

To investigate suggestive evidence on how the intangible capital-skill synergy plays a key role in labor productivity across different firm sizes, we plot the annual median of log labor productivity levels for different groups based on intangible capital ratio and skill ratio in small and large firms. Each group is constructed using the median of the corresponding variable within industry (*NAICS*) and year. Figures 5a and 5b suggest that the highest levels of labor productivity occur in large firms with high skill ratio and high intangible capital ratio, whereas we do not observe such evidence for small firms. This finding provides suggestive evidence that high intangible capital or high-skilled labor alone might not be sufficient to explain productivity dynamics in large firms. Therefore, the synergy between these two components must be considered to fully understand firm-level productivity in large firms.

Figure 5: Productivity by Intangible Capital Ratio, Skill Ratio and Firm Size



(a) Small Firms



(b) Large Firms

Note: Panel (a) shows the annual median of log labor productivity within each group of intangible capital ratio and skill ratio for small firms, and Panel (b) shows the same for large firms. We construct each group based on the below and above the median of the corresponding variable within *NAICS* and year.

To sum up, our set of stylized facts provides four related pieces of motivating evidence: i) increasing productivity dispersion driven by large firms, ii) rising intangible capital in large firms, iii) higher skill ratio in large and intangible firms, and iv) higher productivity in large firms that exhibit higher intangible capital ratio and skill ratio. Given these facts, we will now focus on the synergy between intangible capital and skilled labor to quantify its association with firm-level productivity dynamics.

4 Empirical Analysis

In this section, we first quantify the association between intangible capital and skilled labor. Then, we estimate the association between the intangible capital-skilled labor synergy and firm-level labor productivity.

4.1 Intangible Capital and Skilled Labor

The main goal in this section is to investigate the role of intangible capital in skill ratio at the firm-level through the following regression specification:

$$y_{it} = \beta_0 + \beta_1 \textit{intangible capital ratio}_{it} + \Gamma' X_{it} + u_t + u_s + \epsilon_{it} \tag{4}$$

where the dependent variable is the firm-level skill ratio for firm i at time t, and *intangible capital ratio*$_{it}$ represents the firm-level intangible capital ratio. Our firm-level control variables are denoted by the vector X_{it}, which includes firm size, age, markup, and Tobin's Q. Firm size is measured as the logarithm of total assets held by the firm. Markup is calculated based on the methodology of De Loecker et al. (2020) to account for the role of market power in firm-level decisions. We include Tobin's Q to capture firm-level investment opportunities, which may be correlated with intangible capital investment. Due to unobserved heterogeneity, we also include year (u_t) and industry (u_s) fixed effects.[5] We cluster the standard errors at the firm level. We standardize all variables and include one-year lagged values of independent variables to address potential endogeneity issues.

By considering the one-year lag of the intangible capital ratio, we assume that firms first invest in and install their intangible capital, and this decision influences the skill ratio they will have in the following period. Controlling for firm-level observable determinants and including several fixed effects, our identifying assumption is that the firm-level intangible capital decision from the previous period is uncorrelated with firm-level unobservable characteristics that might be associated with the current period's skill ratio.

Table 3 reports the results of equation (4). We observe that an increase in intangible

[5]Since we cannot measure skill composition precisely at the firm level and capture quasi-variation across firms using different categorizations (as mentioned in Section 2), we are unable to include firm fixed effects; doing so would dramatically reduce the underlying variation in our regression estimation.

capital is positively and significantly associated with the skill ratio. Specifically, a one standard deviation (0.32) increase in the intangible capital ratio is associated with an increase of up to 0.60 standard deviations (0.17) in the skill ratio, which translates to a 0.11 increase in the skill ratio. This result indicates a positive and significant association between intangible capital and skilled labor.

Table 3: Intangible Capital Ratio and Skill Ratio

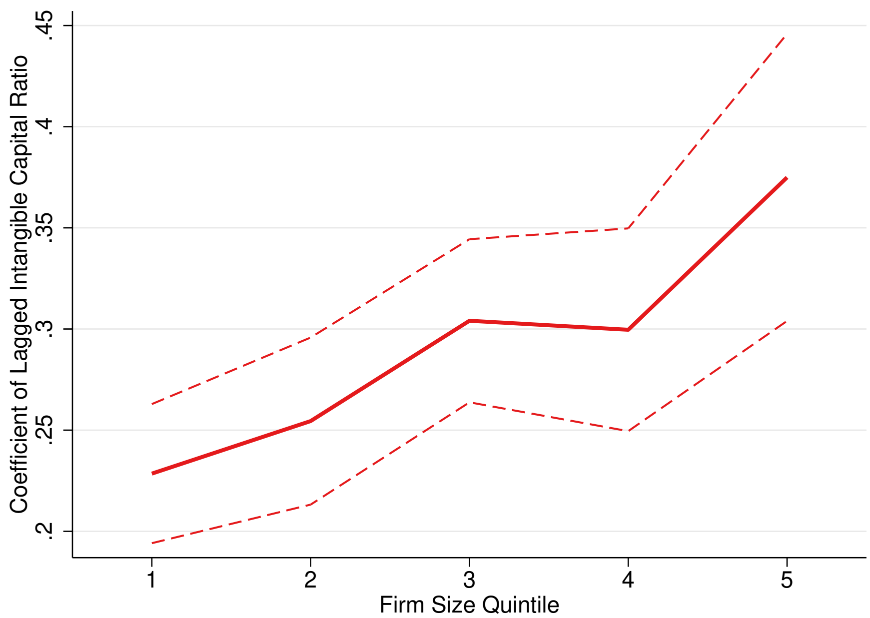
	(1) Skill Ratio	(2) Skill Ratio	(3) Skill Ratio	(4) Skill Ratio
L.Intangible Capital Ratio	0.311***	0.320***	0.322***	0.0210*
	(0.0116)	(0.0123)	(0.0126)	(0.00938)
Control Variables	No	Yes	Yes	Yes
Industry FE	No	No	No	Yes
Year FE	No	No	Yes	Yes
Adjusted R^2	0.0957	0.119	0.122	0.772
N	76621	73964	73964	73962

Note: This table displays the results of the regression specification where the dependent variable is the firm-level skill ratio, and the main explanatory variable is the one-year lag of the intangible capital ratio. Control variables include the one-year lag of firm-level logarithm of total assets, age, markup, and Tobin's Q. Standard errors (in parentheses) are clustered at the firm level. * $p < .10$, ** $p < .05$, *** $p < .01$.

In Table A.6, we present a similar regression specification using the levels of variables instead of ratios. We find that a one percent increase in intangible capital is associated with a 0.15% to 0.33% increase in the number of skilled workers, depending on the fixed effects. Additionally, the association between firm size and the number of skilled workers is both positive and significant. Specifically, a one percent increase in firm size is associated with a 0.60% to 0.76% increase in the number of skilled workers, depending on the fixed effects. This suggests that larger firms are more likely to employ a greater number of skilled workers.

To investigate the role of firm size in the synergy between the intangible capital ratio and skill ratio, we construct firm size quintiles within each industry (*NAICS*) and year. We then run the regression equation (4) within each firm size quintile. Figure 6 shows the coefficient of the intangible capital ratio in the regression and indicates that, although the coefficient is positive and significant across all firm size quintiles, it increases substantially as firm size grows. We also conduct a similar analysis using the levels of variables, as depicted in Figure B.9, and find a comparable result: the positive association between intangible capital and the number of skilled workers is stronger in larger firms. In other words, the positive relationship between intangible capital and skilled labor is amplified with increasing firm size.

Figure 6: Quintile Regression - Intangible Capital Ratio and Skill Ratio



Note: This figure shows the coefficient of the intangible capital ratio from the regression (4) within firm size quintiles, with year fixed effects included. Firm size quintiles are constructed based on total assets within each industry and year.

4.2 Intangible Capital-Skilled Labor Synergy and Productivity

The previous section provides suggestive reduced-form evidence of a synergy between intangible capital and skilled labor, which appears to be stronger in larger firms. Building on these findings, this section explores how this synergy is related to firm-level productivity and whether the strength of this association varies with firm size. To investigate this, we perform the following regression analysis:

$$y_{it} = \beta_0 + \beta_1 \textit{skill ratio}_{it} + \beta_2 \textit{intangible capital ratio}_{it} + \Gamma' X_{it} + u_t + u_s + \epsilon_{it} \tag{5}$$

where the dependent variable is the firm-level log labor productivity for firm i at time t. The variable *skill ratio*$_{it}$ denotes the firm-level skill ratio, and *intangible capital ratio*$_{it}$ represents the firm-level intangible capital ratio. As in the previous regression model, X_{it}

includes firm-level control variables such as firm size, age, markup, and Tobin's Q, along with year (u_t) and industry (u_s) fixed effects. We standardize the skill ratio and intangible capital ratio over the entire sample, so the units are in standard deviations relative to the mean. Standard errors are clustered at the firm level.

Table 4 shows that both the skill ratio and the intangible capital ratio are positively and significantly associated with firm-level labor productivity. Specifically, a one standard deviation (0.17) increase in the firm-level skill ratio is associated with a 3.1% to 3.4% increase in firm-level labor productivity. Similarly, a one standard deviation (0.32) increase in the firm-level intangible capital ratio is associated with an approximately 8.4% increase in labor productivity.

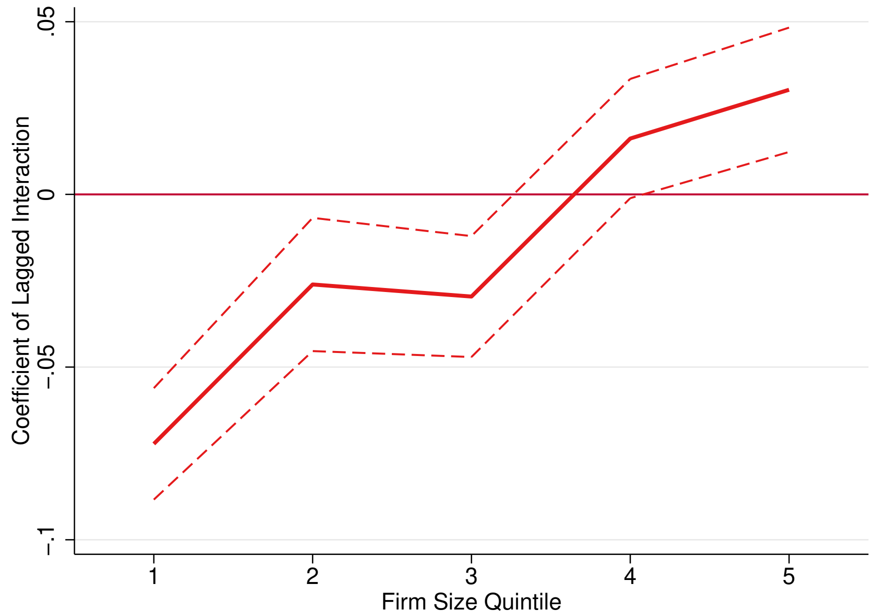
Table 4: Intangible Capital, Skill Ratio and Productivity

	(1) Labor Productivity	(2) Labor Productivity	(3) Labor Productivity
L.Skill Ratio	0.0348**		0.0310**
	(0.0143)		(0.0142)
L.Intangible Capital Ratio		0.0849***	0.0843***
		(0.0151)	(0.0152)
Control Variables	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R^2	0.466	0.472	0.472
N	81590	81015	81015

Note: This table displays the results of the regression specification where the dependent variable is the firm-level logarithm of labor productivity, and the main explanatory variables are the one-year lag of the skill ratio and intangible capital ratio. Control variables include the one-year lag of firm-level logarithm of total assets, age, markup, and Tobin's Q. Standard errors (in parentheses) are clustered at the firm level. * $p < .10$, ** $p < .05$, *** $p < .01$.

To investigate whether the synergy between intangible capital and skilled labor has varying effects on productivity across different firm sizes, we create an interaction term between the skilled labor ratio and the intangible capital ratio. This interaction term is included in the regression specification (5), and the regression is performed within each firm size quintile. Figure 7 shows that the coefficient of the interaction term becomes positive and significant for larger firms. In other words, while the synergy between intangible capital and skilled labor does not have a significant positive effect on productivity in smaller firms, it positively impacts productivity in larger firms. This suggests that larger firms are better positioned to leverage this synergy to enhance their productivity.

Figure 7: Quintile Regression - Synergy and Labor Productivity



Note: This figure pilots the coefficient of interaction term between intangible capital ratio and skill ratio in the regression (5) within size quintiles, with year and industry fixed effects included. Firm size quintiles are constructed within each industry and year.

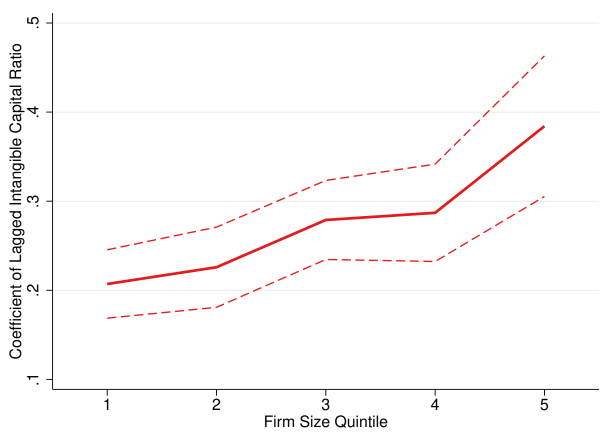
Given our data limitations in capturing the ideal variation in firm-level skill decomposition and performance for each skill category, our measurement of skill ratio serves as a reduced-form approximation. To address this, we take an additional step by providing a micro-founded approach with a more detailed measure of skill composition. We conduct supplementary analyses to explore firm-level inventor dynamics and their relationship to intangible capital, as detailed in Appendix C. By merging USPTO patent and inventor data with Compustat, we observe individual-level variations in skill components at both the firm and inventor levels, offering a more granular view that supports our benchmark mechanism. Consistent with our baseline approach, we hypothesize that intangible capital requires skilled inventors to realize its economic benefits for innovation. Our findings indicate that inventors who move to large firms with high intangible capital become more productive in patent production. Thus, the synergy between intangible capital and skilled inventors is more pronounced in larger firms, which confirms our benchmark empirical evidence.

5 Robustness Checks

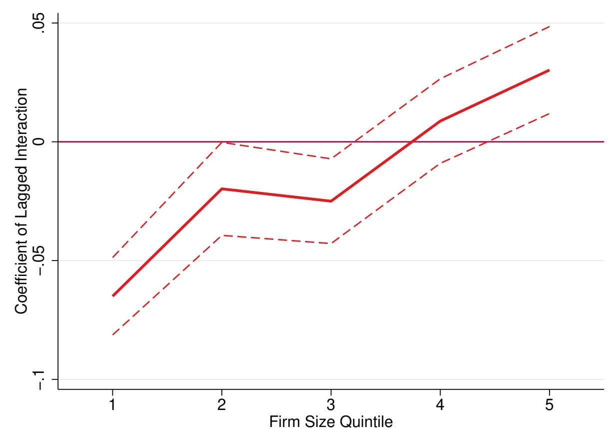
This section presents a set of robustness checks for our benchmark empirical evidence, including using an alternative measurement of intangible capital and excluding the crisis periods.

Alternative Measurement of Intangible Capital One potential concern with our measurement of intangible capital is that the external intangible capital component might not be directly related to the synergy between intangible capital and skilled labor. Including it in our analysis could therefore misrepresent our mechanism. As a robustness check, we focus only on internal intangible capital (the sum of knowledge capital and organizational capital) and replicate our key empirical findings using a quintile regression framework.

Figure 8: Quintile Regressions with Internal Intangible Capital



(a) Internal Intangible Capital Ratio and Skill Ratio



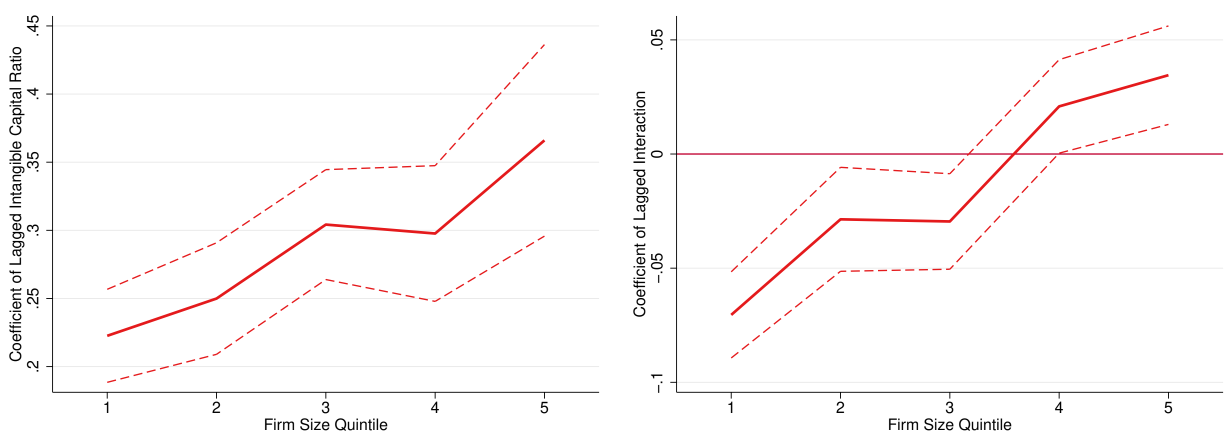
(b) Synergy and Labor Productivity

Note: Panel (a) displays the coefficient of the internal intangible capital ratio from regression (4) across firm size quintiles, including year fixed effects. Panel (b) presents the coefficient of the interaction term between the internal intangible capital ratio and the skill ratio from regression (5) across size quintiles, with both year and industry fixed effects included. Internal intangible capital is defined as the sum of knowledge capital and organizational capital. Firm size quintiles are constructed based on total assets within each industry and year.

Figures 8a and 8b present results consistent with our baseline findings. They demonstrate that (i) larger firms with a higher internal intangible capital ratio also have a higher skilled labor ratio, confirming the evidence shown in Figure 6, and (ii) larger firms with a higher interaction between internal intangible capital ratio and skill ratio also exhibit higher labor productivity, confirming the evidence in Figure 8b. Therefore, we argue that our baseline specification, which includes both internal and external intangible capital, provides robust evidence.

Exclusion of Crisis Periods Crisis periods can affect different firms in varying ways. For instance, during such times, tightening financial constraints might impact firms differently based on their size. Smaller firms may face greater financing challenges compared to larger firms, which could influence their decisions regarding intangible capital investment and skill accumulation. Therefore, including crisis periods in our analysis could significantly affect the identifying variation in our regression models. To mitigate this concern, we exclude the crisis periods (1990-1991, 2001, 2007-2009) from our sample and rerun the benchmark quintile regressions.

Figure 9: Quintile Regressions without Crisis Periods



(a) Intangible Capital Ratio and Skill Ratio

(b) Synergy and Labor Productivity

Panel (a) displays the coefficient of the intangible capital ratio from regression (4) across firm size quintiles, including year fixed effects and excluding the crisis periods (1990-1991, 2001, 2007-2009). Panel (b) presents the coefficient of the interaction term between the intangible capital ratio and the skill ratio from regression (5) across firm size quintiles, including both year and industry fixed effects, and excluding the crisis periods (1990-1991, 2001, 2007-2009). Firm size quintiles are constructed based on total assets within each industry and year.

Figures 9a and 9b demonstrate that excluding these periods does not alter our results: (i) larger firms with a greater proportion of internal intangible capital also tend to have a higher proportion of skilled labor, and (ii) larger firms that exhibit a stronger interaction between internal intangible capital and the skill ratio show greater labor productivity. Thus, we conclude that our original sample, which includes the crisis periods, offers a robust empirical analysis.

6 Stylized Model

This section presents a stylized model that offers a basic explanation for our empirical findings, illustrating how firms with higher intangible capital benefit from skilled labor. We utilize a simplified and modified version of the model proposed by Acemoglu and Autor (2011) to derive testable predictions about the heterogeneous relationship between intangible capital ratio and skill premium.

In the model, the primary channel through which the accumulation of intangible capital attracts skilled labor is through changes in the skill premium, driven by shifts in the relative demand for skilled labor. To explore this, we begin with a competitive supply-demand framework within a simple closed economy setting, where factors are compensated according to their marginal products, and the economy functions based on its supply and demand curves.

Setup We have two distinct sectors, each employing skilled and unskilled workers, respectively. The production function for the aggregate economy is specified in the constant elasticity of substitution (CES) form:

$$Y(t) = \left[\Big(K_T(t)L(t)\Big)^{\rho} + \Big(K_I(t)H(t)\Big)^{\rho}\right]^{1/\rho} \tag{6}$$

where $K_T(t)$ denotes the tangible capital stock in the unskilled sector, $L(t)$ represents the number of unskilled workers, $K_I(t)$ denotes the intangible capital stock in the skilled sector, and $H(t)$ represents the number of skilled workers. The elasticity of substitution between skilled ($H(t)$) and unskilled ($L(t)$) workers is $\sigma \equiv 1/(1-\rho)$, where $\rho \in (0,1)$. In our model, we assume complementarity between intangible capital and skilled workers, consistent with our empirical findings.

Assuming competitive labor markets, wages are determined by the marginal products. The wages for unskilled and skilled workers are respectively given by:

$$w_L = \frac{\partial Y}{\partial L} = K_T^{\rho}\left[K_T^{\rho} + K_I^{\rho}\big(H/L\big)^{\rho}\right]^{(1-\rho)/\rho} \tag{7}$$

$$w_H = \frac{\partial Y}{\partial H} = K_I^\rho \Big[K_T^\rho (H/L)^{-\rho} + K_I^\rho \Big]^{(1-\rho)/\rho} \tag{8}$$

Combining equations (7) and (8), we can derive the skill premium π as follows:

$$\pi = \frac{w_H}{w_L} = \left(\frac{K_I}{K_T}\right)^\rho \left(\frac{H}{L}\right)^{-(1-\rho)} \tag{9}$$

We can rearrange equation (9) and express it in logarithmic form as follows:

$$ln(\pi) = \left(\frac{\sigma - 1}{\sigma}\right) ln\left(\frac{K_I}{K_T}\right) + \frac{1}{\sigma} ln\left(\frac{L}{H}\right) \tag{10}$$

Here, we can directly test our main empirical finding that intangible capital is associated with skilled labor. Specifically, the response of the skill premium to an increase in the intangible capital intensity $\frac{K_I}{K_T}$ is given by:

$$\frac{\partial ln(\pi)}{\partial (K_I/K_T)} = \frac{\sigma - 1}{\sigma} \tag{11}$$

which increases when $\sigma > 1$. Specifically, we find that when the elasticity of substitution between skilled (H) and unskilled (L) workers is sufficiently high and rising, an increase in intangible capital intensity is also associated with an increase in the skill premium.

Empirical Test Our stylized model provides a testable prediction to validate our approach of considering K_I as intangible capital and K_T as tangible capital, as expressed by equation (11):

$$ln(\pi(t)) = \gamma_0 + \gamma_1 ln\left(\frac{K_I(t)}{K_T(t)}\right) + \gamma_2 ln\left(\frac{L(t)}{H(t)}\right) + \epsilon(t) \tag{12}$$

To assess whether our model passes the empirical test, we fit the empirical model (12) using a simple OLS regression at the industry level, with K_I and K_T representing industry-level intangible and tangible capital, respectively. Following the approach of Eisfeldt et al. (2021), we use the NBER-CES database to measure industry-level skill premium and the unskilled-skilled labor ratio at the industry (4-digit *NAICS*) level. We aggregate our measures of intangible and tangible capital to the industry (4-digit *NAICS*) level and impose the constraints on the regression coefficients as specified by the model equation (10).

Table 5 shows that an increase in the intangible-to-tangible capital ratio is positively and significantly associated with industry-level skill premium. More importantly, our regression coefficients align with the elasticity of substitution parameter between skilled and unskilled workers at the industry level, as derived in the literature. The coefficient for unskilled-skilled labor ($0.4 = 1/\sigma$) suggests that the elasticity of substitution (σ) is $1/0.4$, or 2.5, which is very close to the average estimated elasticity of substitution (2.2) reported in related studies, as discussed by Havranek et al. (2020). Therefore, this supports the plausibility of modeling intangible capital within the CES production technology framework. We will extend this stylized model to the firm level while maintaining the CES framework in a similar manner.

Table 5: Empirical Test of Motivating Model

	(1) Skill Premium	(2) Skill Premium
Intangible/Tangible	0.837***	0.603***
	(0.004)	(0.005)
Unskilled/Skilled	0.163***	0.397***
	(0.004)	(0.005)
Constant Term	Not Included	Included
N	14865	14865

Note: This table displays the results of the regression specification where the dependent variable is the logarithm of the skill premium at the industry level (the ratio of skilled wages to unskilled wages). The explanatory variables are the industry-level logarithms of the intangible capital-to-tangible capital ratio and the unskilled labor-to-skilled labor ratio. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Discussion Besides validating our motivating model, these results highlight another important takeaway: our modeling framework provides a plausible identification for the unobserved skill-specific TFP. Unlike Acemoglu and Autor (2011) and many other standard approaches that require proxies for measuring unobserved skill-specific TFP to predict skill premium, our approach addresses this need by using observable measures of intangible and tangible capital. We incorporate these measures into the industry-level skill-biased technical change framework developed by Acemoglu and Autor (2011).

After validating our stylized model, which incorporates a channel through which intangible capital influences skill premium within the CES framework and has been supported by empirical tests, we now construct a firm-level general equilibrium model. This model maintains the CES framework but incorporates non-homotheticity to account for the role of firm size. Thus, we extend the skill-biased technical change framework by integrating the concept of economies of scale to capture how it influences the degree of complementarity between intangible capital and skilled labor.

7 Firm-level General Equilibrium Model

The objective of this section is to develop a firm-level general equilibrium model within the workhorse neoclassical production framework. This model focuses on integrating the channel of complementarity between intangible capital and skilled labor, along with the economies of scale that govern the role of firm size. Our primary goal is to incorporate a model framework that elucidates how economies of scale shape the complementarity within the firm-level production framework, enabling us to discipline our related empirical evidence.

7.1 Model Environment

Setup The economy is comprised of various distinct sectors denoted by the index s. Each sector differs in exogenous productivity terms for factor inputs. Within this setup, there exists a final consumption good, which is made up of diverse intermediate input varieties. Intermediate input firms produce these varieties through combining both intangible capital and different skills of labor. Our model assumptions include perfect competition in the markets for final goods and inputs, while intermediate input markets operate under monopolistic competition. Furthermore, we assume that there is a free trade of final good, intermediate input varieties and capital, and free labor mobility across sectors. To effectively convey the primary arguments of our paper, we prefer to employ a static model framework.

In brief, the model comprises three primary blocks: i) A representative final goods producer who manufactures goods using a combination of varieties produced by intermediate input producers, ii) Intermediate input producers who produce each variety by combining capital and labor, and iii) A representative household that maximizes its utility by selecting consumption bundles.

Our model builds heavily on the model developed by Eckert et al. (2022) in the sense that we embed an extension of a neoclassical production function with capital-labor complementarity along with the role of economies of scale based on their fundamental insight. We extend their model in two ways. First, we add the margin of intangible capital into the production framework of Eckert et al. (2022), which helps us investigate the role of intangible capital on labor choice within firms. Second, instead of constructing a spatial model that Eckert et al. (2022) propose, we rather focus the implications of intangible capital-skilled labor complementarity on firm-level production across different sectors.

Production Structure As in Eckert et al. (2022), the final good Y is produced by a final good firm that combines intermediate input varieties using a fixed elasticity of substitution denoted as ι_s. These sectoral bundles are combined into nested final constant elasticity of substitution (CES) bundle with across-sector elasticity ζ_F.

We specify the production technology of intermediate input producer in line with the spirit of Eckert et al. (2022), which provides a non-homothetic CES production technology to introduce the importance of capital-labor complementarity with the scale of production. In that respect, the model framework is an extension of the workhorse neoclassical production functions with capital-labor complementarity such as Acemoglu (1998), Krusell et al. (2000), and Violante (2008).

Intermediate input firms in sector s produce their output, y, with a non-homothetic CES production technology as follows:

$$y = z\left(\left(\alpha_s^K(y)k^{\frac{\sigma-1}{\sigma}} + \alpha_s^H h^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{1-\sigma}\frac{\kappa-1}{\kappa}} + \alpha_s^L l^{\frac{\kappa-1}{\kappa}}\right)^{\frac{\kappa}{1-\kappa}} \tag{13}$$
$$\text{where } \alpha_s^K(y) \equiv y^{\epsilon/\sigma}\phi_s^K Z_s^H,\ \alpha_s^H \equiv Z_s^H,\ \alpha_s^L \equiv Z_s^L$$

where y is the output quantity, k, h, and l denote the firm's choices for intangible capital, high-skilled labor (type-H labor) and low-skilled labor (type-L labor). z denotes the firm-specific efficiency which is drawn by Pareto distribution with a tail parameter υ. $\alpha_s^K(y)$, α_s^H and α_s^L represent an efficiency (share) parameter of intangible capital, high-skilled labor and low-skilled labor, respectively. Z_s^H and Z_s^L are sector-specific productivity terms for high-skilled and low-skilled workers. The parameter σ represents the elasticity of substitution of type-H labor and intangible capital, and the parameter κ denote the elasticity of substitution between the bundle of type-H labor and intangible capital, and type-L labor.

In line with the spirit of Eckert et al. (2022), the parameter called "non-homotheticity," denoted as ϵ, plays a pivotal role in the model. When ϵ is not equal to zero, the marginal productivity of capital for a firm is influenced by its level of output, y. In contrast, if ϵ is equal to zero, the production technology simplifies to the standard CES production function, where the marginal product of each factor remains unaffected by the scale of production. Therefore, the non-homotheticity parameter ϵ makes the complementarity between intangible capital and high-skilled labor size-dependent, as inspired by our empirical evidence.

We make the assumption that the price of the final product is the numeraire, and consequently, the revenue of an intermediate input firm in sector s as a function of Y can be expressed as $D_s Y^{\zeta_s}$, where ζ_s is calculated as $1 - 1/\iota_s$, and D_s represents the sectoral demand.

Based on the model framework, the marginal rate of substitution between high-skilled labor and intangible capital can be written as follows:

$$\begin{aligned} \frac{\frac{\partial y}{\partial h}}{\frac{\partial y}{\partial k}} &= \frac{\alpha_s^H}{\alpha_s^K}\left(\frac{k}{h}\right)^{1/\sigma} \\ &= y^{-\epsilon/\sigma}\left(\frac{k}{h}\right)^{1/\sigma} \end{aligned} \tag{14}$$

As long as $\epsilon > 0$ and $\sigma > 0$, the marginal rate of substitution is decreasing in firm output. In other words, intangible capital and high-skilled labor are more complementary at firms operating at larger scale, as we also found in the empirical section. As a result, in line with Eckert et al. (2022), we refer to ϵ as the "scale elasticity." For the rest of the paper, we assume that intangible capital and high-skilled labor are complements, and that this complementarity is stronger at larger firms.

Assumption *Intangible capital and high-skilled labor are complements and this complementarity is increasing in the level of firm output, i.e., $\epsilon > 0$ and $\sigma > 0$.*

Given the demand system which intermediate good producer faces, the firm problem can be written as follows:

$$\pi^*(Z_s^H, Z_s^L, w_s^H, w_s^L, p, D_s) = \max_y [D_s Y^{\zeta_s} - C(y; Z_s^H, Z_s^L, w_s^H, w_s^L, p, D_s)] \tag{15}$$

where w_s^H and w_s^L are the wage rates for high-skilled and low-skilled labor in sector s, respectively, and the function $C(.)$ represents the cost of production, including wage bills and capital rents, given all the state variables.

To enter the sector, firms pay a fixed cost ε denoted in units of high-skilled and low-skilled labor at each sector. Firms enter in each sector until profits equal the fixed entry cost through the following free-entry equation:

$$\varepsilon(w_s^H + w_s^L) = \pi^*(Z_s^H, Z_s^L, w_s^H, w_s^L, p, D_s) \tag{16}$$

The total number of firms entering each sector s will be represented by the term N_s, which is determined by the free-entry equation.

A representative capital-producing firm converts the final product into capital at a constant rate of Z. Given that the price of the final product serves as the numeraire, the price of one unit of intangible capital is represented as $p = 1/Z$.

Preferences, Worker Heterogeneity and Sectoral Choice We follow the approach of Eckert et al. (2022) and consider an economy with two categories of workers: high-skilled (referred to as type-H) and low-skilled (referred to as type-L) workers. Each type, denoted by $e = H, L$, is populated by a mass of 1 of identical workers who inelastically supply one unit of labor. Workers derive utility from final good consumption and sectoral amenities. They receive idiosyncratic preference shocks for sectors and make choices to maximize their overall utility, which is derived from final good consumption and a sector-specific amenity factor denoted as A_s^e, which we will introduce in this section. For each type $e = \{H, L\}$, workers draw sector-specific shocks from a Fréchet distribution characterized by inverse scale parameters A_s^e and shape parameters ρ_s^e.

In equilibrium, utility is equalized across sectors, yielding the fraction of workers choosing to work in sector s, μ_s^e, as:

$$\mu_s^e = \frac{A_s^e (w_s^e)^{\rho_s^e}}{\sum_s A_s^e (w_s^e)^{\rho_s^e}}$$

where the parameter ρ_s^e can be treated as a sectoral labor supply elasticity. We denote the aggregate supply of type e workers by $\bar{L}^e$, and in equilibrium, the quantity of type e workers in sector s is written as $L_s^e = \mu_s^e \bar{L}^e$.

7.2 General Equilibrium

An equilibrium is a set of wages, rental rates, intangible capital, worker allocations, and number of firms, $w^H, w^L, r, k, h, l, N_s$, within each sector s, and a price of capital, p, such that the following conditions are met: (i) Both high-skilled and low-skilled workers in each sector maximize utility from final good consumption. (ii) Intermediate input firm choices maximize profit given wages and prices in each sector. (iii) Profits are equal to the entry cost in each sector. (iv) Intangible capital, labor, final good, and intermediate goods markets clear.

After solving the first-order conditions in the general equilibrium framework, we find that the factor input ratios satisfy the following equations:

$$\frac{k}{h} = \left(\frac{p}{w_s^H}\right)^{-\sigma} y^{\epsilon} \tag{17}$$

$$\frac{h}{l} = (\tilde{w}_s^H)^{-\sigma(1-\sigma)} \left(\frac{\tilde{w}_s^H}{w_s^L}\right) (Z_s^L)^{-1} \tag{18}$$

where $\tilde{w}s^H \equiv (ws^H)^{1-\sigma}(Z_s^H)^{\sigma} + p^{1-\sigma}(Z_s^H)^{\sigma} y^{\epsilon}$. Equation (17) implies that the ratio of intangible capital to high-skilled labor within a firm varies with firm output with an elasticity ϵ, i.e., the ratio is higher for firms with higher output given prices and wages. Therefore, our model characterizes in equilibrium that larger firms have a higher intangible capital-to-high-skilled labor ratio, which is in line with our empirical evidence on the existence of this synergy.

We acknowledge a data limitation in our paper concerning the quantitative analysis of the firm-level model. While the model successfully incorporates the complementarity channel and economies of scale, consistent with our empirical evidence, the absence of available data moments for certain firm-level variables (e.g., skilled labor) prevents us from conducting a full-fledged quantitative analysis. Nevertheless, in the Online Appendix, we provide a preliminary quantitative analysis using the available data moments, which can still highlight the quantitative importance and magnitude of synergy within the firm-level production framework. We find that the calibrated model attributes 80% of the complementarity between intangible capital and skilled labor over time to economies of scale. This observation provides further suggestive evidence that the distribution of firm size and the presence of scale elasticity play a pivotal role in influencing the interplay between intangible capital and skilled labor in the economy.

8 Limitations

While this study makes significant contributions to our understanding of the synergy between intangible capital and skilled labor, it is also crucial to acknowledge certain limitations that affect the interpretation and generalizability of the paper's findings and discussions.

One notable limitation stems from constraints related to data availability. Our analysis relies on data from Compustat, focusing on publicly traded firms. Consequently, we are unable to analyze private firms, including startups or small businesses. Recognizing that private firms also possess a significant amount of intangible capital, our study unfortunately does not capture their dynamics. Caution should be exercised when generalizing these results to a broader set of private firms in the economy. To address this limitation, we aim to access micro-level census data in our companion project to provide a more comprehensive understanding of the dynamics in private firms.

Another related data limitation arises from the measurement of skilled labor. Since we lack detailed data that includes firm-level skill ratio, we proxy it using industry-level skill ratio. While this approach enables us to capture quasi-variation in skill measurement across firms in our sample, it does not provide a direct firm-level measure. To provide a micro-founded and detailed approach for the skill composition, we conduct supplementary analyses to explore firm-level inventor dynamics and their relationship to intangible capital, as detailed in Appendix C. Ideally, measuring firm-level skilled labor would require access to micro-level employee-employer matched census data, a resource currently unavailable for this study.

The next limitation is related to the scope of our empirical inference. Firstly, despite our efforts to control for various fixed effects and observable factors, unobserved heterogeneity at the firm level may influence the synergy dynamics. We acknowledge that factors not accounted for in the analysis, such as management practices, could potentially confound the relationship between intangible capital and skilled labor. Secondly, our empirical framework is unable to provide causal inference due to the lack of exogenous variation in intangible capital and skill ratio at the firm level. In future projects, we aim to incorporate plausibly exogenous policy changes in either intangible capital or skill ratio, which would provide a basis for causal inference in our context.

9 Conclusion

In this paper, we investigate how the accumulation of intangible capital influences the increasing productivity dispersion in the U.S. economy. To delve into firm-level heterogeneity in productivity dynamics, we examine a new channel of the synergy between intangible capital and skilled labor.

Utilizing firm-level measures from Compustat and industry-level variables from Quarterly Workforce Indicators (QWI), we document four main stylized facts: (i) Increasing productivity dispersion driven by large firms, (ii) Rising intangible capital in large firms,

(iii) Higher skill ratio in large and intangible firms, and (iv) Higher productivity in large firms that exhibit higher levels of intangible capital and skill ratio. This set of empirical results provides two key predictions. First, it indicates the presence of synergy between intangible capital and skilled labor, as their joint interaction enhances firm-level productivity. Second, it suggests that the association between this synergy and productivity is heterogeneous across the firm-size distribution and is more pronounced in large firms.

These stylized facts lead us to quantify the association between the intangible capital-skilled labor synergy and productivity across different firm sizes. We find that a one-standard-deviation increase in the skill ratio is associated with an increase in firm-level productivity of approximately 3.4%, while a one-standard-deviation increase in the firm-level intangible capital ratio is associated with an increase in firm-level productivity of about 8.4%. Additionally, we investigate how the joint interaction between intangible capital and skill ratio enhances firm-level productivity. We find that the coefficient of this interaction becomes positive and significant for larger firms. Specifically, a one-standard-deviation joint increase in intangible capital and skill ratio is associated with an increase in firm-level productivity of around 2% for large firms. This empirical evidence suggests that firms with higher intangible capital and skill ratio experience higher productivity, and this effect is amplified by firm size.

To rationalize the reduced-form empirical evidence, we first outline a stylized model that offers a basic explanation of how firms with higher intangible capital benefit from skilled labor. We then introduce a firm-level general equilibrium model with a non-homothetic constant elasticity of substitution (CES) framework, which incorporates the channel of intangible capital-skilled labor complementarity into the workhorse firm-level production framework. The model elucidates how economies of scale shape this complementarity within the firm-level production framework.

Our empirical evidence and theoretical discussion illuminate several policy implications. There is ongoing debate about how global and local technological changes affect the overall economy. Our paper suggests that investment in intangible capital represents a crucial form of technological change with significant implications for firm-level productivity dynamics, directly related to the skill composition in the economy. Our findings indicate that, while larger firms become more adept at combining intangible capital with skilled labor to enhance productivity, smaller firms struggle to attract skilled workers and consequently face productivity losses. Therefore, designing a policy framework to incentivize technological change must consider the implications of labor market frictions and economies of scale.

This paper also highlights avenues for future research. We plan to extend our analysis in both empirical and theoretical directions. Empirically, we aim to access firm-level data on skill and occupation decomposition. Additionally, we plan to develop an empirical approach to examine how the synergy between intangible capital and skilled labor is associated with other firm dynamics, such as sales, profitability, market share, market power, and markups. Theoretically, using the firm-level general equilibrium model, we plan to conduct counterfactual exercises through quantitative analysis to address questions such as how changes in intangible capital affect skill premiums and labor reallocation across firms.

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Appendix

A Tables

Table A.1: Firm-Level Constructed Variables and Descriptions - Compustat

Variable	Description	Reference
Productivity	$\frac{\text{Sales } (\textit{sale})}{\text{Employee } (\textit{emp})}$	Comin and Philippon (2005), Gutiérrez and Philippon (2016), Autor et al. (2020)
Intangible Capital Ratio	$\frac{\text{Intangible Capital}}{\text{Intangible Capital + Property, Plant and Equipment } (\textit{ppegt})}$	Peters and Taylor (2017)
Tobin's Q	$\frac{\text{Assets } (\textit{at}) + (\text{Common Shares } (\textit{csho}) \text{ x Price } (\textit{prcc\_f})) - \text{Common Equity } (\textit{ceq})}{\text{Assets } (\textit{at})}$	
Markup	$0.85\frac{\text{Sales } (\textit{sale})}{\text{Cost of Goods Sold } (\textit{cogs})}$	De Loecker et al. (2020)
Age	Number of years a firm is present at point of time	

Note: This table summarizes the firm-level constructed variables and their brief descriptions in the Compustat sample.

Table A.2: Summary Statistics - Compustat Variables

	Mean	SD	P50	Min	Max	Count
Assets (Real, million $)	1325.19	6834.13	117.14	2.84	335969.7	131973
Sales (Real, million $)	1227.30	6124.55	121.02	0	274613.9	131973
Employees	7.91	37.35	.9	0	2300	124386
Age	9.44	7.11	8	1	31	131973
Property, Plant and Equipment (Gross, million $)	1121.84	7259.42	54.69	0	447337	130771
Intangible Capital (million $)	782.42	4594.32	58.74	0	278772.4	128188
Tobin's Q	2.05	2.40	1.45	.02	203.51	117727
Markup	1.82	8.28	1.27	0	1115.2	129995

Note: This table documents the summary statistics of some selected firm-level variables in the Compustat. P25: 25^{th} percentile, P50: median and P75: 75^{th} percentile.

Table A.3: Summary Statistics - Intangible Capital Ratio

	Mean	SD	P25	P50	P75	Min	Max	Count
Intangible Capital Ratio	0.54	0.28	0.32	0.58	0.77	0.00	1.00	127025

Note: This table documents the summary statistics of intangible capital ratio. p25: 25^{th} percentile, p50: median and p75: 75^{th} percentile.

Table A.4: Summary Statistics by Intangible Capital Ratio Quintiles

	Q1	Q2	Q3	Q4	Q5
Intangible Capital Ratio	0.38	0.54	0.64	0.73	0.86
Assets (Real, million \$)	148.91	148.79	122.96	86.61	40.49
Sales (Real, million \$)	149.89	152.98	132.29	92.15	37.04
Employees	1.22	1.10	0.97	0.62	0.24
Age	8.00	8.00	8.00	7.00	6.00
Tobin's Q	1.38	1.47	1.47	1.50	1.58
Markup	1.22	1.30	1.30	1.33	1.36

Note: This table documents the pool sample median of some selected firm-level variables within each quintile of intangible capital ratio. Q1 is the bottom quintile and Q5 is the top quintile in terms of intangible capital ratio. Intangible capital ratio is defined as $\frac{\text{Intangible capital stock}}{\text{Intangible capital stock + Tangible capital stock}}$ where intangible capital stock is constructed based on the perpetual inventory method of Peters and Taylor (2017). Tangible capital stock is the total net plant,property and equipment.

Table A.5: Summary Statistics - Skill Intensity

	Mean	SD	P25	P50	P75	Min	Max	Count
Skill Intensity	0.29	0.14	0.17	0.27	0.39	0.00	1.00	85542

Note: This table documents the summary statistics of skill intensity. P25: 25^{th} percentile, P50: median and P75: 75^{th} percentile.

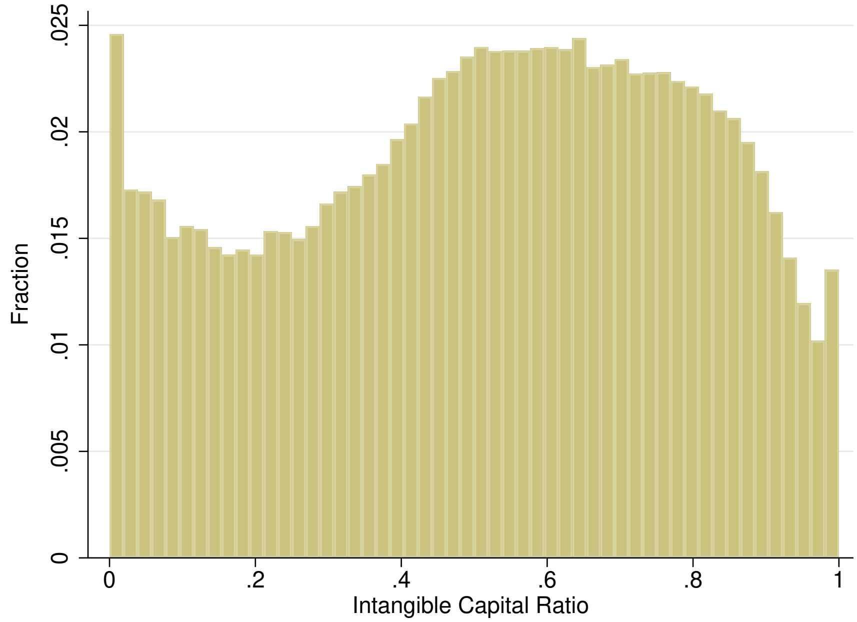
Table A.6: Intangible Capital and Skilled Workers

	(1) Skilled Workers	(2) Skilled Workers	(3) Skilled Workers	(4) Skilled Workers
L.Intangible Capital	0.791***	0.294***	0.329***	0.153***
	(0.00833)	(0.0191)	(0.0191)	(0.0167)
L.Asset		0.616***	0.602***	0.762***
		(0.0176)	(0.0175)	(0.0156)
Control Variables	No	Yes	Yes	Yes
Industry FE	No	No	No	Yes
Year FE	No	No	Yes	Yes
Adjusted R^2	0.642	0.741	0.762	0.877
Observation	76456	73821	73821	73818

Note: This table displays the results of the regression specification where the dependent variable is the firm-level logarithm of the number of skilled workers, and the main explanatory variable is the one-year logarithm of the intangible capital. Control variables include the one-year lag of firm-level logarithm of total assets, age, markup, and Tobin's Q. Standard errors (in parentheses) are clustered at the firm level. * $p < .10$, ** $p < .05$, *** $p < .01$.

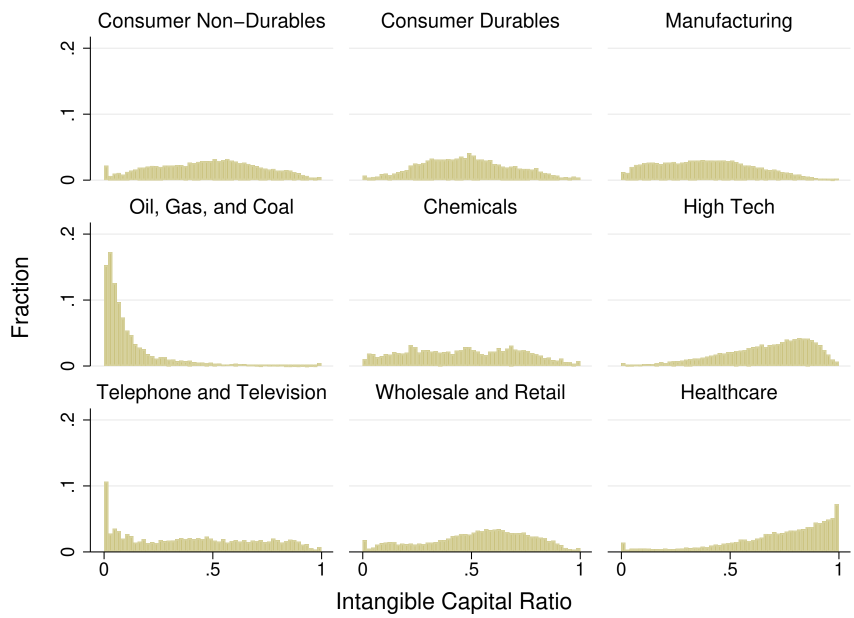
B Figures

Figure B.1: Intangible Capital Ratio - Histogram



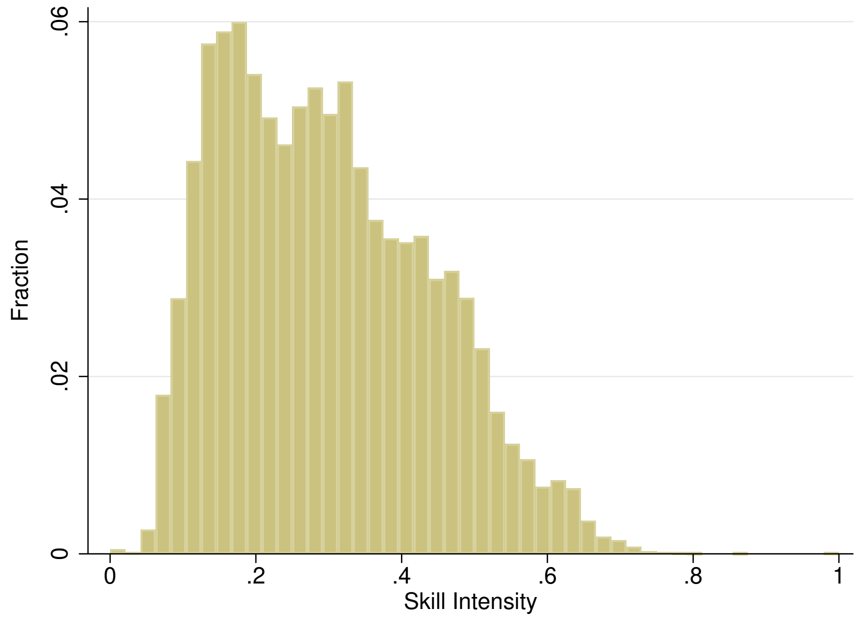
Note: This figure shows the histogram of intangible capital ratio.

Figure B.2: Intangible Capital Ratio - Industry Variation



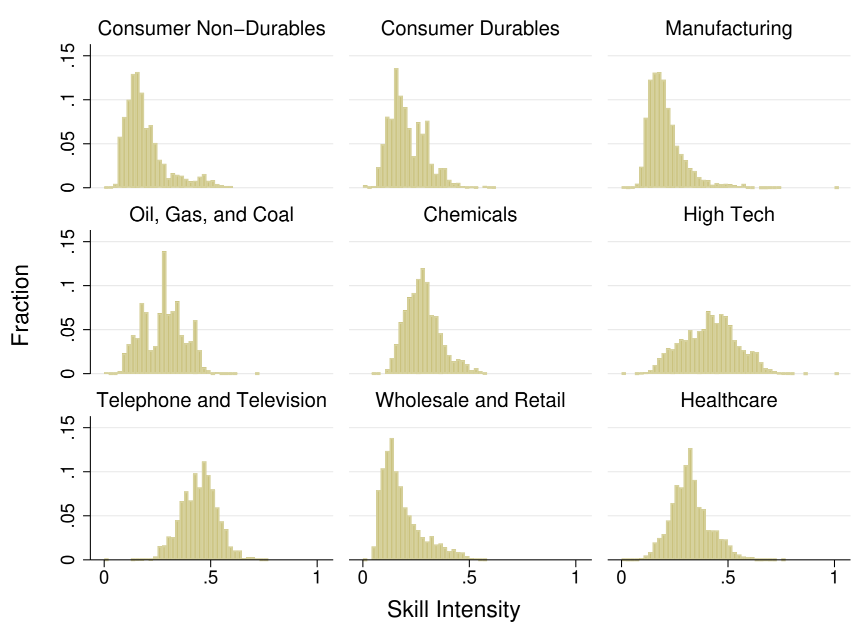
Note: This figure shows the histogram of intangible capital ratio for some selected industries.

Figure B.3: Skill Intensity - Histogram



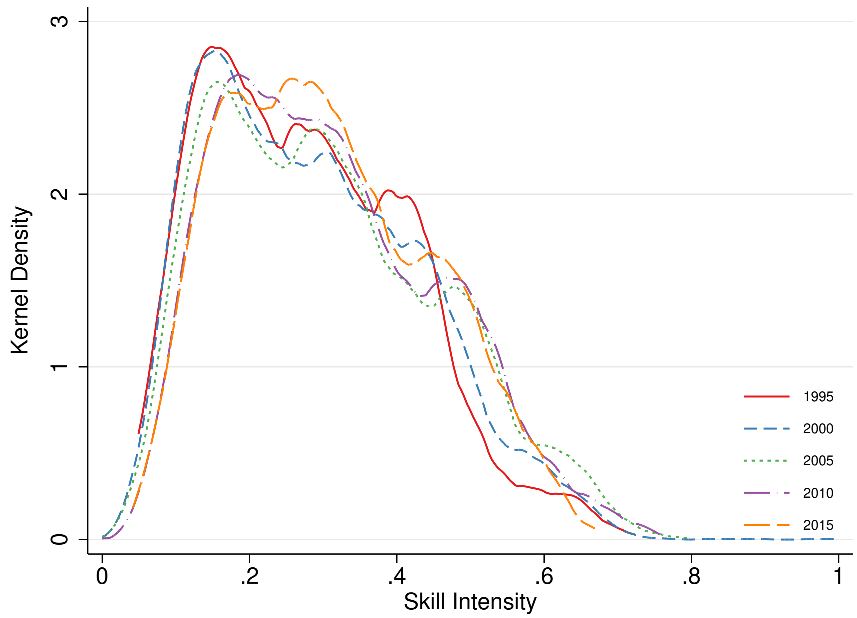
Note: This figure shows the histogram of skill intensity.

Figure B.4: Skill Intensity - Industry Variation



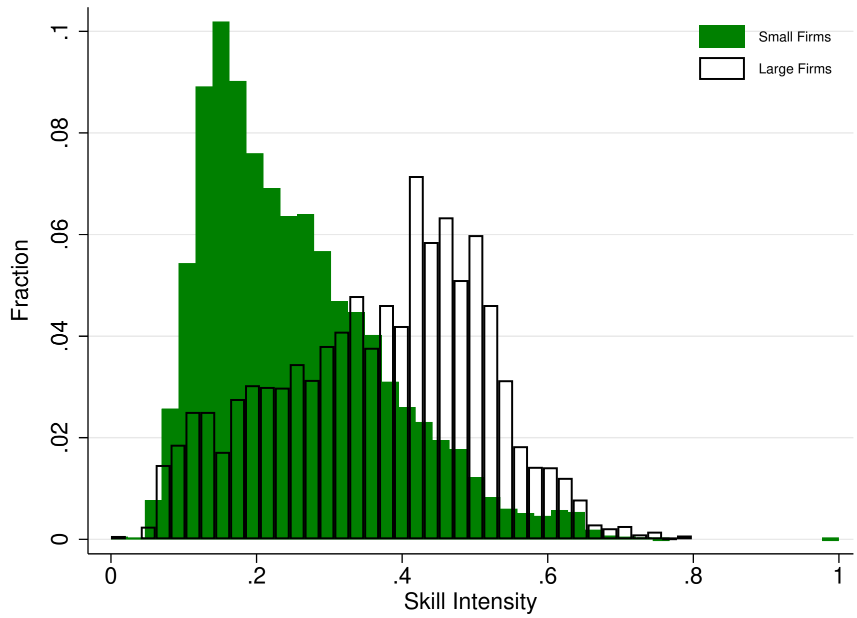
Note: This figure shows the histogram of skill intensity for some selected industries.

Figure B.5: Skill Intensity - Kernel Density



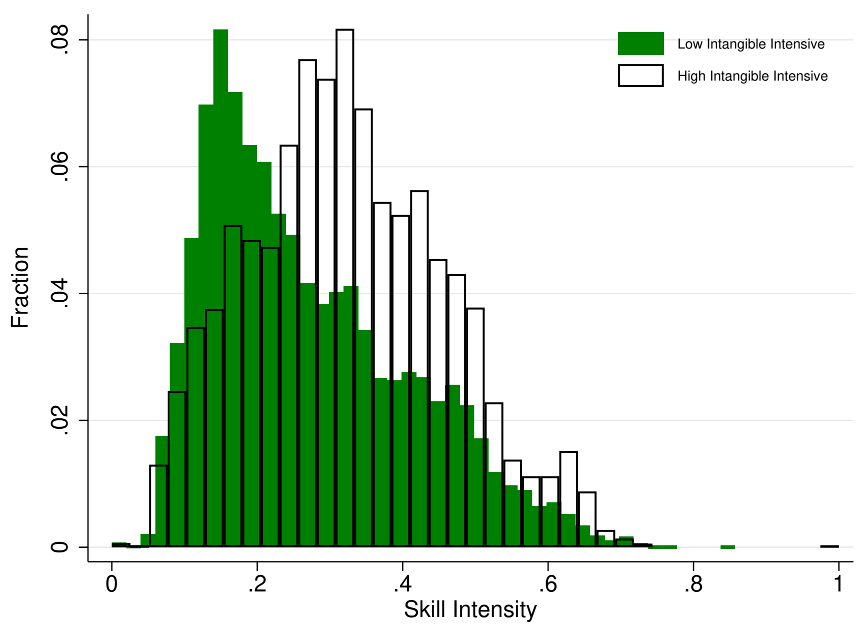
Note: This figure shows the kernel density of skill intensity for several selected years.

Figure B.6: Skill Intensity - Histogram by Firm Size



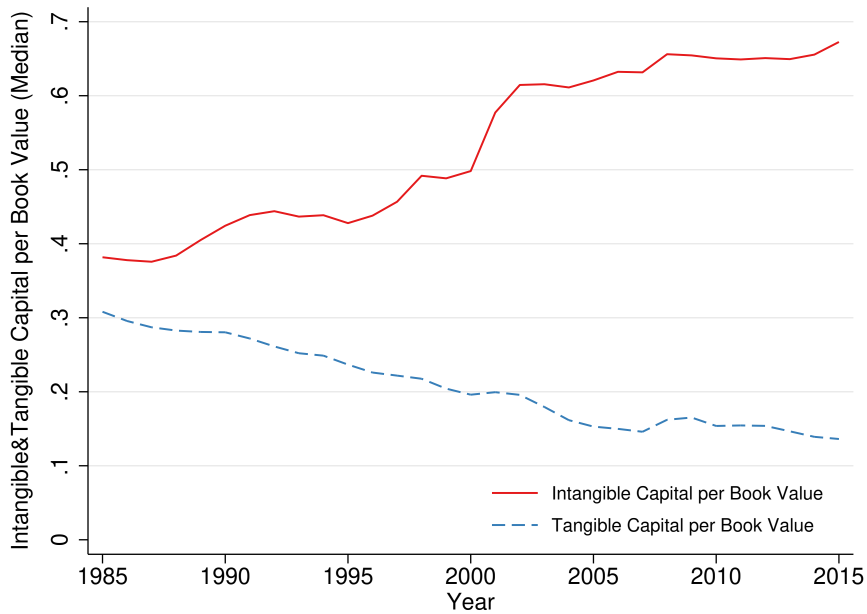
Note: This figure shows the histogram of skill intensity by small and large firms.

Figure B.7: Skill Intensity - Histogram by Intangible Capital Ratio



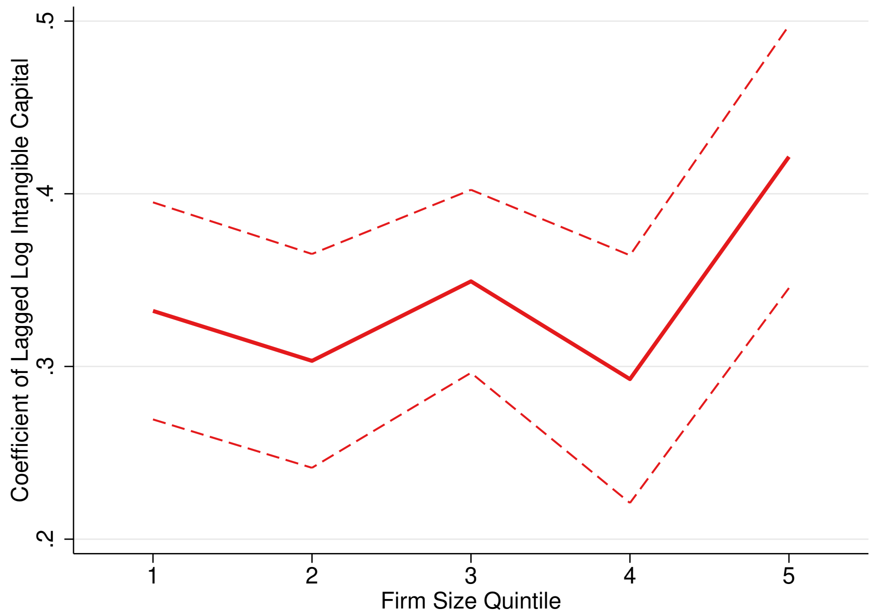
Note: This figure shows the histogram of skill intensity by low and high intangible intensive firms.

Figure B.8: Intangible & Tangible Capital per Book Value



Note: This figure shows the yearly simple median of intangible and tangible capital per book value in the Compustat. Book value is computed as the total assets.

Figure B.9: Quintile Regression - Intangible Capital and Skilled Workers



Note: This figure shows the coefficient of logarithm of one-year lagged intangible capital in the regression of Table A.6 within firm size quintiles, with year fixed effects included. Firm size quintiles are constructed based on total assets within each industry and year.

C Synergy between Intangible Capital and Inventors

This section offers a micro-founded and complementary analysis to our benchmark approach by examining the role of synergy between intangible capital and inventors in productivity dynamics. The advantage of this complementary approach is that it allows us to access individual-level disaggregated data on skill components at both the firm and inventor levels, using USPTO patent and inventor data combined with Compustat. This integration provides a detailed perspective on skill intensity and supports the justification of our benchmark mechanism.

C.1 Data

Patent Data We analyze utility patents granted by the United States Patent and Trademark Office (USPTO). Our analysis uses the registered names on the original patent applications to better capture the entities involved in innovation activities. Each patent record provides information about the invention, such as technology classifications and citations of related patents, as well as details about the inventors who submitted the application.

We then merge the USPTO patent data with the Compustat firm sample using a crosswalk provided by Autor et al. (2016). This crosswalk matches corporate patents granted by the USPTO between 1975 and March 2013 to Compustat firm identification numbers (GVKEY).[6] The algorithm uses a web search engine to match company name variations found on patents to the corresponding firm records. The matching results uniquely link assignee identification numbers from patent data to public firms' permanent identification numbers (i.e., "GVKEY") in the Compustat database.

Inventor Mobility We define inventor mobility across different firms as follows: An inventor i is considered to have moved from firm X to firm Y if at least one patent application authored or co-authored by inventor i was submitted by firm X (the source firm) before any application authored or co-authored by inventor i was submitted by firm Y (the destination firm). Thus, according to the structure of the USPTO patent data, we identify the timing of inventor i's move from firm X to firm Y as the year in which the patent application is submitted by inventor i at firm Y.

We acknowledge that determining the exact timing of inventor mobility poses a challenge, as the earliest observable patent activity by the mobile inventor is the year of the

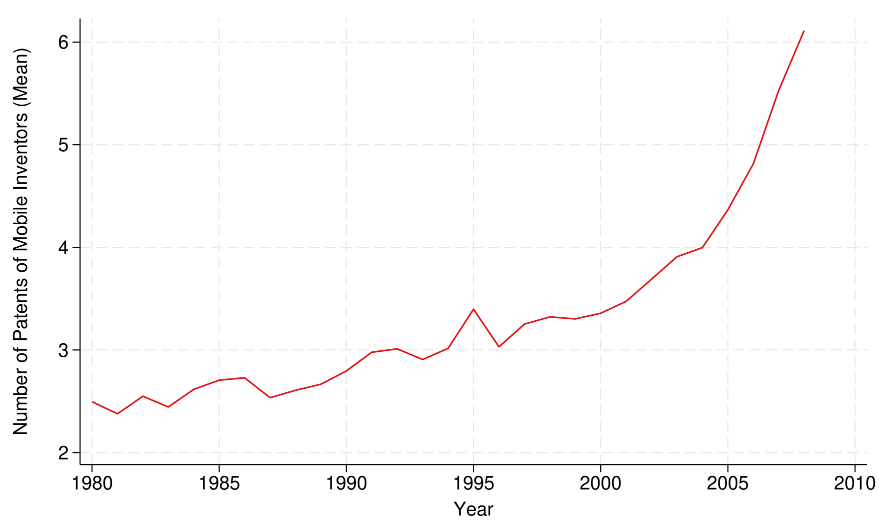
[6]For details of the matching algorithm, see David Dorn's data page.

first patent application submitted at the destination firm. However, the mobility of the inventor could have occurred before the year of the patent application at the destination firm. There may be a significant period required for the mobile inventor to collaborate with other inventors at the destination firm before a patent application can be filed. Ideally, we would precisely observe when the inventor moves from firm X to firm Y. Unfortunately, due to data limitations, this level of detail is not available.

C.2 Stylized Facts

This section presents several stylized facts suggesting that the association between productivity and intangible capital may also be linked to factor reallocation, such as inventor mobility. Our underlying conjecture is that small and medium-sized firms experiencing a productivity slowdown may lose their skilled inventors to larger firms. In this context, Figure C.1 illustrates that inventors with a higher number of patents become increasingly likely to move across firms over time. This figure can be interpreted to indicate that the skill requirements for inventor mobility have increased over time in the U.S. economy. Consequently, we argue that skilled inventors are becoming a scarce resource in the labor market.

Figure C.1: Patent Needed to Change a Company

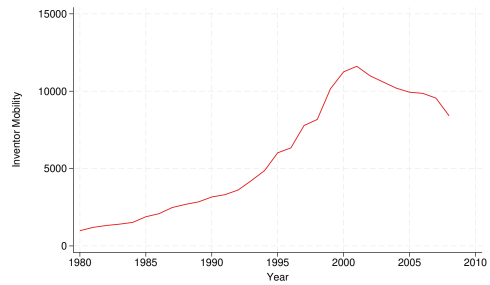


Note: This figure shows the average total patent of mobile inventors received at the (source) firm from which they leave.

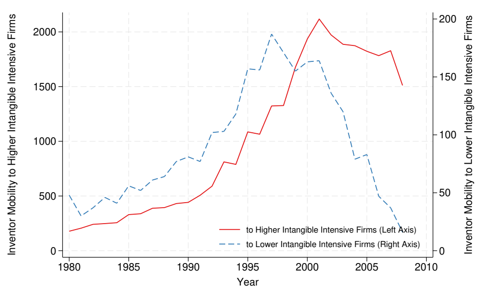
Figure C.2a shows that while total inventor mobility increased over time until the

2000s, it has exhibited a declining trend since then. Consequently, scarce skilled inventors have become even more valuable to firms, as their mobility decreased after the 2000s.

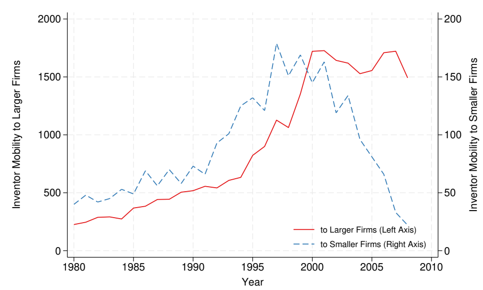
Figure C.2: Inventor Mobility and Intangible Capital



(a) Inventor Mobility



(b) Inventor Mobility by Intangible Capital

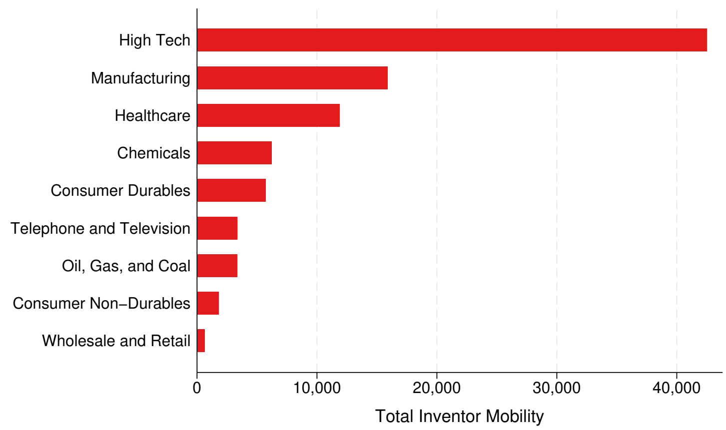


(c) Inventor Mobility by Firm Size

Note: Panel (a) shows the total inventor mobility, Panel (b) shows the inventor mobility to higher and lower intangible firms, and Panel (c) shows the inventor mobility to larger and smaller firms, where the right axis is inventors moving to the lower intangible firms and smaller firms respectively.

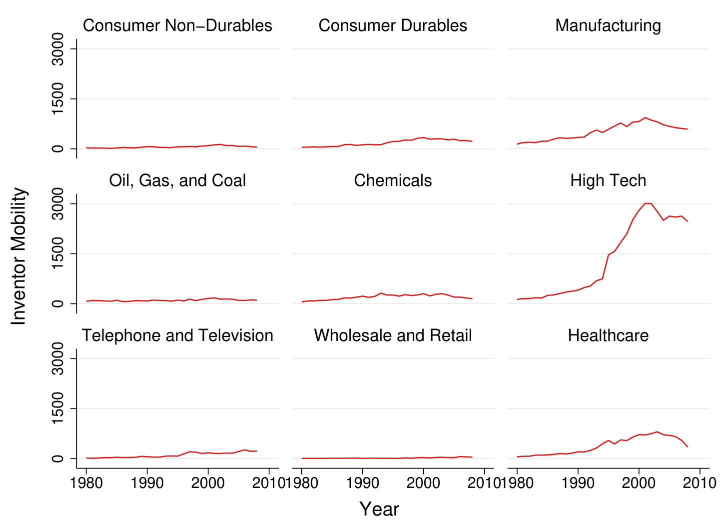
Given these phenomena, we argue that firms need to develop alternative strategies to attract these scarce skilled inventors. One such strategy is leveraging effective intangible capital. Firm-level intangible capital includes R&D expenditures, organizational capital such as employee training, restructuring of organizational structure, and improvements in business culture. Since intangible capital can be used to enhance inventors' personal and career development, firms with higher levels of effective intangible capital are more likely to attract and poach these valuable inventors from the labor market. We find confirming evidence for our argument. Figures C.2b and C.2c show that while inventor mobility to firms with lower intangible capital and smaller size has been declining—particularly after the 2000s, a period marked by productivity slowdown and increasing productivity dispersion—there has been no decline in inventor mobility to firms with higher size and higher intangible capital during this time. Thus, we can argue that firms with high intangible capital are better positioned to attract scarce skilled inventors, especially as the availability of such inventors decreases and their value increases.

Figure C.3: Total Number of Inventor Mobility - Industry-level



Note: This figure shows the total number of inventor mobility at the Fama-French industries.

Figure C.4: Inventor Mobility by Fama-French Industries

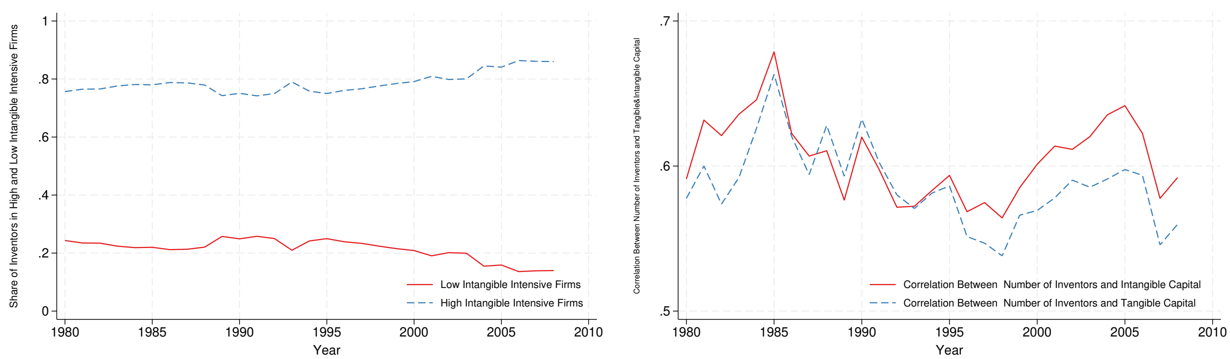


Note: This figure shows the inventor mobility at the Fama-French industries over time.

We also investigate inventor mobility at the industry level. Figure C.3 shows striking heterogeneity in inventor mobility across industries, with most inventor mobility occurring in the High Tech, Manufacturing, and Healthcare industries. Figure C.4 indicates that inventor mobility exhibited an increasing trend across different industries until the 2000s, but has since shown a declining trend.

Suppose we focus on the total number of inventors rather than only those who move. In that case, we observe a similar overarching pattern: a strong and positive association between the firm-level total number of skilled inventors and intangible capital. Figure C.5a shows that inventors are more likely to work at firms with high intangible capital intensity. Specifically, we find that approximately 80% of inventors work at firms where the intangible capital intensity is above the economy-wide average. Additionally, Figure C.5b indicates that the correlation between the firm-level total stock of inventors and intangible capital is generally higher than the correlation between the firm-level total stock of inventors and tangible capital. Hence, we argue that fluctuations in the total stock of inventors align more closely with fluctuations in intangible capital rather than tangible capital.

Figure C.5: Intangible Capital Intensity for Inventors



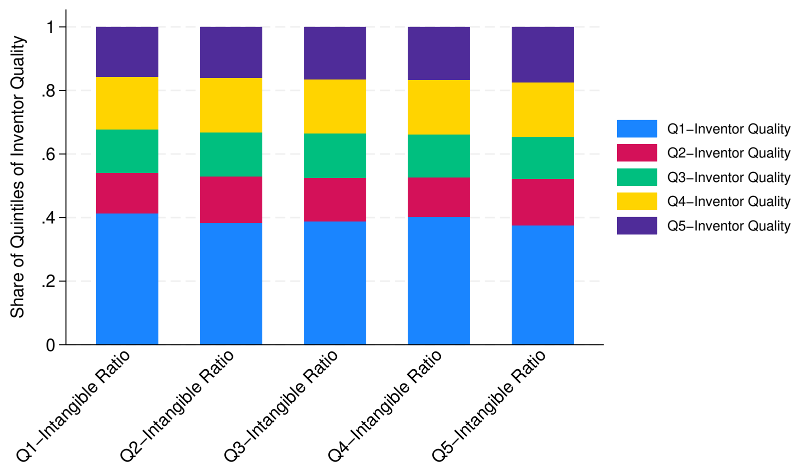
(a) Intangible Capital Intensity for Inventors

(b) Correlation

Note: Panel (a) shows the intangible capital intensity for inventors. Blue line shows the share of inventors working at the firms above the mean of economy-wide intangible capital intensity. Red line shows the share of inventors working at the firms below the mean of economy-wide intangible capital intensity. Panel (b) shows the correlation between the firm-level number of inventors and tangible capital and the correlation between the firm-level number of inventors and intangible capital. The correlations are computed between the firm-level number of total inventors and tangible capital and intangible capital in each year and industry (*NAICS*).

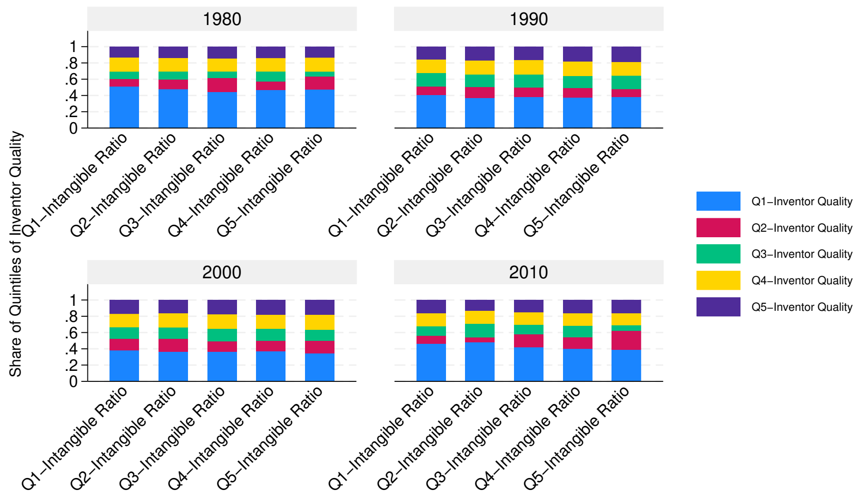
We align inventor quality and intangible capital intensity at the firm level to provide more direct evidence. First, we rank inventors based on their quality (measured by the 5-year citation count per total patents) and construct corresponding inventor quality quintiles. Next, we rank firms according to their intangible capital per asset and create corresponding intangible capital per asset quintiles. Finally, we calculate the shares of matches between each possible pair of quintiles. Figure C.6 shows that as firms' intangible capital share increases, the share of higher quality inventors they attract also increases. This suggests an assortative matching between inventor quality and intangible capital, even when controlling for firm size. In other words, after accounting for firm size, firms with higher intangible capital are more likely to attract higher quality inventors on average. This assortative matching is not limited to a specific time period; Figure C.7 demonstrates that this pattern persists across different 10-year windows.

Figure C.6: The Share of Inventor Quality by Intangible Capital Ratio (Quintiles)



Note: This figure shows the match between all potential quintiles of inventor quality and intangible capital ratio at the firm level. Inventor quality is based on the annual $\frac{\text{5-year window citation}}{\text{total patent}}$. x-axis denotes each intangible capital ratio quintile. y-axis denotes the corresponding share of each quintile of inventor quality within each quintile of intangible capital ratio.

Figure C.7: The Share of Inventor Quality by Intangible Capital Ratio (Quintiles) - 10-year window



Note: This figure shows the match between all potential quintiles of inventor quality and intangible capital ratio at the firm-level within 10-year window. For instance, the sub-part of the figure called "1980" denotes an average of the particular match for the years between 1980-1989. The inventor quality is based on the annual $\frac{\text{5-year window citation}}{\text{total patent}}$. x-axis denotes each intangible capital ratio quintile. y-axis denotes the corresponding share of each quintile of inventor quality within each quintile of intangible capital ratio.

C.3 Empirical Analysis

In this section, we investigate how intangible capital is associated with productivity of inventors.

C.3.1 Intangible Capital and Productivity of Inventors

The main goal of this section is to quantify how intangible capital and firm size are associated with inventors' productivity. Inventors are key drivers of productivity improvements within firms. When an inventor grants a patent to a firm, it enhances productivity and fosters greater innovation. Therefore, our benchmark regression aims to explore how intangible capital and firm size relate to the productivity of inventors, as outlined in the following analysis:

$$\Delta^{patent_{i,c}} = \beta_1 \Delta^{intangible_{i,c}} + \beta_2 \Delta^{asset_{i,c}} + \beta_3 X_{i,c} + u_i + u_t + u_s + \epsilon_{it} \tag{19}$$

$$\mathbb{1}^{patent_{i,c}} = \beta_1 \mathbb{1}^{intangible_{i,c}} + \beta_2 \mathbb{1}^{asset_{i,c}} + \beta_3 X_{i,c} + u_i + u_t + u_s + \epsilon_{it} \tag{20}$$

where the subscripts i, c, t, s refer to the inventor, firm, year, and sector, respectively. Our dependent variable in (19) is $\Delta^{patent_{i,c}}$, which denotes the difference between the number of patents produced in the destination firm c by inventor i and the number produced in the source firm from which inventor i moves. The dependent variable in (20) is $\mathbb{1}^{patent_{i,c}}$, a dummy variable equal to 1 if the number of patents produced by inventor i in the destination firm c is higher than in the source firm. For the specification (19), $\Delta^{intangible_{i,c}}$ represents the difference in intangible capital between the destination firm c and the source firm from which inventor i moves, while $\Delta^{asset_{i,c}}$ represents the difference in total assets between these firms. In specification (20), $\mathbb{1}^{intangible_{i,c}}$ is a dummy variable equal to 1 if the inventor i moves to a firm c with higher intangible capital than the source firm, and $\mathbb{1}^{asset_{i,c}}$ is a dummy variable equal to 1 if the inventor i moves to a firm c with higher assets than the source firm.

Our coefficients of interest are β_1 and β_2. The firm-level control variables are represented by the vector $X_{i,c}$, which includes firm size and the level of intangible capital. Firm size is measured as the logarithm of the assets, and intangible capital is measured as the logarithm of intangible capital per worker at firm c. We control for intangible capital per worker because the average use of intangible capital is a key determinant of patent creation. To account for unobserved heterogeneity, we include several fixed effects: inventor, year, and sector. Given that more productive inventors can benefit more from intangible capital, we use inventor fixed effects, u_i. Additionally, there are industrial differences in the likelihood of receiving patents. For instance, it may be easier to obtain a patent in the computer, software, and electronic equipment sectors, while it may be more challenging in the agricultural sector. As shown in Figure C.3, inventor mobility exhibits sectoral differences. Therefore, we also control for sector fixed effects, u_s. Finally, innovation may become increasingly difficult over time, so we capture time-related unobserved heterogeneity with u_t.

Table C.1: Association between Intangible Capital and Patent Production of Mobile Inventors - Level

	$\Delta^{patent_{i,c}}$	$\Delta^{patent_{i,c}}$	$\Delta^{patent_{i,c}}$
$\Delta^{intangible_{i,c}}$	1.235***		0.918***
	(0.097)		(0.258)
$\Delta^{asset_{i,c}}$		1.834**	0.841***
		(0.724)	(0.293)
Control Variables	Yes	Yes	Yes
Inventor FE	No	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.085	0.490	0.651
N	22142	2351	1945

Note: This table shows the results of the regression specification (19). The dependent variable is the difference between number of patents produced in the destination firm c by inventor i and the one in the source firm the inventor i moves from. $\Delta^{intangible_{i,c}}$ denotes the difference between the intangible capital in the destination firm c and the one in the source firm the inventor i moves from, and $\Delta^{asset_{i,c}}$ denotes the difference between the firm total assets in the destination firm c and the one in the source firm the inventor i moves from. Firm-level controls are firm size (the logarithm of the assets firm holds) and the logarithm of intangible capital per worker. Each column represents a particular regression specification which differs in terms of inventor, year and industry (*NAICS*) fixed effects. Standard errors (in parentheses) are clustered at the inventor-level. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table C.1 presents the results of equation (19). We find that a unit increase in the difference in intangible capital (or assets) between the destination and source firms is associated with an increase of approximately 0.91 (0.84) patents. Thus, Table C.1 indicates that higher intangible capital and larger firm size contribute to greater productivity among inventors.

Table C.2: Association between Intangible Capital and Patent Production of Mobile Inventors - Dummy

	$\mathbb{1}^{patent_{i,c}}$	$\mathbb{1}^{patent_{i,c}}$	$\mathbb{1}^{patent_{i,c}}$
$\mathbb{1}^{intangible_{i,c}}$	0.054***		0.085**
	(0.007)		(0.039)
$\mathbb{1}^{asset_{i,c}}$		0.090***	0.020
		(0.028)	(0.040)
Control Variables	Yes	Yes	Yes
Inventor FE	No	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.119	0.643	0.647
N	24430	3429	3212

Note: This table shows the results of the regression specification (20). The dependent variable ($\mathbb{1}^{patent_{i,c}}$) is a dummy variable with 1 if the inventor i moving to the firm c produces higher number of patents compared to the source firm the inventor i moves from. $\mathbb{1}^{intangible_{i,c}}$ ($\mathbb{1}^{asset_{i,c}}$) is a dummy variable with 1 if the inventor i moving to the firm c with higher intangible capital (asset) compared to the source firm the inventor i moves from. Firm-level controls are firm size (the logarithm of the assets firm holds) and the logarithm of intangible capital per worker. Each column represents a particular regression specification which differs in terms of inventor, year and industry (*NAICS*) fixed effects. Standard errors (in parentheses) are clustered at the inventor-level. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table C.2 reports the results of equation (20). The second column in Table 3 shows that inventors moving to larger firms (firms with higher assets) increase their number of patents by 0.09 compared to their previous firms. Note that in this column, we do not control for the intangible capital dummy variable. When we include only the intangible capital dummy variable (column 1), we observe that inventors moving to firms with higher intangible capital generate 0.05 more patents than at their previous firm. In the final column, where both dummy variables for assets and intangible capital are included, the effect of moving to larger firms becomes insignificant once we control for intangible capital. However, inventors moving to firms with higher intangible capital still increase their number of patents by 1, even when firm size is controlled for. These results suggest that the primary driver of increased patent production for inventors is intangible capital. Therefore, Table C.2 indicates that higher intangible capital enhances inventor productivity, even when controlling for firm size.

Even though we claim that intangible capital is the main driver of generating patents, there can still be an interaction between the intangible capital and firm size. In that regard, we follow the following regression:

$$\Delta^{patent_{i,c}} = \beta_1[\mathbb{1}^{intangible_{i,c}} \times \mathbb{1}^{asset_{i,c}}] + \beta_2 X_{c,t} + u_i + u_t + u_s + \epsilon_{it} \tag{21}$$

where $\Delta^{patent_{i,c}}$ denotes the difference between the number of patents produced in the destination firm c by inventor i and the number produced in the source firm from which inventor i moves. Our firm-level control variables are represented by the vector $X_{i,c}$, which includes the logarithm of firm-level assets and the logarithm of firm-level intangible capital per worker. $\mathbb{1}^{intangible_{i,c}}$ is defined as a dummy variable with a value of 1 if the inventor moves to a firm with higher intangible capital and 0 if the inventor moves to a firm with lower intangible capital. Similarly, $\mathbb{1}^{asset_{i,c}}$ is a dummy variable with a value of 1 if the inventor moves to a firm with higher assets and 0 if the inventor moves to a firm with lower assets. The coefficient of interest is β_1. To address concerns about unobserved heterogeneity, as in equations (19) and (20), we also include fixed effects for inventor (u_i), year (u_t), and sector (u_s).

Table C.3 reports the estimation results of equation (21). In the second column, we observe that inventors moving to firms with both higher intangible capital and higher assets generate 0.59 more patents than those moving to firms with lower intangible capital and lower assets. When an inventor moves to a firm with higher intangible capital, but lower assets, they generate 1.26 more patents than inventors moving to firms with lower intangible capital. However, for inventors moving to firms with lower intangible capital, moving to a firm with higher assets does not significantly affect the number of patents produced. In fact, it even decreases the number of patents when sector fixed effects are not controlled for, as seen in column 1. Thus, Table C.3 indicates that inventors become more productive when moving to larger firms or firms with higher intangible capital. The synergy between assets and intangible capital enhances inventor productivity.

Table C.3: Interaction between Intangible Capital and Firm Size and Patent Production of Mobile Inventors

	$\Delta^{patent_{i,c}}$	$\Delta^{patent_{i,c}}$
$\mathbb{1}^{asset_{i,c}} = 0 \times \mathbb{1}^{intangible_{i,c}} = 0$	0	0
	(.)	(.)
$\mathbb{1}^{asset_{i,c}} = 1 \times \mathbb{1}^{intangible_{i,c}} = 0$	-0.226	-0.317
	(0.383)	(0.438)
$\mathbb{1}^{asset_{i,c}} = 0 \times \mathbb{1}^{intangible_{i,c}} = 1$	0.983	1.269*
	(0.605)	(0.676)
$\mathbb{1}^{asset_{i,c}} = 1 \times \mathbb{1}^{intangible_{i,c}} = 1$	0.417	0.591**
	(0.262)	(0.289)
Control Variables	Yes	Yes
Inventor FE	No	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
R^2	0.488	0.518
N	6522	6264

Note: This table shows the results of the regression specification (21). The dependent variable is the difference between number of patents produced in the destination firm c by inventor i and the one in the source firm the inventor i moves from. $\mathbb{1}^{intangible_{i,c}}$ ($\mathbb{1}^{asset_{i,c}}$) is defined as a dummy variable with 1 for the inventors moving to the firm with higher intangible (asset) firm and 0 for the inventors moving to lower intangible (asset) capital. Firm-level controls are firm size (the logarithm of the assets firm holds) and the logarithm of intangible capital per worker. Each column represents a particular regression specification which differs in terms of inventor, year and industry (*NAICS*) fixed effects. Standard errors (in parentheses) are clustered at the inventor-level. * $p < .10$, ** $p < .05$, *** $p < .01$.

In Section 3, we showed that productivity dispersion is rising and that intangible capital dispersion is positively correlated with productivity dispersion. Table C.3 suggests a potential reason for the increasing productivity dispersion favoring larger firms in the

U.S. economy. Intangible capital is a significant determinant of patent production for both small and large firms, but inventors at larger firms with higher intangible capital produce more patents. Consequently, this increased productivity among inventors at larger and higher intangible capital firms contributes to the observed productivity dispersion in favor of larger firms in the U.S. economy.