Intangible Capital Meets Skilled Labor: The Implications for U.S. Productivity Dynamics[*]

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Abstract: The U.S. economy has been experiencing an increase in productivity dispersion, which also co-moves with the rise of intangible capital. How would intangible capital lead to heterogeneous effect on productivity patterns? To explore this question, we introduce a new channel in which intangible capital meets skilled labor to operationalize its economic benefits, which requires economies of scale. Using firm-level measures of intangible capital and skill intensity, we document four related stylized facts: i) increasing productivity dispersion driven by large firms, particularly in intangible-intensive sectors, ii) a rise in intangible capital concentration among large firms, iii) higher skill intensity in large and intangible firms, and iv) higher productivity in large firms that exhibit higher levels of intangible capital and skill intensity. Based on these motivating facts, we build an empirical framework to quantify the impact of the intangible capital - skilled labor complementarity on firm-level productivity dynamics. We document that firms with higher intangible capital and skill intensity have higher productivity, which is amplified with firm size. To rationalize the reduced-form empirical evidence, we build a general equilibrium model with non-homothetic CES production technology to elucidate how the economies of scale shapes the complementarity within the firm-level production framework. Our calibrated model suggests that 80% of the complementarity between intangible capital and skilled labor over time is attributable to the economies of scale.

JEL Codes: D22, D24, E22, J24

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

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1 Introduction

There is a vast range of evidence in the literature that suggests an increase in productivity dispersion among firms in the U.S. economy (Andrews et al. (2016), Decker et al. (2018), Akcigit and Ates (2023)). Well-documented studies indicate that this increase is primarily attributable to the growing relative productivity of large firms (Andrews et al. (2016), Bessen (2017), Autor et al. (2020)). One strand in the literature explains this phenomenon based on the argument that the economy becomes less competitive due to tight regulations, which gives market power to large incumbent firms (Gutiérrez and Philippon (2017)). Another strand argues that the industries and firms that have a larger increase in concentration also experience stronger growth in productivity and innovation (Bessen (2017), Autor et al. (2020)). In that respect, the evidence on what are the causes and channels of the increasing productivity dispersion in the U.S economy is still mixed.

In parallel, within the same episode, U.S. economy has been also experiencing two important trends. First, there is an increasing degree of skill-biased technological change in the U.S. economy (Acemoglu (1998), Krusell et al. (2000), Violante (2008)). Second, the U.S. economy has a dramatic increase in intangible capital such as information technology, knowledge, human, and organizational capital (Corrado et al. (2009), Haskel and Westlake (2017)). Hence, this technological change influences the firm dynamics in various aspects because the firm production function has shifted so that the share of intangible capital becomes as essential as tangible capital. As we will also discuss in this paper, these trends are more pronounced in large firms, suggesting heterogeneous impacts across the firm-size distribution.

Based on these observations, we propose that the trends in intangible capital and skilled labor collectively constitute potential factors shaping firm-level productivity dynamics. We hypothesize and explore the existence of complementarity between intangible capital and skilled labor, grounded in the understanding that effective utilization of intangible capital requires skilled labor. This potential complementarity influences firm-level productivity by enhancing efficiency in converting inputs into outputs. In our context, we define complementarity between intangible capital and skilled labor as the positive and significant impact of their joint presence on firm-level productivity, a term consistently used throughout the paper.

We also investigate how the association between complementarity and productivity varies across the firm-size distribution, taking into account economies of scale as a crucial factor affecting the implications of this complementarity. Our underlying motivation is rooted in the scalability and non-rival nature of intangible capital, providing larger firms with a greater advantage in scaling up intangible capital across multiple business lines and units. In other words, large firms benefit disproportionately from the rising intangible capital by combining it with skilled labor to scale up and increase their productivity due to the advantages of economies of scale, along with the distinct features of intangible capital, which are scalability and non-rivalry.

In this context, we explore several questions: Through which channels do firms effectively use their intangible capital for productivity gains? What contributions do skilled labor make to the relationship between intangible capital and productivity? How significant is firm-size heterogeneity for the complementarity channel? What potential underlying heterogeneity explains why some firms benefit from the complementarity between intangible capital and skilled labor while others do not? To address these questions, we introduce a new channel of complementarity between intangible capital and skilled labor, aiming to account for productivity dispersion in the U.S. economy. To our best knowledge, even though it contains some limitations as described in Section 7, our study is one of the first attempts to explore the role of complementarity between rising intangible capital and skill intensity on firm-level productivity and emphasizes its heterogeneous implications across firm-size distribution.

We approach these questions based on our central argument that skilled labor is required to implement high-stakes intangible capital. Firms typically invest in intangible capital to enhance productivity, but it is not merely a process of developing software or advertising goods and services. Instead, firms need to employ skilled workers to effectively utilize their high-stakes intangible capital and reach an efficient level of production capacity, thereby establishing complementarity between intangible capital and skilled labor. Additionally, we argue that the degree of complementarity and its implications for productivity are amplified with firm size. This is because intangible capital possesses a distinctive feature of scalability and non-rivalry, emphasizing 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 its crucial input of consumer data. Similarly, Microsoft hires many IT engineers to leverage its extensive software investment. As anecdotal evidence, Table 1 reports the average intangible capital ratio and skilled labor intensity for a group of selected well-known large firms in the U.S. economy. We observe that these large firms exhibit both a high intangible capital ratio and skilled labor intensity, surpassing the economy's average.

Table 1: Anecdotal Evidence on the Intangible Capital Ratio and Skilled Labor Intensity

Firm	Intangible Ratio	Skill Intensity	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 skilled labor intensity for selected well-known large firms in the U.S economy.

We examine the particular channel of intangible capital - skilled labor complementarity using both empirical and theoretical frameworks. After documenting several motivating stylized facts from the data sample, our empirical analysis quantifies the effect of intangible capital-skilled labor complementarity on firm-level productivity. Next, we develop a theoretical framework to incorporate the role of the complementarity 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 several stylized data facts that motivate our investigation into the association between productivity dispersion, intangible capital, and skilled labor. With the use of data points and simple statistical techniques, we identify four main stylized facts: i) increasing productivity dispersion driven by large firms, particularly in intangible-intensive sectors, ii) a rise in intangible capital concentration among large firms, iii) higher skill intensity in large and intangible firms, and iv) higher productivity in large firms that exhibit higher levels of intangible capital and skill intensity. We interpret the last stylized fact as indicative of a potential complementarity between intangible capital and skilled labor. Overall, this set of stylized facts highlights the importance of economies of scale in influencing the degree of complementarity between intangible capital and skilled labor and its role in productivity.

The next section of the empirical analysis develops a more systematic approach through reduced-form econometrics techniques, including regression analysis, which quantifies the main insights captured by the stylized data facts. First, we estimate the role of intangible capital in firm-level productivity. After estimating the firm-level production function, we find that intangible capital has a positive and dramatic contribution to total factor productivity (TFP) compared to tangible capital. This suggests that firms have a higher incentive to operationalize effective intangible capital for productivity gains than tangible capital. Second, we estimate the association between firm-level intangible capital and skill intensity. We find that one standard deviation increase in intangible capital ratio increases up to 0.60 of standard deviation of skill intensity, which implies an increase in skill intensity by 0.11, depending on different fixed effects. This effect is further amplified with firm size. In other words, larger firms with higher intangible capital are more likely to exhibit higher skill intensity. Third, we quantify the effect of intangible capital and skilled workers on firm-level productivity. We demonstrate that firms with higher intangible capital and skill intensity have higher productivity, and this effect is magnified with firm size. A one-standard-deviation increase in firm-level skill intensity increases firm-level productivity by up to 3.4%, while a one-standard-deviation increase in the firm-level intangible capital ratio results in an approximately 8.4% increase in firm-level productivity.

To empirically quantify the complementarity effect between intangible capital and skill intensity, we investigate how their joint interaction enhances firm-level productivity. We find that the coefficient of the interaction term is nearly zero and insignificant for small firms, whereas it becomes positive and significant for larger firms, indicating that a one-standard-deviation joint increase in intangible capital and skill intensity boosts firm-level productivity by around 2% for large firms. This set of empirical results aligns with our hypothesis and offers several insights. Firstly, it indicates the presence of complementarity between intangible capital and skilled labor, as their joint interaction enhances firm-level productivity on average. Secondly, it suggests that the complementarity effect on productivity is heterogeneous across firm-size distribution, generating a positive impact on productivity at larger firms. This implies that larger firms can leverage the economic effects of complementarity to increase their productivity.

We also provide an additional set of analyses to our benchmark approach by examining the role of synergy between intangible capital and inventors on productivity dynamics. The advantage of this complementary approach is that we utilize individual-level disaggregated identifying variations in the skill component at the firm and inventor levels using USPTO patent and inventor data, merging it with Compustat. This approach provides us with a laboratory to capture a more granular level of skill intensity and to justify our benchmark mechanism. In this additional exercise, we investigate how the accumulation of intangible capital influences inventor reallocation across firms, focusing on the degree of inventor mobility across firms. We find that while inventor mobility to the firms with lower intangible capital has been declining, especially after the 2000s when we observe an increasing productivity dispersion, there is no decline in inventor mobility to the firms with higher intangible capital during that period. This finding indicates a potential complementarity between intangible capital and skilled inventors, aligning with our baseline evidence. Motivated by this finding, we also explore how intangible capital affects inventors' productivity across different firm sizes. We find that inventors produce more patents as they move to larger firms with higher intangible capital, implying that the synergy between intangible capital and skilled inventors is especially pronounced in large firms.

To rationalize the reduced-form empirical evidence, we first present a simple motivating model that provides a basic explanation for our empirical findings, explaining why firms with higher intangible capital benefit from skilled labor. Our goal is to construct a simple model illustrating that intangible capital needs to be incorporated into the standard production framework to accurately capture its increasing role as a factor input in the real economy. In this regard, we employ a simplified and modified version of the model developed by Acemoglu and Autor (2011) to elucidate the channels through which a complementarity between intangible capital and skilled labor arises. In our motivating model, the primary channel through which the accumulation of intangible capital attracts skilled labor is disciplined by changing skill premia due to the shift in the relative demand for skilled labor resulting from an increase in intangible capital intensity in the economy. The model predicts that an increase in intangible capital intensity also raises the skilled premium, aligning with our empirical evidence that sectors with higher intangible capital intensity exhibit greater skill intensity. We conduct an empirical test for the basic model prediction using the NBER-CES database to measure industry-level skill premium and unskilled-skilled labor ratios at the 4-digit *NAICS*. Our findings reveal that an increase in the intangible capital ratio has a positive and significant effect on 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 in the literature. This alignment indicates that the incorporation of intangible capital into a standard production framework is able to capture the existing and well-known parameters in the related literature, which suggests that our motivating model framework is a plausible approach. An additional noteworthy insight from our motivating modeling framework is its potential to provide an alternative identification for the unobserved skill-specific TFP. While Acemoglu and Autor (2011) rely on proxies for measuring unobserved skill-specific TFP to predict the skill premium, our approach addresses this requirement by 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 insights and plausibility derived from the motivating model, we develop an extended version using a general equilibrium model that incorporates heterogeneous firms investing in intangible capital and hiring skilled and unskilled labor. Our primary goal is to incorporate a model framework that elucidates how the economies of scale shapes the complementarity within the firm-level production framework, which enables us to disciple our related empirical evidence. The model features a non-homothetic CES production technology to introduce the importance of intangible capital-skilled labor complementarity with economies of scale. In that sense, our model builds heavily on the model developed by Eckert et al. (2022) through embedding an extension of a neoclassical production function with capital-labor complementarity based on their insight. The model has three main 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 create 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 is decreasing in firm output, i.e. intangible capital and high-skilled labor are more complementary at firms operating at larger scale, a finding supported by our empirical analysis. Moreover, our calibrated model documents that 80% of the complementarity between intangible capital and skilled labor over time is attributable to the economies of scale, which is consistent with the empirical evidence that the intangible capital-skilled labor complementarity is more pronounced at large firms, which increases over time. Therefore, our general equilibrium model confirms the empirical evidence that there is a heterogeneous pattern in complementarity across the firm size distribution, and large firms benefit disproportionately from the complementarity over time. That is, the non-homothetic CES model, with the incorporation of the scale elasticity parameter, enables us to capture the heterogeneous complementarity that varies across firm-size groups.

Related Literature. Our paper is related to several strands of the literature. The first strand of the literature focuses on the declining business dynamism in the U.S. economy. Some potential explanations behind the decline are slowing technological diffusion (Akcigit and Ates (2023)), factors reallocation toward superstar firms (Autor et al. (2020)), implementation and restructuring lags of breakthrough technology (Brynjolfsson et al. (2018)), structural changes in the cost structure with intangible capital (De Ridder (2019)), market power driven by intangible capital (Crouzet and Eberly (2019)), and many others. Our contribution to this strand is to emphasize another channel in which the synergy between intangible capital and skilled labor favors large firms, which results in an increasing productivity dispersion that is mainly driven by large firms.

The second strand of the literature studies 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); McGrattan (2020)). The literature documents that the accumulation of intangible capital affects several dimensions in firm dynamics such as 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 (2020)). Our contribution to this literature is to argue that together with a rising share of intangible capital in the U.S. economy, the heterogeneity in intangible capital across different firm size can partially account for the increasing productivity dispersion in the U.S. economy.

The third strand of the literature investigates the role of technical change on the labor market dynamics. In that regard, there are several papers studying 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)), capital-skill complementarity (Griliches (1969), Greenwood and Yorukoglu (1997), Goldin and Katz (1998b), Bresnahan et al. (2002), Autor et al. (2003)). Most of the previous papers emphasize the implications of technical change in the aggregate economy and labor market. In contrast, data limitations tend to attribute the technical change to either some subset of technological trends (computers, robots, or IT revolution) or some unobservable TFP components. On the contrary, in this paper, we consider the technological change in a broader sense and emphasize the role of intangible capital in the structural transformation of the economy. In that sense, instead of focusing on a narrower subset of a particular technological invention or loading a key role to unobservable TFP components, we instead observe and quantify an overall trend in intangible capital that accounts for the technical change in the economy. Hence, our contribution emphasizes the role of intangible capital as a new form of technical change in the U.S. economy and then highlights its effect on firm-level productivity and labor reallocation.

The last related strand of the literature investigates driving forces for increasing skill premium. In that regard, there is a vast range of studies that focus on the implications of skilled-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)), trade induced changes (Pissarides (1997), Parro (2013), Caselli (2014), Harrigan and Reshef (2015), Burstein and Vogel (2017)), and so many others to account for variations in skill premium. In that regard, our contribution is to study the role of the complementarity between intangible capital and skilled labor in productivity, which raises the demand for skilled labor under the environment where there is a rising trend in intangible capital and hence it results in increasing skill premium. Moreover, our another contribution is that the synergy between intangible capital and skilled labor is directly related to the firm size, which results in increasing skill premium driven by large and intangible intensive firms.

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

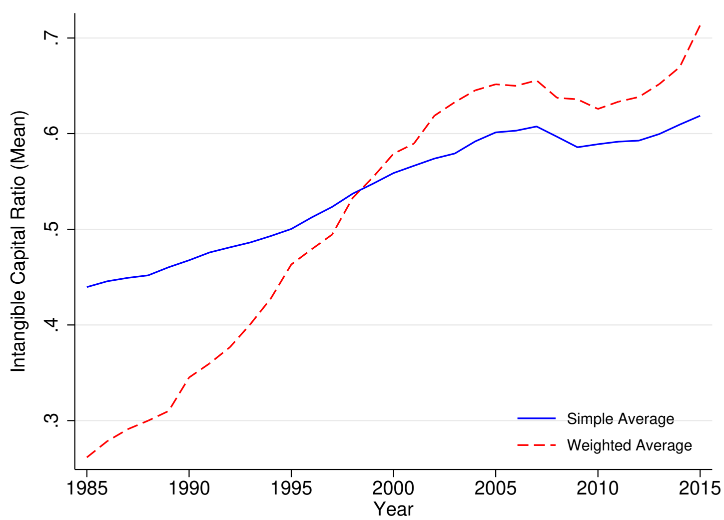
2 Stylized Facts

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 *NAICS* three-digit sectors 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.

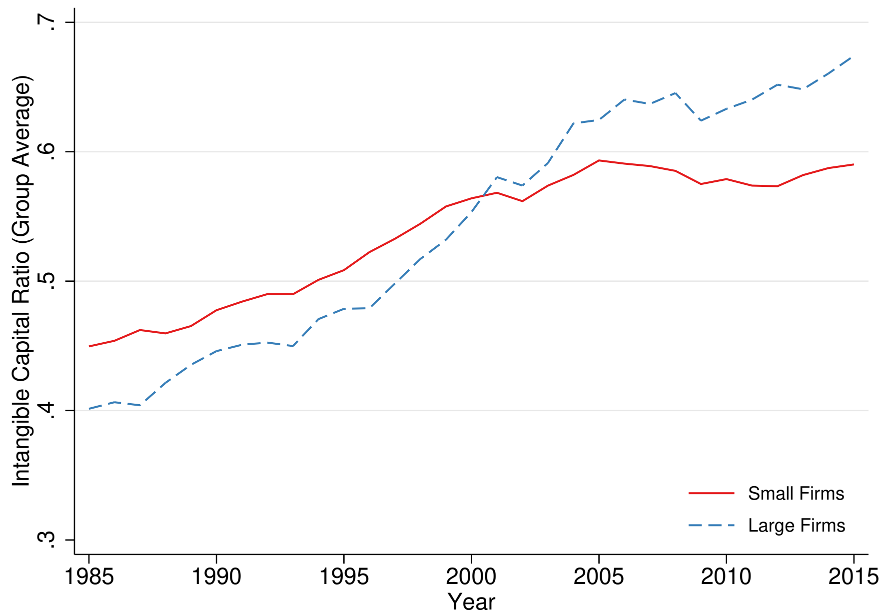
Figure 1: Intangible Capital Ratio



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.1 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



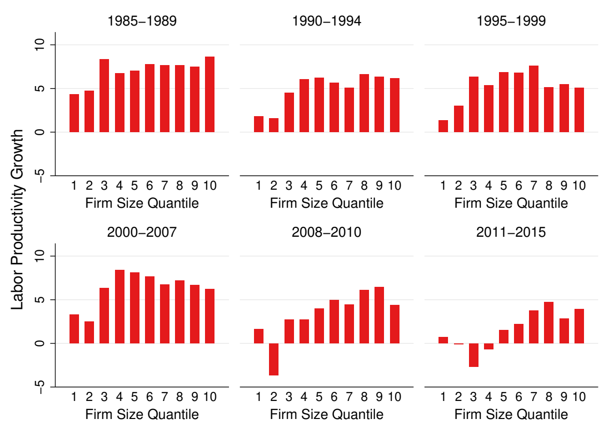
Note: This figure shows the annual average of intangible capital ratio over time for small and large firms. Small firms are the ones that are within Quantile 1, where quantiles are constructed based on the firm-level total asset within industry (*NAICS*) and year. Large firms are the ones that are within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

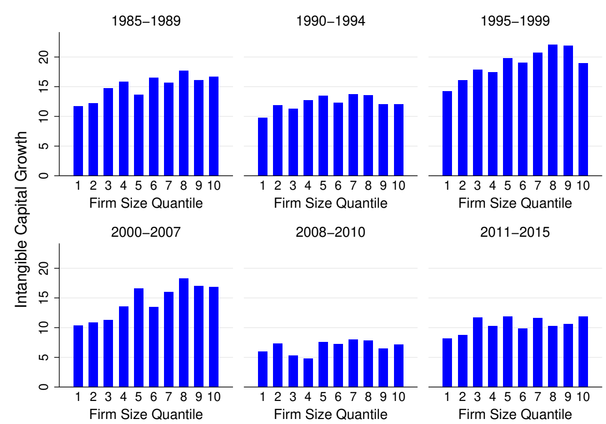
Fact 2: Decline in labor productivity and intangible capital growth during the last two decades is driven by small firms.

Figure 3a shows a selected time-window average of labor productivity growth for each firm size quantile. We first observe that even though medium- and large-scale firms perform well between 1985 and 2008, smallest firms have relatively lower productivity growth after 1990. Moreover, after the 2008 financial crisis, small-scale firms do not have a quick recovery, whereas large-scale firms relatively have better performance in terms of productivity growth in that period. It overall implies that a decline of productivity growth seems to be mostly driven by small-scale firms rather than large-scale firms.

Figure 3: Labor Productivity and Intangible Capital Growth



(a) Labor Productivity Growth



(b) Intangible Capital Growth

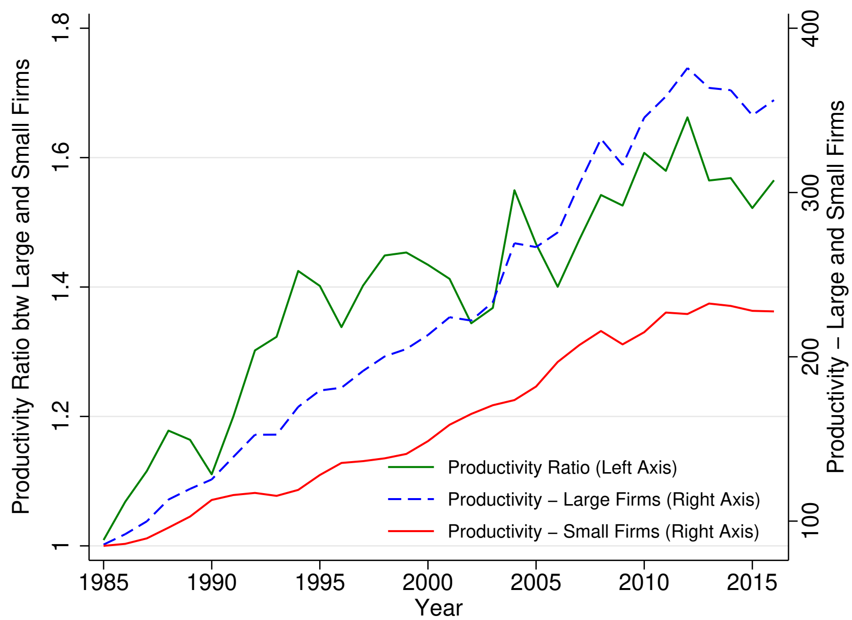
Note: Panel (a) shows a selected time-window average of labor productivity growth for each firm size quantile. Panel (b) shows it for intangible capital growth. Firm size is captured by firm-level total sales and firm size quantiles are measured within each industry (*NAICS*) and year. Quantile 1 is the smallest firms, and Quantile 10 is the largest firms.

To emphasize the role of firm size in intangible capital growth, Figure 3b first show that all firm-sizes have a positive intangible capital growth, which tends to be an increasing order with firm-size, on average between 1985 and 2008. However, small- and medium-scale firms experience a slower growth in intangible capital during the 2008 financial crisis period, but large-scale firms continue to have a slighlty higher growth even though its level is relatively lower compared to the pre-crisis period. Moreover, small-scale firms still end up with having a lower growth during the recovery period between 2011 and 2015, whereas large-firms perform better in intangible capital accumulation compared to the crisis period.

Fact 3: Labor productivity gap between large and small firms widens over time in favor of large firms.

Figure 4 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.

Figure 4: Labor Productivity Ratio Between Large and Small Firms



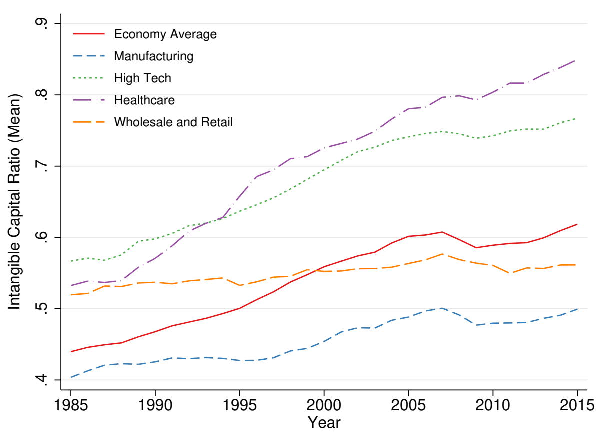
Note: The left axis of the figure shows an average labor productivity ratio between large firms and small firms. The right axis of the figure shows the average productivity of large and small firms. Firm size is captured by firm-level total assets. Small firms are the ones which are at the 10th percentile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

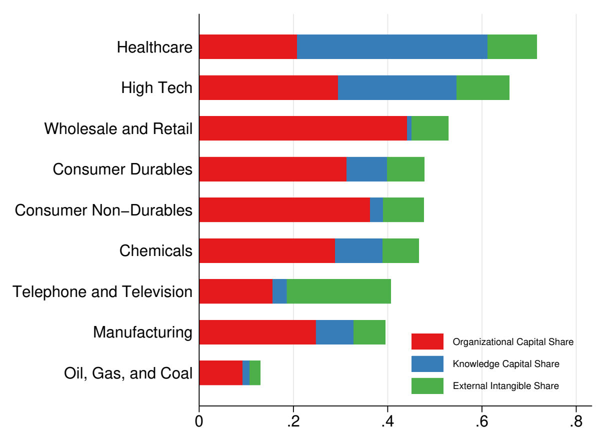
Fact 4: Industry-level heterogeneity in intangible capital accounts for productivity dispersion.

We first document that the trends in intangible capital show striking heterogeneity across different industries. For instance, Figure 5a shows that even though there is a dramatic increase in the intangible capital ratio for selected industries, the highest average of intangible capital ratio is observed in Healthcare and High Tech industries. In contrast, the average intangible capital ratio in Manufacturing and Wholesale and Retail industries is below the economy-wide average intangible capital ratio after mid-1990s. Looking at the components of intangible capital, we also observe a pattern of heterogeneity. Figure 5b documents that even though the share of organizational capital is bigger for almost all selected industries, the component of knowledge capital constitutes an important share for the Healthcare and High Tech.

Figure 5: Industry-level Heterogeneity in Intangible Capital



(a) Intangible Capital Ratio



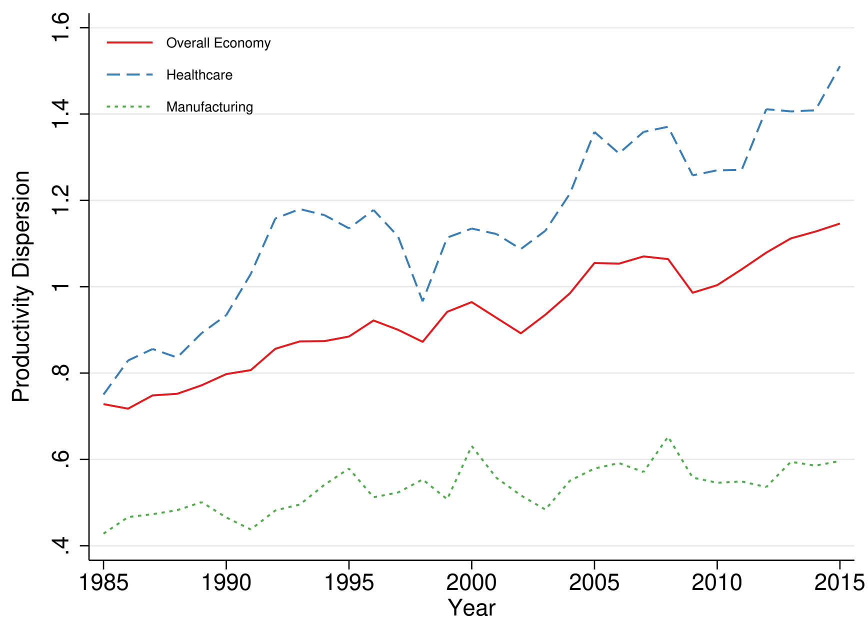
(b) Intangible Capital Components

Note: Panel (a) shows the annual average of intangible capital ratio for overall economy, Manufacturing, High Tech, Healthcare and Wholesale and Retail industries. Panel (b) shows the pooled sample average of intangible capital components for selected Fama-French industries.

We also find a similar heterogeneity in productivity dispersion across different industries. Figure 6 shows that productivity dispersion increases in the overall economy, which is line with the literature evidence (Andrews et al. (2016), Decker et al. (2018), Akcigit and

Ates (2023)). Moreover, since we aim to link the overall trend in productivity dispersion to intangible capital, in line with the evidence from Figure 5a, we take two representative industries: Healthcare industry as a representative for highly intangible, and Manufacturing industry as a representative for highly tangible. We observe that the Healthcare has a dramatic and sharp increase in productivity dispersion over time, whereas we do not find such evidence for Manufacturing. It suggests that industrial heterogeneity in intangible capital would be a key factor in the overall productivity dispersion. Our industry-level regression analysis in Table A.6 also supports the stylized fact that intangible intensive industries have higher productivity dispersion on average, especially after the 2000s.

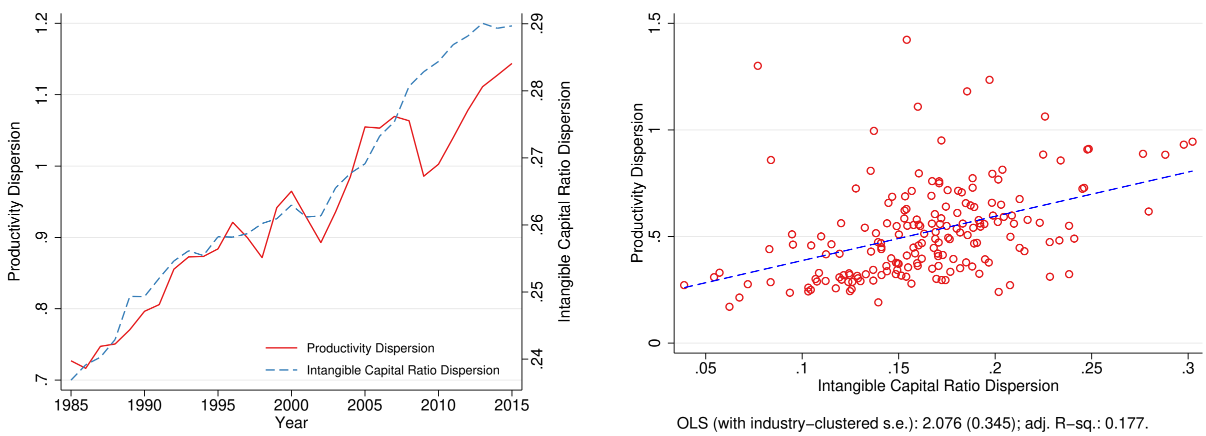
Figure 6: Industry-level Productivity Dispersion



Note: This figures shows the productivity dispersion in the overall economy, Healthcare, and Manufacturing industries. Productivity dispersion is measured based on the standard deviation of firm-level productivity within each industry and year.

Given our observation that the productivity dispersion seems to be more pronounced in intangible intensive industries, we now focus on the association between productivity and intangible capital ratio dispersion. Firstly, Figure 7a suggests that there is a similar pattern over time between productivity dispersion and intangible capital ratio dispersion. Moreover, Figure 7b shows a positive association between productivity dispersion and intangible capital ratio dispersion at the 3-digit *NAICS* industry level. In other words, we observe that industries with higher intangible capital ratio dispersion also have higher productivity dispersion on average.

Figure 7: Productivity and Intangible Share Dispersion



(a) Annual Average

(b) Scatter plot

Note: Panel (a) shows the annual standard deviation of intangible share and productivity based on the base year of 1988. Panel (b) shows the scatter plot of 3-Digit SIC average productivity dispersion and average intangible capital ratio dispersion.

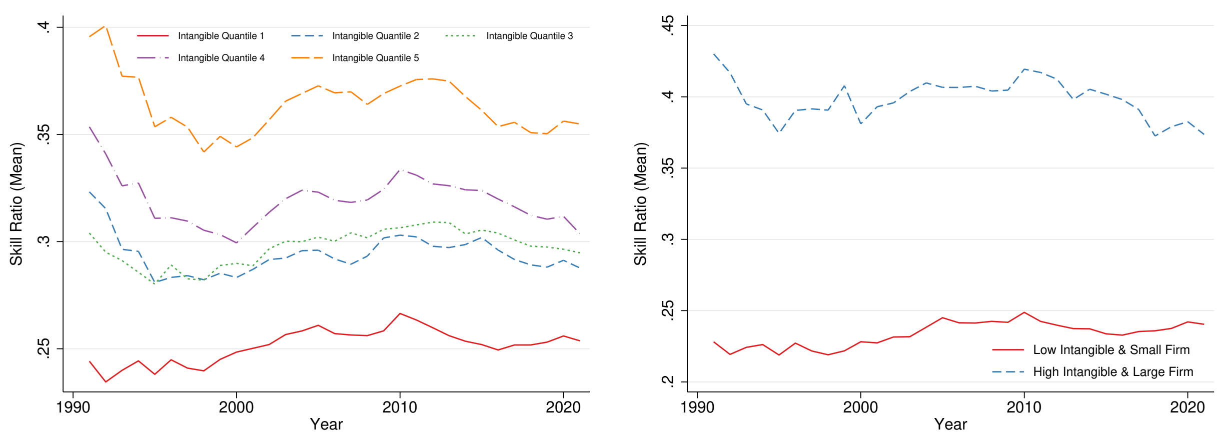
Given that we have some suggestive stylized facts regarding a positive association between intangible capital and productivity dispersion, from now on, we focus on through which channel intangible capital leads to a heterogeneous pattern in the productivity dispersion across firms and industries. In particular, we investigate a channel of the complementarity between intangible capital and skilled labor.

Fact 5: Intangible intensive firms and industries have higher skilled labor intensity.

Now, we show some stylized facts to document the linkage between intangible capital and skill components, potentially influencing productivity dynamics. 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 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 8a 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 8b 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.

Figure 8: Intangible Capital and Skill Ratio



(a) Skill Ratio by Intangible Quintile

(b) Skill Ratio by Intangible and Firm Size

Note: Panel (a) shows the annual average of skill ratio by intangible capital ratio quintiles. Panel (b) shows the skill intensity for low intangible small firms, and high intangible large firms.

To emphasize the relation between intangible capital and skill ratio at the industry-level, Figure 9a shows that intangible intensive industries (Health and High-tech) have higher skill ratio than tangible intensive industries (Manufacturing and Wholesale and Retail). Moreover, Figure 9b suggests that there is a strong and positive association between skill ratio and intangible capital ratio at the 3-digit *NAICS* industry-level. In other words, industries with higher intangible capital also have higher-skilled labor.

Figure 9: Skill Ratio - Industry Level

(a) Skill Ratio of Selected Industries

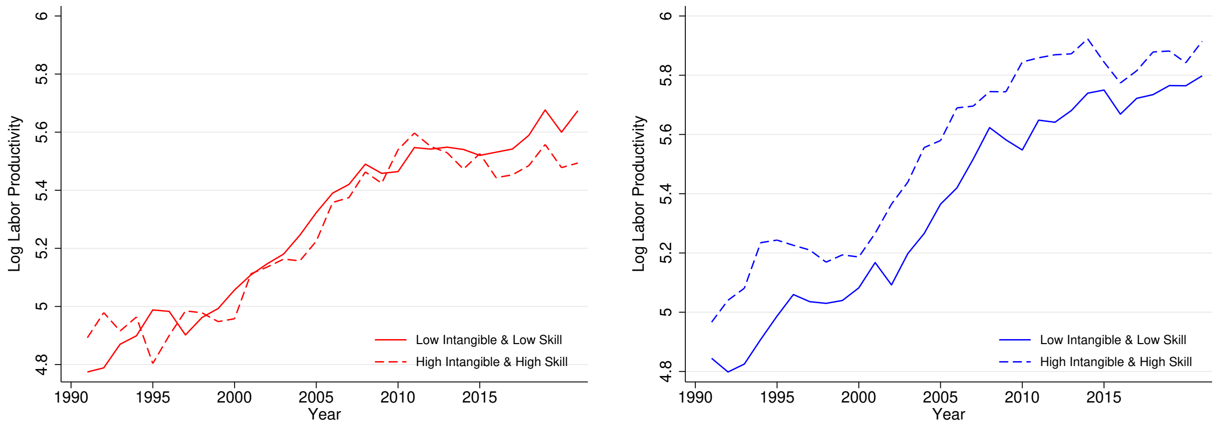
(b) Scatter Plot

Note: Panel (a) shows the annual average of skill ratio by selected Fama-French industries. Panel (b) shows the scatter plot of 3-Digit *NAICS* average skill ratio and intangible capital ratio.

Fact 6: Large firms with high intangible capital ratio and skill ratio have higher labor productivity.

To investigate a suggestive evidence on how the intangible capital - skill complementarity plays a key role for productivity across different firm sizes, we plot an annual median of log labor productivity level for different groups of intangible capital ratio and skill ratio in small and large firms. We construct each group based on the below and above median of the corresponding variable within *NAICS* and year. Figure 10a and 10b suggest that the highest level of labor productivity occurs at high skill ratio and high intangible capital ratio groups in large firms, whereas we do not see such evidence for small firms. We argue that this fact provides some suggestive evidence that only high intangible capital or only high skilled labor might not be sufficient to explain productivity dynamics in large firms. Hence, we need to consider the complementarity between these two components to discover the firm-level productivity in large firms.

Figure 10: 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 show four related motivating evidence: i) increasing productivity dispersion driven by large firms, particularly in intangible-intensive sectors, ii) a rise in intangible capital concentration among large firms, iii) higher skill intensity in large and intangible firms, and iv) higher productivity in large firms that exhibit higher levels of intangible capital and skill intensity. Given these facts, from now on, we focus on the complementarity between intangible capital and skilled labor to quantify its effect on the firm-level productivity dynamics in the U.S. economy.

3 Data

We use the U.S. Compustat database to measure firm-level intangible capital and other financial balance-sheet variables at the annual level. In addition to Compustat, we also use Quarterly Workforce Indicators (QWI) by the Longitudinal Employer-Household Dynamics (LEHD) of the U.S. Census Bureau to measure industry-level and firm-level skill intensity.

Our Compustat sample data covers from 1985 to 2015. Following the sampling procedures in the literature, we exclude financial firms (SIC codes 4900 - 4999), utilities (SIC codes 6000 - 6999), and government (SIC code 9000 and above). We also exclude firms with missing or negative assets or sales, negative CAPX, R&D, or SG&A expenditure, and tiny firms with physical capital under $5 million. We drop firm observations where acquisitions are more than 5% of total assets. We also drop firms with less than 5 years of presence in the sample. Trimming is done by year.

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)). Table A.1 presents the firm-level constructed data variables and their descriptions in the Compustat sample.

Measurement of Intangible Capital. We define intangible capital at the firm level following the perpetual inventory method of Peters and Taylor (2017) (also other studies on measuring intangible capital such as Lev and Radhakrishnan (2005), Eisfeldt and Papanikolaou (2014), Ewens et al. (2019)). Intangible capital consists of external and internal parts. External intangibles are the ones when a firm acquires it from another firm during Merger and Acquisition activities[1].

The internal intangibles are considered as knowledge and organizational capital. Different from the external intangibles, internal intangibles are are not capitalized on balance sheets. Hence, we need to implement the perpetual inventory method to capitalize the off-balance-sheet internal intangible expenses.

In that regard, we construct the stock of knowledge capital from past R&D expenses using the perpetual inventory method:

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

where A_{it} is the end-of-period stock of knowledge capital, $R\&D_{it}$ is the expenditures on R&D 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 A_{i0} is zero.

Similarly, we construct organizational capital by using Selling, General and Adminin-

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

istrative expenses (SG&A). In particular, we measure the stock of organizational capital from past SG&A expenses using the perpetual inventory method:

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

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:

$$INT_{it} = G_{it} + A_{it} + B_{it}$$

Table A.2 presents the summary statistics for all firms and 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 intensity (intangible-to-total asset ratio).

Figure B.2 shows the histogram of the measured intangible capital ratio, in which we see a sufficient degree of heterogeneity across firms. Figure B.3 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.

Skill Intensity. Access to the database which includes firm-level skill components is challenging and hence it prevents us from having an ideal variation in skill intensity at the firm level. To address this challenge, we use Quarterly Workforce Indicators (QWI) by the Longitudinal Employer-Household Dynamics (LEHD) of the U.S. Census Bureau, which is a local labor market database reporting various economic indicators such as employment, earnings, job creation and destruction, and worker turnover by geography, industry, worker and firm characteristics[2]. The data begins in the early 1990s and covers

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

almost all states and industries in the U.S. economy.

To measure skill intensity, in line with the related literature, we use the variable of education characteristics in QWI and compute the share of "Bachelor's degree or advanced degree" (which has a variable label E4 in the database) in total workers within each state, year, 4-digit *NAICS*, and firm size. It provides us to capture a disaggregated and detailed level of measurement of skill intensity which varies across industries, states, firm size categories, and years.

Then, to have a proxy for a firm-level skill intensity, we merge our skill intensity measurement with the Compustat firm sample using a crosswalk by state, year, 4-digit *NAICS*, and firm size. We pin down the state information of a particular firm based on the location of its headquarter information in the Compustat. In order to match the two databases, we categorize Compustat firms based on their size (total asset) by using the same categorization rule applied in the QWI database to determine the firm size groups.

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

Firm	4-digit *NAICS*	State	Firm Size	Year	Skill Intensity
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

Matching the two databases by state, year, 4-digit *NAICS*, and firm size helps us capture a detailed variation in skill intensity across firms. For instance, we can think of two similar firms but operating in different states and industries. Even if these two firms have a similar scale of production, they will end up with a different measurement of skill intensity based on our matching algorithm, which provides a sufficient level of variation to implement our empirical analysis. Table 2 shows an example in the sample of how we capture the variation in skill intensity across the industry, state, firm size, and year.

Table A.5 reports the summary statistics for skill intensity, and Figure B.4 shows the histogram of skill intensity in our sample. Figure B.5 documents the histogram of skill intensity for some selected industries, and we observe that intangible intensive industries such as Healthcare and High tech have higher skill intensity compared to tangible intensive industries such as Consumer Goods and Manufacturing. We also see that there is a significant variation across firms and industries in terms of skill intensity. Figure B.6 plots the kernel density of skill intensity across several years, and we observe that the variation changes across years. There is an increase in the density of skill intensity over time. Figure B.7 and B.8 shows the histogram of skill intensity across small and large firms and low and high intangible firms, respectively. We observe that large and high intangible intensive firms have higher skill intensity than small and low intangible intensive firms.

4 Empirical Analysis

In this section, we first explore the role of intangible capital in firm-level productivity. Then, we quantify the effect of intangible capital on skilled labor. Finally, we estimate the effect of the intangible capital-skilled labor complementarity on firm-level productivity.

4.1 Intangible Capital and Firm-level Productivity

To estimate the role of intangible capital in firm-level productivity, we implement a production function estimation using Olley and Pakes (1996) as follows:

$$y_{it} = \beta_0 + \beta_1 l_{it} + \beta_2 tan_{it} + \beta_3 intan_{it} + \omega_{it} + \epsilon_{it} \tag{1}$$

where y_{it} is firm-level sales, l_{it} is firm-level total labor, tan_{it} is firm-level tangible capital, and $intan_{it}$ is firm-level intangible capital for firm i at time t. All variables are derived from Compustat data between 1985 to 2015. As in Olley and Pakes (1996), we assume that ω_{it} is total factor productivity (TFP) that the firm knows and ϵ_{it} is the TFP that the firm does not know. As a robustness check for the productivity estimation, we also implement the two-step control function estimation developed by Ackerberg et al. (2015) integrated in the framework of Olley and Pakes (1996). In this framework, we are interested in capturing a measure of productivity (ω_{it}) based on a residual from the regression.

Table 3 shows that both intangible and tangible capital contribute a significant share and the share of intangible capital is even slightly higher than the share of tangible capital.

Table 3: Production Function Estimation

	(1) Sale	(2) Sale	(3) Sale	(4) Sale	(5) Sale
Employment	0.683***	0.538***	0.658***	0.526***	0.517
	(0.00216)	(0.00230)	(0.00563)	(0.00347)	(.)
Tangible Capital	0.295***	0.248***	0.0549***	0.132***	0.232
	(0.00180)	(0.00175)	(0.00685)	(0.0222)	(.)
Intangible Capital		0.252***		0.277***	0.234
		(0.00184)		(0.00347)	(.)
Method	OLS	OLS	OP	OP	OP-ACF
Adjusted R^2	0.836	0.858			
Observation	121270	116741	119671	115205	115205

Note: This table shows the production function estimation by simple OLS, Olley and Pakes (1996), and the two-step control function estimation developed by Levinsohn and Petrin (2003) and Ackerberg et al. (2015) integrated in the framework of Olley and Pakes (1996). Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.2 Intangible Capital and Skilled Labor

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

$$y_{it} = \beta_0 + \beta_1 \textit{intangible ratio}_{it} + \Gamma' X_{it} + u_t + u_s + \epsilon_{it} \tag{2}$$

where the dependent variable is the firm-level skill intensity for a firm i at time t and $\textit{intangible ratio}_{it}$ represents the firm-level intangible capital ratio. Our firm-level control variables are denoted by the vector of X_{it} which includes firm size, age, markup and Tobin's Q. Firm size is measured as the logarithm of the assets firm holds. Markup is calculated based on the insight of De Loecker et al. (2020). Due to the unobserved heterogeneity, we also include year (u_t) and industry (u_s) fixed effects. We standardize all variables and include one-year lagged values of independent variables to address potential endogeneity issues.

Table 4 reports the results of the equation (2). We observe that an increase in intangible capital has a positive and significant effect on skill intensity, i.e., one standard deviation (0.32) increase in intangible capital ratio increases up to 0.60 of standard deviation (0.17) of skill intensity, which implies an increase in skill intensity by 0.11. This result suggests that there is a positive and significant association between intangible capital and skilled labor.

Table 4: Intangible Capital Ratio and Skill Intensity

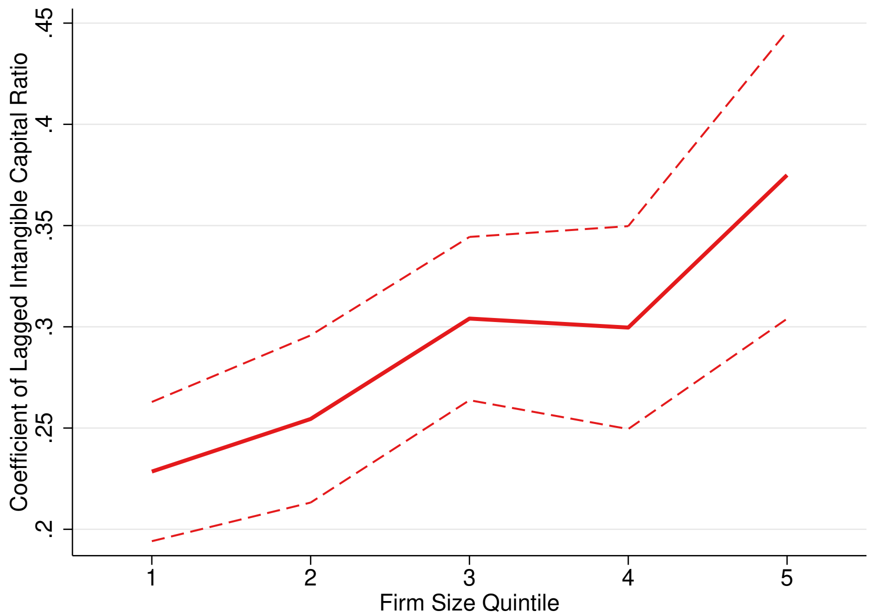
	(1) Skill Ratio	(2) Skill Ratio	(3) Skill Ratio	(4) Skill Ratio
L.Intangible Ratio	0.311***	0.320***	0.322***	0.0210*
	(0.0116)	(0.0123)	(0.0126)	(0.00938)
Control Variables	No	Yes	Yes	Yes
Industry FE	No	No	No	Yes
Year FE	No	No	Yes	Yes
Adjusted R^2	0.0957	0.119	0.122	0.772
Observation	76621	73964	73964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

Note: This table shows the regression of skill intensity on the lagged values of intangible capital ratio and control variables. Each variable in the regression is standardized. Standard errors (in parentheses) are clustered at the firm-level.
* $p < .10$, ** $p < .05$, *** $p < .01$.

In Table A.7 we also implement the similar regression specification but for the levels of variables instead of ratios, and we find that one percent increase in intangible capital increases the number of skilled workers by 0.15%-0.33% depending on the different fixed effects. We also see that the effect of firm size on the number of skilled workers is positive and significant, i.e. one percent increase in firm size increases the number of skilled workers by 0.60%-0.76% depending on the different fixed effects. It indicates that large firms are more likely to have a higher number of skilled workers.

To investigate the role of firm size in the complementarity between intangible capital ratio and skill intensity, we construct firm size quintiles within each *NAICS* industry and year. Then we run the regression equation (2) within each firm size quantile. Figure 11 documents the coefficient of intangible capital ratio in the regression and shows that even though the coefficient is positive and significant in all of the firm size quintiles, it gets much bigger as the firm size gets larger. We also implement a similar exercise but for the levels of variables in Figure B.9 and we find a similar result that the positive effect of intangible capital on the number of skilled workers is higher at larger firms, i.e., the positive association between intangible capital and skilled labor is amplified with firm size.

Figure 11: Quintile Regression



Note: This figure pilots the coefficient of intangible capital ratio in the regression (2) within size quintiles.

4.3 Intangible-Skilled Labor Complementarity and Productivity

The previous section shows a suggestive reduced-form evidence on a complementarity between intangible capital and skilled labor, which seems to be higher in larger firms. Given these results, in this section, we investigate how this complementarity has an effect on firm-level productivity and whether the degree of association is influenced by firm size. In order to have an analysis on this direction, we pursue the following regression:

$$y_{it} = \beta_0 + \beta_1 \textit{skill intensity}_{it} + \beta_2 \textit{intangible ratio}_{it} + \Gamma' X_{it} + u_t + u_s + \epsilon_{it} \tag{3}$$

where the dependent variable is the firm-level log labor productivity for firm i at time t. The variable *skill intensity*$_{it}$ denotes the firm-level skill intensity and *intangible ratio*$_{it}$ represents 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, and we have year (u_t) and industry (u_s) fixed effects. We standardize skill intensity and intangible ratio over the entire sample, so the units are in standard deviations relative to the mean.

Table 5: Intangible Capital, Skill Intensity and Productivity

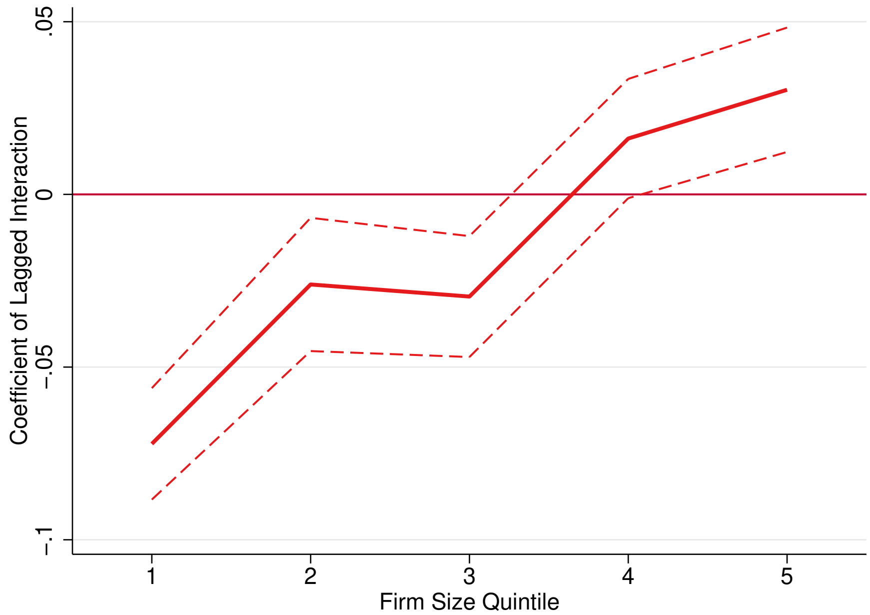
	(1) Log Productivity	(2) Log Productivity	(3) Log Productivity
L.Skill Ratio	0.0348**		0.0310**
	(0.0143)		(0.0142)
L.Intangible Ratio		0.0849***	0.0843***
		(0.0151)	(0.0152)
Control Variables	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R^2	0.466	0.472	0.472
Observation	81590	81015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

Note: This table shows the results of the regression specification (3). Standard errors (in parentheses) are clustered at the firm-level. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 5 shows that both skill intensity and intangible capital ratio have positive and significant effect on firm-level productivity. One standard deviation (0.17) increase in firm-level skill intensity increases the firm-level productivity by around 3.1%-3.4%. One standard deviation (0.32) increase in firm-level intangible capital ratio increases the firm-level productivity by around 8.4%.

To investigate whether the complementarity between intangible capital and skilled labor generates differential effect on productivity for different firm sizes, we construct an interaction term between skilled ratio and intangible capital ratio and include this term in the regression specification (3) through running this regression within each firm size quintile. We see in Figure 12 that the coefficient of the interaction term becomes positive and significant for large firms. In other words, the complementarity between intangible capital and skilled labor has no positive effect on productivity for small firms, but it only generates positive effect on productivity at larger firms. It implies that larger firms can operationalize the economic effects of the complementarity and increase their productivity.

Figure 12: Quintile Regression



Note: This figure pilots the coefficient of interaction term between intangible capital and skill intensity in the regression (3) within size quintiles.

Given that we have a data limitation to capture the ideal variation in the firm-level skill decomposition and firm-level performance of each skill categorization, our measurement of skill intensity can be interpreted as a reduced-form approximation to the ideal case. As a robustness check and an empirical verification that our reduced-form approximation provides a valid framework, we also investigate the firm-level inventor dynamics and its relation with intangible capital in Appendix C. The underlying reason is that using USPTO patent and inventor data and merging it with Compustat, we observe individual-level identifying variations in the skill component both at the firm- and inventor-level, which provides us a laboratory to motivate our benchmark mechanism. In line with the baseline approach, we hypothesize that intangible capital requires skilled inventors to operationalize its economic benefits for innovation dynamics. In that regard, we document that once inventors move to big firms with high intangible capital, they would become more productive in patent production. The caveat of this approach is that the inventor perspective provides a much narrower and limited interpretation for its complementarity with intangible capital because of its relatively low share within firms. However, an analysis for the role of the interaction between intangible capital and inventors on productivity helps us understand several key mechanisms behind our baseline results and confirms our benchmark insights.

5 Motivating Model

This section shows a motivating model that provides a basic explanation for our empirical evidence of why firms with higher intangible capital benefit from skilled labor. We use a simplified and modified version of the model by Acemoglu and Autor (2011) to argue through which channels there would be a complementarity between intangible capital and skilled labor. Then we take this basic model to deliver some testable predictions on the heterogeneous relationship between intangible capital intensity and skill-premium.

In the model, the main channel through which the accumulation of intangible capital attracts skilled labor is disciplined by changing skill premium due to the change in the relative demand of skilled labor. In that respect, we start with a competitive supply-demand framework in a simple closed economy setting, where factors are paid their marginal products, and the economy operates on its supply and demand curves.

Setup. We have two types of workers, skilled and unskilled, which are imperfect substitutes. In other words, we have two distinct sectors which employ skilled and unskilled workers respectively. The production function for the aggregate economy takes the constant elasticity of substitution (CES) form:

$$Y(t) = \left[\Big(K_T(t) L(t) \Big)^{\rho} + \Big(K_I(t) H(t) \Big)^{\rho} \right]^{1/\rho} \tag{4}$$

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

Given our assumption of the competitive labor markets, wages are set according to marginal products. The unskilled wage and the skilled wage are respectively given by

$$w_L = \frac{\partial Y}{\partial L} = K_T^\rho \Big[K_T^\rho + K_I^\rho (H/L)^\rho \Big]^{(1-\rho)/\rho} \tag{5}$$

$$w_H = \frac{\partial Y}{\partial H} = K_I^\rho \Big[K_T^\rho (H/L)^{-\rho} + K_I^\rho \Big]^{(1-\rho)/\rho} \tag{6}$$

Combining the equations (5) and (6), we can derive the skill premium π as follows:

$$\pi = \frac{w_H}{w_L} = \left(\frac{K_I}{K_T}\right)^\rho \left(\frac{H}{L}\right)^{-(1-\rho)} \tag{7}$$

We can arrange the equation (7) to write down in logarithmic form as follows:

$$ln(\pi) = \left(\frac{\sigma - 1}{\sigma}\right) ln\left(\frac{K_I}{K_T}\right) + \frac{1}{\sigma} ln\left(\frac{L}{H}\right) \tag{8}$$

Here, we can easily test our main empirical evidence that higher intangible capital attracts skilled workers. In other words, the response of skill premium to the increase in the intangible capital intensity $\frac{K_I}{K_T}$ is given by

$$\frac{\partial ln(\pi)}{\partial (K_I/K_T)} = \frac{\sigma - 1}{\sigma} \tag{9}$$

which increases when $\sigma > 1$. In that regard, we find that when the elasticity of substitution between skilled (H) and unskilled (L) workers is sufficiently big and increasing, an increase in the intangible capital intensity also increases the skilled premium. This theoretical observation also holds in our empirical evidence that higher intangible capital intensive sectors are more likely to replace unskilled workers with skilled workers. Moreover, from the equation (9), we also see that the skilled wage relative to the unskilled wage ($\frac{w_H}{w_L}$) also increases with $\frac{K_I}{K_T}$.

Empirical Test. Our basic model delivers a testable prediction whether it is meaningful to model K_I as intangible capital and K_T as tangible capital through the empirical reducing form from the model equation (9):

$$ln(\pi(t)) = \gamma_0 + \gamma_1 ln\left(\frac{K_I(t)}{K_T(t)}\right) + \gamma_2 ln\left(\frac{L(t)}{H(t)}\right) + \epsilon(t) \tag{10}$$

In order to assess whether our model passes the empirical test, we fit this empirical model (10) using a simple OLS regression at the industry-level by loading K_I and K_T as industry-level intangible and tangible capital, respectively. Following the spirit of Eisfeldt et al. (2021), we use the NBER-CES database to measure industry-level skill premium and unskilled-skilled labor ratio at the 4-digit *NAICS*. We aggregate our measurement of intangible capital and tangible capital to the 4-digit *NAICS* industry level. We impose the corresponding constraints for regression coefficients governed by the model equation (8). Table 6 shows the results that an increase in intangible-tangible ratio has a positive and significant effect on industry-level skill premium. Moreover, we find a positive and significant effect of the unskilled-skilled labor ratio on skill premium, making sense due to the standard wage-labor supply relationship. More importantly, our regression coefficients are in line with the elasticity of substitution parameter between skilled and unskilled workers at the industry level derived in the literature. The coefficient of unskilled-skilled labor ($0.4 = 1/\sigma$) implies that the elasticity of substitution (σ) is ($1/0.4$) 2.5, which is very close to the average of the estimated elasticity of substitution (2.2) coming from the existing related studies in the literature based on the discussion by Havranek et al. (2020).

Table 6: Empirical Test of Motivating Model

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

Note: This table shows the results of the empirical model (10). Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Discussion. Besides these results imply that the empirical test validates our motivating model, another important takeaway is that our modeling framework provides a plausible identification for the unobserved skill-specific TFP. Acemoglu and Autor (2011) require some proxies for the measurement of the unobserved skill-specific TFP to predict the skill premium and in that direction our approach satisfies this prediction by measuring the intangible and tangible capital stocks that are indeed observable and incorporating them into the workhorse industry-level skill-biased technical change framework developed by Acemoglu and Autor (2011).

After we have a motivating model which incorporates a basic channel through which asset intangibility would affect labor reallocation based on the two-sector model, we now construct a firm-level general equilibrium model which echoes the key takeaways of our two-sector motivating model. We will extend the workhorse model of skill-biased technical change framework by incorporating the concept of economies of scale to capture how it affects the degree of the complementarity between intangible capital and skilled labor.

6 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 the complementarity between intangible capital and skilled labor along with the economies of scale. Our primary goal is to incorporate a model framework that elucidates how the economies of scale shapes the complementarity within the firm-level production framework, which enables us to disciple our related empirical evidence.

6.1 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 create 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_s in sector s is produced by a final good firm that combines intermediate input varieties using a fixed elasticity of substitution denoted as ι_s. Additionally, 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_s 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. These sectoral bundles are combined into one final CES bundle with 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:

$$y = z\Bigg(\bigg(\alpha_s^K(y)k^{\frac{\sigma-1}{\sigma}} + \alpha_s^H h^{\frac{\sigma-1}{\sigma}}\bigg)^{\frac{\sigma}{1-\sigma}\frac{\kappa-1}{\kappa}} + \alpha_s^L l^{\frac{\kappa-1}{\kappa}}\Bigg)^{\frac{\kappa}{1-\kappa}} \tag{11}$$
$$\text{where } \alpha_s^K(y) \equiv y^{\epsilon/\sigma}\phi_s^K Z_s^H,\ \alpha_s^H \equiv Z_s^H,\ \alpha_s^L \equiv Z_s^L$$

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.

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

$$\begin{aligned}\frac{\frac{\partial y}{\partial h}}{\frac{\partial y}{\partial k}} &= \frac{\alpha_s^H}{\alpha_s^K}\left(\frac{k}{h}\right)^{1/\sigma} \\ &= y^{-\epsilon/\sigma}\left(\frac{k}{h}\right)^{1/\sigma}\end{aligned} \tag{12}$$

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 1. *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:

$$\pi^*(Z_s^H, Z_s^L, w_s^H, w_s^L, p, D_s) = \max_{y_s}[D_s y^\zeta - C(y_s; Z_s^H, Z_s^L, w_s^H, w_s^L, p, D_s)]$$

where the function of $C(.)$ is the cost of production including the 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:

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

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 spirit of Eckert et al. (2022) and in this economy, there are 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 1 of identical workers who inelastically supply one unit of labor. Workers derive utility from the final good consumption, and sectoral amenities. Workers receive idiosyncratic preference shocks for sectors. They make choices to maximize their overall utility, which is the result of the utility derived from the final good consumption and the sector-specific amenity factor denoted as the term of A_s^e which we will introduce it in this section. For each type $e = \{H, L\}$, they draw sector-specific shocks from Fréchet distribution which is characterized by inverse scale parameters A_s^e and shape parameters ρ_s^e.

In equilibrium, utility is equalized across sector, which yields the fraction of workers choosing to work in 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 we can treat the parameter of ρ_s^e as a sectoral labor supply elasticity. We denote the aggregate supply of type e workers by $\bar{L}^e$ and in the equilibrium the quantity of type e worker is written as $L_s^e = \mu_s^e \bar{L}^e$.

6.2 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 (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, and (iv) Intangible capital, labor, final good, and intermediate goods markets clear.

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

$$\frac{k}{h} = \left(\frac{p}{w_s^H}\right)^{-\sigma} y^{\epsilon} \tag{13}$$

$$\frac{h}{l} = (\tilde{w}_s^H)^{-\sigma(1-\sigma)} \left(\frac{\tilde{w}_s^H}{w_s^L}\right) (Z_s^L)^{-1} \tag{14}$$

where $\tilde{w}_s^H \equiv (w_s^H)^{1-\sigma}(Z_s^H)^{\sigma} + p^{1-\sigma}(Z_s^H)^{\sigma} y^{\epsilon}$. Equation (13) 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 the firms with higher output given prices and wages. From now on, we will take this equilibrium ratio and do a calibration exercise to emphasize its implications for the production dynamics across firm-size distribution.

6.3 Calibration

In this section, we calibrate our model to the data from the U.S. economy in 1990 to quantitatively investigate the role of the complementarity between intangible capital and skilled labor on firm-level production dynamics. We follow the procedure of Eckert et al. (2022) to calibrate the parameters of the model. We use their calibration methodology because together with some extensions our model framework is similar to theirs, and hence following their steps and parameters is a plausible approach to calibrate the model parameters.

First of all, we set the productivity of intangible capital, denoted by Z, to 1 in 1990 when it is a beginning-of-the-sample after we merge the Compustat firm-level data and skill measures. Given this normalization, following the fashion of Eckert et al. (2022), we opt to set the productivity of intangible capital, denoted as ϕ_s^K, in each sector to align with the total share of intangible capital value added in the BEA asset tables from 1990. Additionally, we set the scale elasticity parameter ϵ according to Eckert et al. (2022). With this parameter in place, the substitution elasticities σ and κ determine how easily one can replace intangible capital, high-skilled, and low-skilled labor within individual firms. Similar to Eckert et al. (2022), we select these elasticity values to ensure that our calibrated model aligns with the established estimates of macro substitution elasticities between these factors, as indicated in Krusell et al. (2000).

To estimate sector-specific productivity levels $\{Z_s^H, Z_s^L\}$ and sectoral amenities $\{A_s^H, A_s^L\}$, we employ a method similar to the one outlined in Eckert et al. (2022). In this approach, these factors are treated as structural residuals that are adjusted to ensure that the model precisely matches average annual wages and employment figures across various worker types, sectors, and locations. The Fréchet dispersion parameters, denoted as ρ_s^e, for the sectoral preference shocks serve as indicators of sectoral labor supply elasticities. We adopt the values for these elasticities as provided by Eckert et al. (2022), who references Artuç et al. (2010).

Table 7 documents the parameterization of the model, which follows the calibration procedure of Eckert et al. (2022).

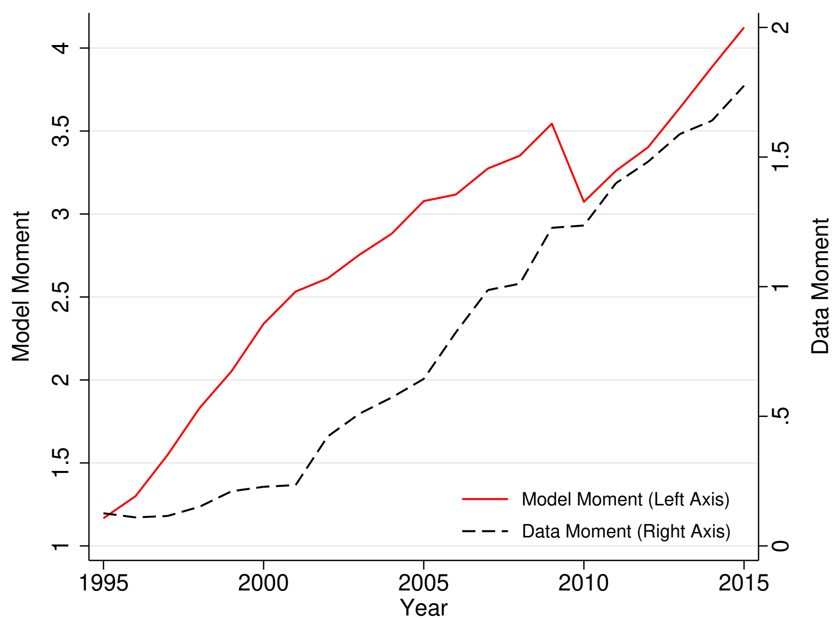
Table 7: Model Parametrization

	Estimated Parameters	Value	Description of Moment	Moment: Model/Data
ϵ	Intangible Scale Elasticity	0.31	Ratio of capital p.w. between 10 and 1000 emp firms	3.8/3.8
σ	EoS: Skilled Labor and Intangible	0.65	Capital-skill macro elasticity of Krusell et al. (2000)	0.61 / 0.67
κ	EoS: Skilled and Unskilled Labor	2.12	Skilled-unskilled macro elasticity of Krusell et al. (2000)	1.27 / 1.67
ϕ_s^K	Sectoral ICT Capital Productivity	(67.2,1.8)	Intangible capital share of value added by sector	(3.5%,0.5%)/(3.5%, 0.5%)
	External Parameters	Value	Source	
ρ_s^e	Sectoral Labor Supply Elasticity	(0.21,0.21)	Artuç et al. (2010)	
ζ_s	Intermediates CES Aggregator	4	Garcia-Macia et al. (2019)	
ζ_F	Final Good CES Aggregator	1.2	Eckert et al. (2022)	
υ	Pareto Shape Parameter	1.1	Axtell (2001)	
	Sectoral Productivities and Amenities	Value	Source	
Z_s^e	Sectoral Productivity Shifter	Various	1990 employment and wages	
A_s^e	Sectoral Amenities	Various	1990 CZ employment and wages	
Z	Productivity of Intangible Capital in 1990	1	Normalized	

Note: This table documents the parameterization of the model, which follows the calibration procedure of Eckert et al. (2022).

Figure 13 shows that the calibrated model moment of intangible capital per high skilled labor dramatically increases over time, which shows that the calibrated model is succesful at reproducing the main patterns in line with the empirical moment we captured before even though the level of model and data moments do not perfectly match in some time periods. This observation is quite important for our mechanism because the calibrated moment of the model provides that intangible capital devoted for a unit of high skilled labor has an increasing trend over time and hence suggests a complementarity of the two factor inputs as we document in the empirical framework.

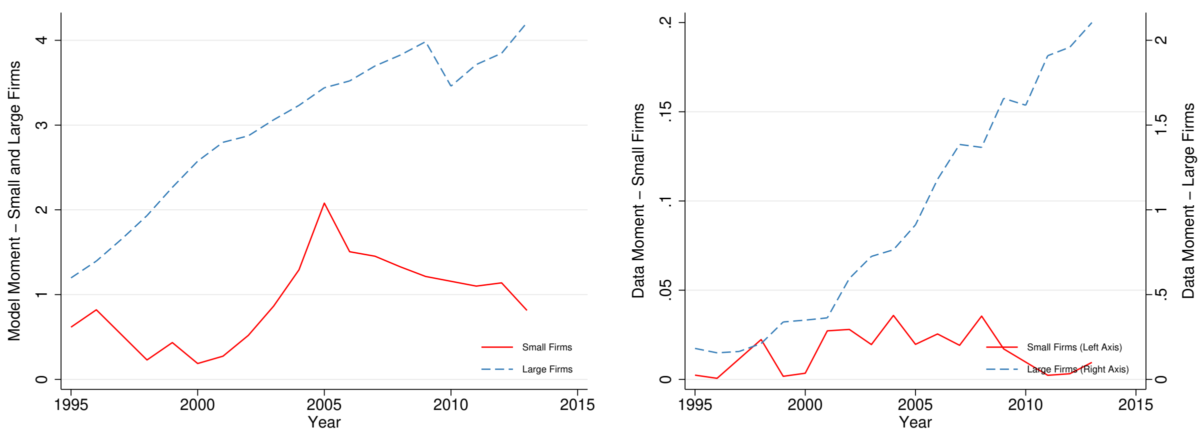
Figure 13: Intangible Capital Share in Model and Data



Note: This figure plots the evolution of the model-implied (left-axis) intangible capital and high skilled labor ratio along with its data moment (right-axis).

Figure 14a and 14b provide similar exercise but this time for across firm size distribution to investigate how the complementarity between intangible capital and skilled labor differs across different firm size in the calibrated model and data moments. Figure 14a suggests that the calibrated model moment of intangible capital per high skilled labor is much higher for large firms and it increases much faster over time in favor of large firms. In other words, the calibrated moment implies that the complementarity is more pronounced at large firms, which is what we also find in the empirical framework. Even though there are some time periods in which the model and data moments do not exactly overlap quantitavely, Figure 14b also confirms this insight in the data moment that there is a heterogenous pattern in the complementarity across firm size distribution and the large firms are the ones which seem to benefit more from it over time. This is an important point to emphasize that this figure would perform a same degree of the complementarity for each firm-size group under the absence of the scale elasticity parameter (i.e. standard CES framework), which is not what we observe in the data as shown in Figure 14b. Therefore, we confirm based on the data pattern that non-homothetic CES model with the incorporation of the scale elasticity parameter enables us to capture the heterogeneous complementarity which differs across firm-size groups.

Figure 14: Intangible Capital Share in Model and Data - By Firm Size



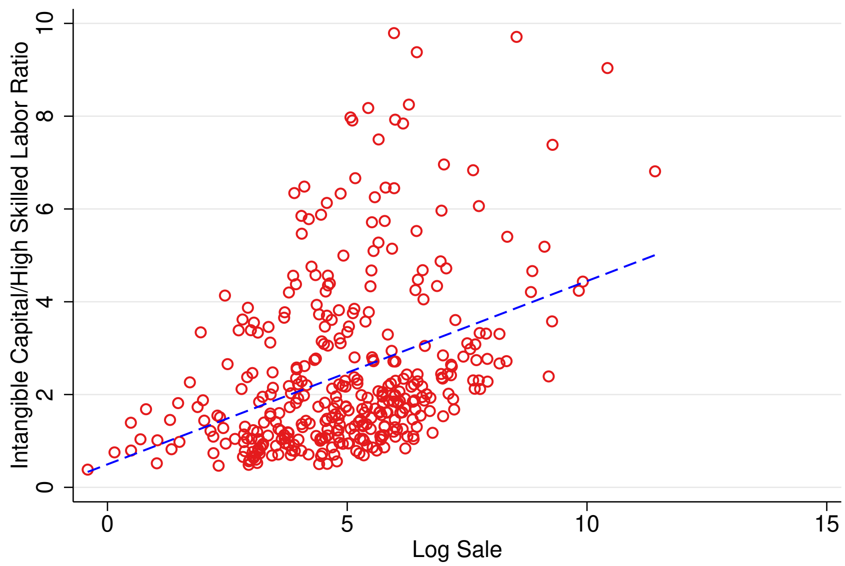
(a) Model Moments

(b) Data Moments

Note: The panel (a) of the figure plots the evolution of the intangible capital and high skilled labor ratio for small and large firms in the model. The panel (b) of the figure plots the same measure in the data for small firms in the left-axis, and for large firms in the right-axis.

Lastly, Figure 15 provides an calibration exercise at the cross-sectional level instead of over time-series in the sense that it shows the scatter-plot between each firm's average model moment of the log sale and intangible capital per high skilled labor. This calibration exercise suggests that in the model firms with higher size (proxied by log sale) are more likely to have higher intangible capital per high skilled labor and this association is statistically significant. In that respect, it provides another model-based evidence that the complementarity between intangible capital and skilled labor in the cross-section is higher at large-scale firms.

Figure 15: Intangible Capital Share and Firm Size in Model



OLS (with firm–level clustered s.e.): 0.395 (0.046); adj. R–sq.: 0.146.

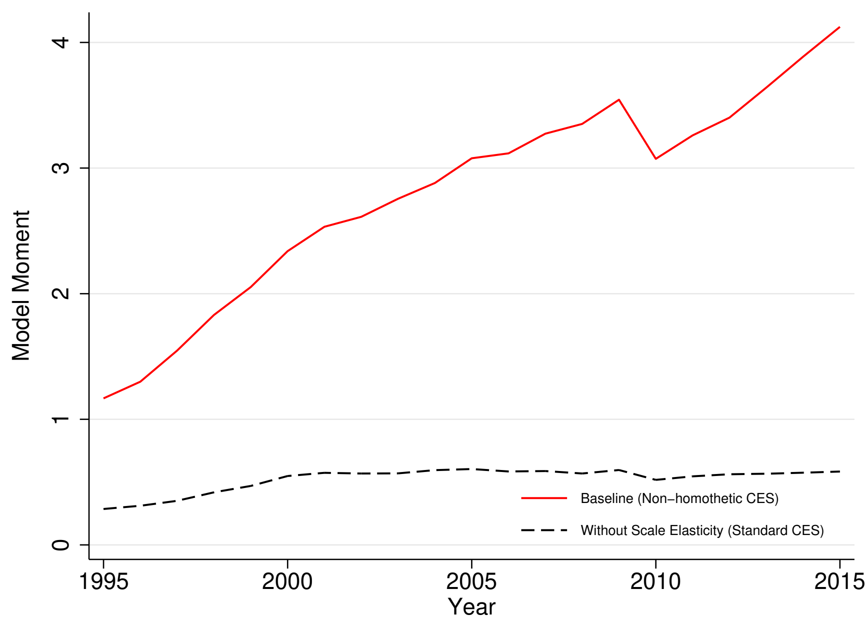
Note: This figure plots the scatter-plot between each firm's average model moment of the log sale and intangible capital per high skilled labor.

6.4 Counterfactual Analysis

To quantify the role of the economies of scale on the complementarity between intangible capital and skilled labor, we implement a simple exercise where we simulate a counterfactual economy under which there is no scale elasticity, i.e. the production technology simplifies to the standard CES production function in which the marginal product of each factor remains unaffected by the scale of production. More precisely, we keep all other parameters of the model as in the baseline values and set the scale elasticity parameter to zero, i.e. $\epsilon = 0$.

Figure 16 displays the baseline calibrated ratio of intangible capital to high-skilled labor and how it changes in the counterfactual economy. As depicted in the figure, in the absence of scale elasticity, this ratio experiences a significant decrease and remains almost constant over time. Moreover, from the counterfactual analysis, we can argue that the calibrated model attributes 80% of the complementarity between intangible capital and skilled labor over time to the economies of scale. This observation indicates 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.

Figure 16: Intangible Capital Share Under Counterfactual Economy



Note: The figure shows the ratio of intangible capital to high-skilled labor which is calibrated in the model under (i) the baseline economy with the presence of scale elasticity (non-homothetic CES) and (ii) the counterfactual economy without the presence of scale elasticity (standard CES).

7 Limitations

While this study makes significant contributions to our understanding of the complementarity 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. As we lack detailed data that includes firm-level skill intensity, we proxy it using industry-level skill intensity. 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. 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 observable factors, unobserved heterogeneity at the firm level may influence the complementarity dynamics. We acknowledge that factors not accounted for in the analysis, such as organizational culture or management practices, could potentially confound the relationship between intangible capital and skilled labor. Secondly, our empirical framework is unable to deliver causal inferences due to the lack of exogenous variation in intangible capital and skill intensity at the firm level. In our future project, we aim to incorporate plausibly exogenous policy changes in either intangible capital or skill intensity, providing a basis for causal inference in our context.

Lastly, another limitation in our paper pertains to the quantitative analysis of the firm-level model. While the model successfully incorporates the complementarity channel along with economies of scale, aligning with our empirical evidence, the absence of available data moments for certain firm-level variables (e.g., skilled labor) in the model counterpart hinders the perfect alignment of quantitative exercises with model and data moments. Our goal is to gain access to micro-level census data in our future project to capture those missing and enhance the performance of our quantitative analysis.

8 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 introducing the complementarity 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, particularly in intangible-intensive sectors, ii) a rise in intangible capital concentration among large firms, iii) higher skill intensity in large and intangible firms, and iv) higher productivity in large firms that exhibit higher levels of intangible capital and skill intensity. This set of empirical results provides two key predictions. First, it indicates the presence of complementarity between intangible capital and skilled labor, as their joint interaction enhances firm-level productivity. Second, it suggests that the complementarity effect on productivity is heterogeneous across firm-size distribution and is more pronounced in large firms.

This set of stylized facts motivates us to quantify the effect of intangible capital-skilled labor complementarity on productivity by different firm sizes. We find that a one standard deviation increase in firm-level skill intensity increases firm-level productivity by around 3.4%, and a one standard deviation increase in the firm-level intangible capital ratio increases firm-level productivity by around 8.4%. We also investigate how the joint interaction between intangible capital and skill intensity enhances firm-level productivity. We find that the coefficient of the interaction term is nearly zero and insignificant for small firms, whereas it becomes positive and significant for larger firms, indicating that a one-standard-deviation joint increase in intangible capital and skill intensity boosts firm-level productivity by around 2% for large firms. This empirical evidence suggests that firms with higher intangible and skill intensity have higher productivity, which is amplified with firm size.

To rationalize the reduced-form empirical evidence and develop quantitative analysis, we first sketch a simple motivating model that provides a basic explanation for our empirical evidence of why firms with higher intangible capital benefit from skilled labor. Then, we introduce a firm-level general equilibrium model that incorporates the channel of intangible capital-skilled labor complementarity into the workhorse firm-level production framework. The model elucidates how economies of scale shape the complementarity within the firm-level production framework. The calibrated model documents that 80% of the complementarity between intangible capital and skilled labor over time is attributable to economies of scale, consistent with the empirical evidence that the intangible capital-skilled labor complementarity is more pronounced at large firms, increasing over time.

Our empirical evidence and theoretical discussion shed light on several policy implications. There is a recent policy discussion on how global and local technological changes affect the overall economy. Our paper suggests that the channel of intangible capital investment constitutes a critical form of technological change. It has key implications for firm-level productivity dynamics directly related to the skill composition in the economy. Our evidence suggests that, although larger firms become more able to combine their intangible capital with skilled labor to increase their productivity, smaller firms would not be able to easily attract skilled workers and thus suffer productivity losses. In that respect, designing a policy framework to incentivize technological changes requires considering the implications of labor market frictions and economies of scale.

This paper also provides an avenue for fruitful future works, and we plan to extend our analysis in both empirical and theoretical directions. For the empirical part, we aim to have access to firm-level data to observe a detailed level of skill and occupation decomposition. Moreover, we plan to develop an empirical approach to investigate how the complementarity between intangible capital and skilled labor affects other firm dynamics, such as sales, profitability, market share, market power, and markups. For the theoretical part, through the lens of the firm-level general equilibrium model, we plan to implement several counterfactual exercises through quantitative analysis to address several questions, such as what happens to skill premium and labor reallocation across firms if there is a change in intangible capital intensity.

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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 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 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 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 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 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: Productivity Dispersion and Intangible Capital - Industry-level Analysis

	Period $<$ 2000	Period $\geq$ 2000
	Productivity Dispersion	Productivity Dispersion
Intangible Ratio	0.372***	0.595***
	(0.07)	(0.128)
Control Variables	Yes	Yes
Industry FE	Yes	Yes
Adjusted R^2	0.462	0.614
Observation	12642	7279

Note: Standard errors (in parentheses) are clustered at the industry-level (*NAICS*). * $p < .10$, ** $p < .05$, *** $p < .01$.

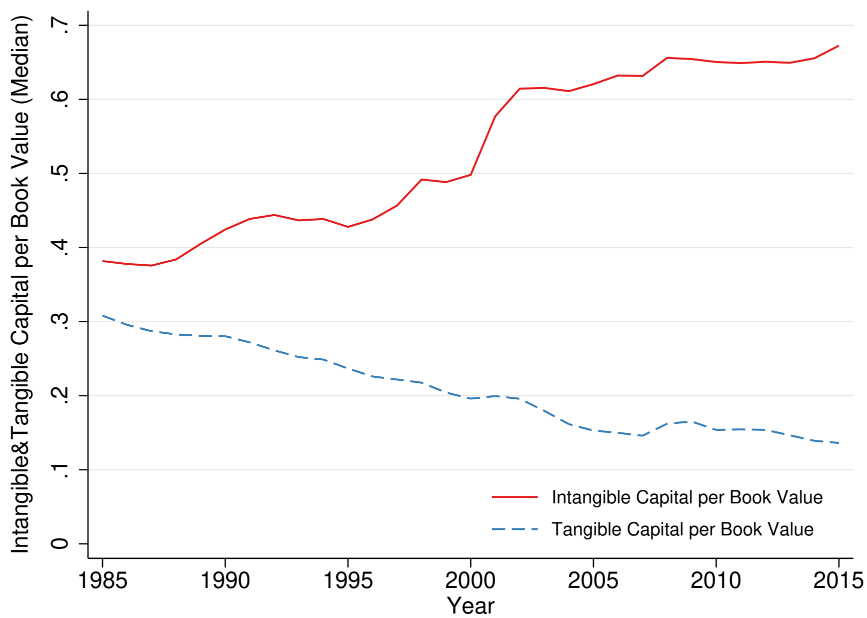
Table A.7: Intangible Capital and Skilled Workers

	(1)	(2)	(3)	(4)
	Skilled Workers	Skilled Workers	Skilled Workers	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 shows the regression of the logarithm of number of skilled workers on one-year lagged of logarithm of intangible capital and control variables. Standard errors (in parentheses) are clustered at the firm-level. * $p < .10$, ** $p < .05$, *** $p < .01$.

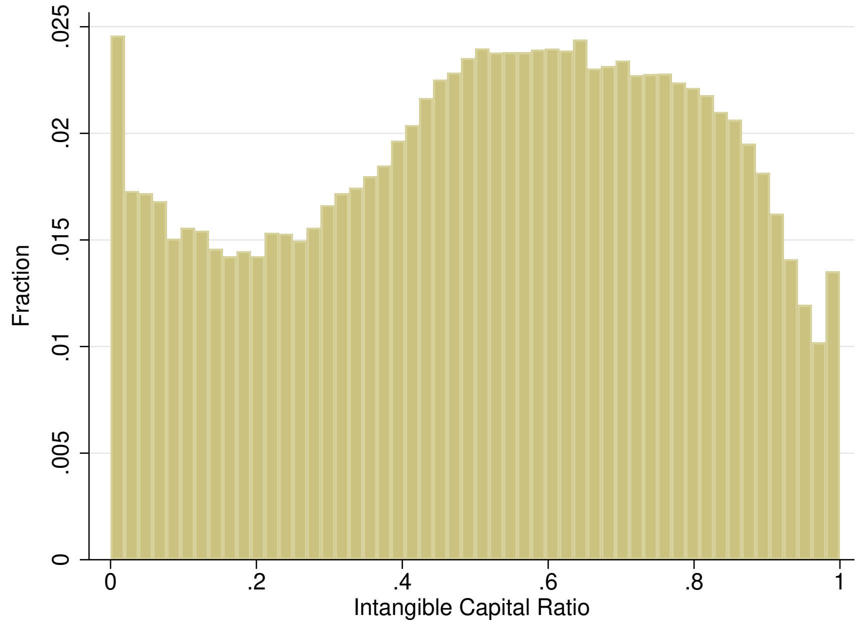
B Figures

Figure B.1: Intangible & Tangible Capital per Book Value



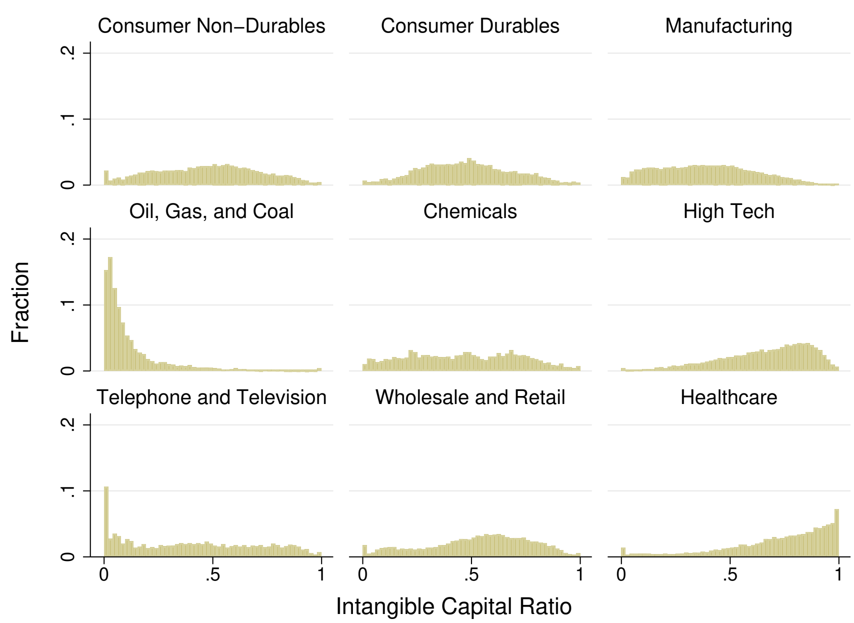
Note: This figure shows the yearly simple median of intangible and tangible capital per book value in the Compustat. Book value is computed as the total assets.

Figure B.2: Intangible Ratio - Histogram



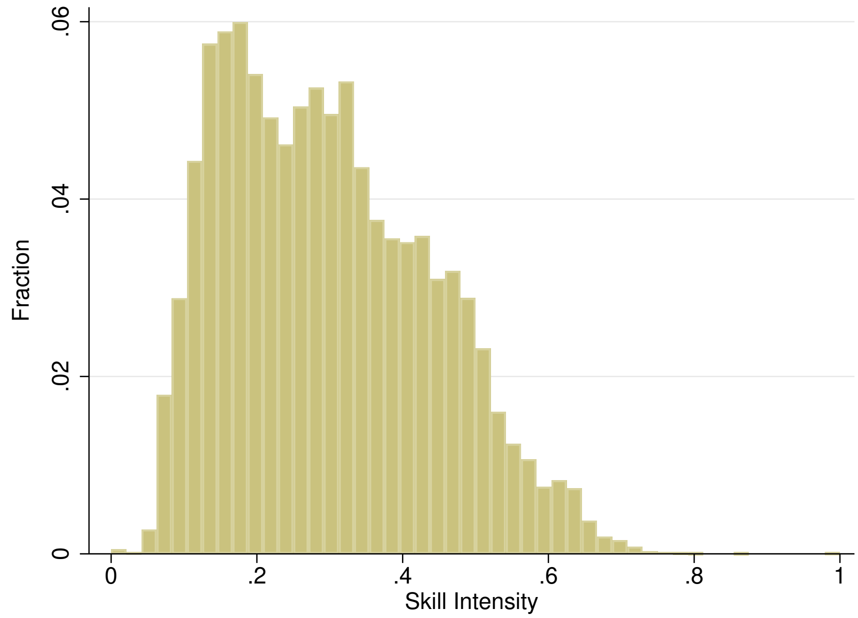
Note: This figure shows the histogram of intangible ratio.

Figure B.3: Intangible Ratio - Industry Variation



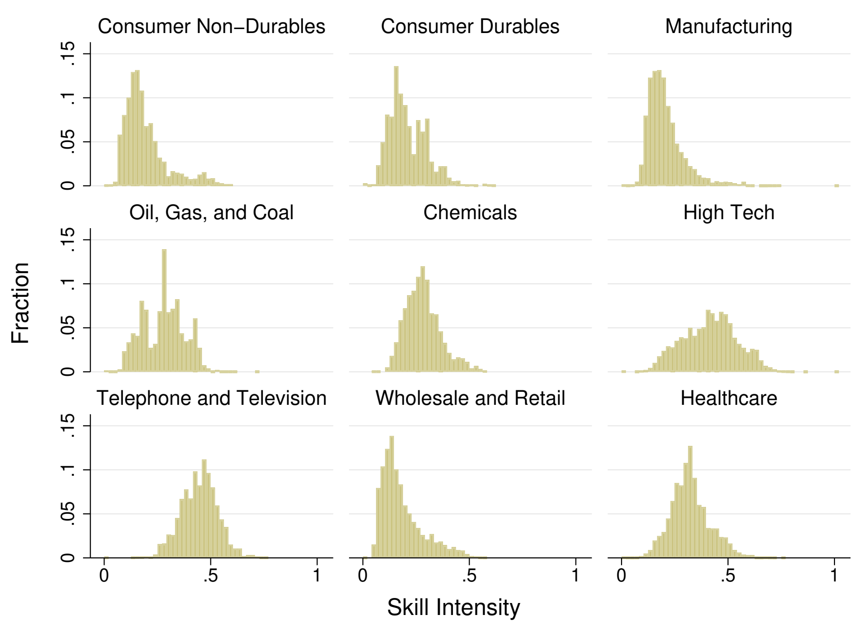
Note: This figure shows the histogram of intangible ratio for some selected industries.

Figure B.4: Skill Intensity - Histogram



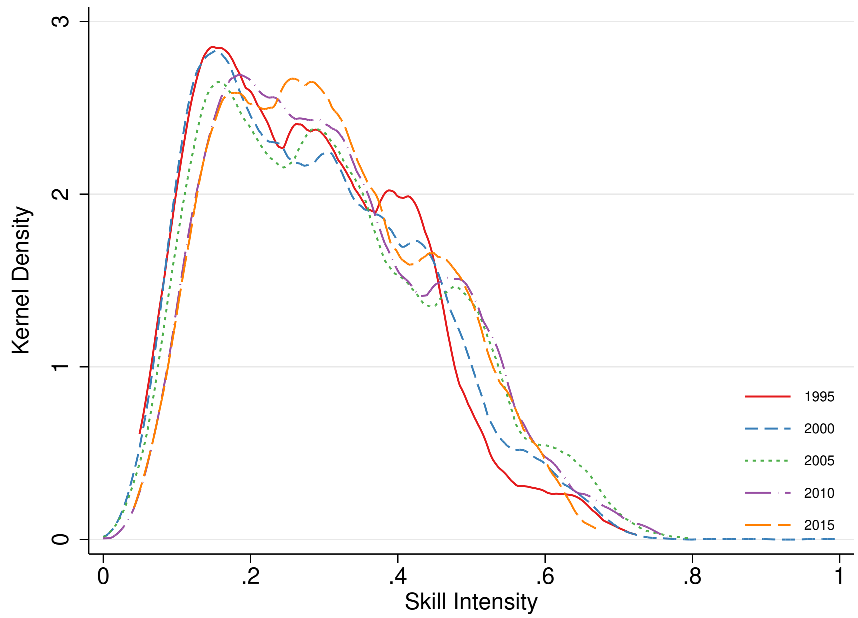
Note: This figure shows the histogram of skill intensity.

Figure B.5: Skill Intensity - Industry Variation



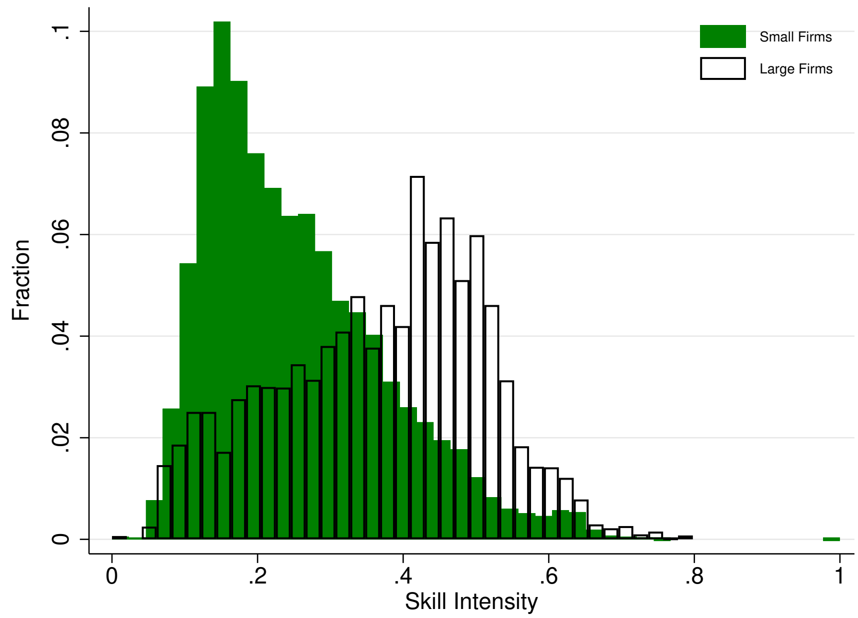
Note: This figure shows the histogram of skill intensity for some selected industries.

Figure B.6: Skill Intensity - Kernel Density



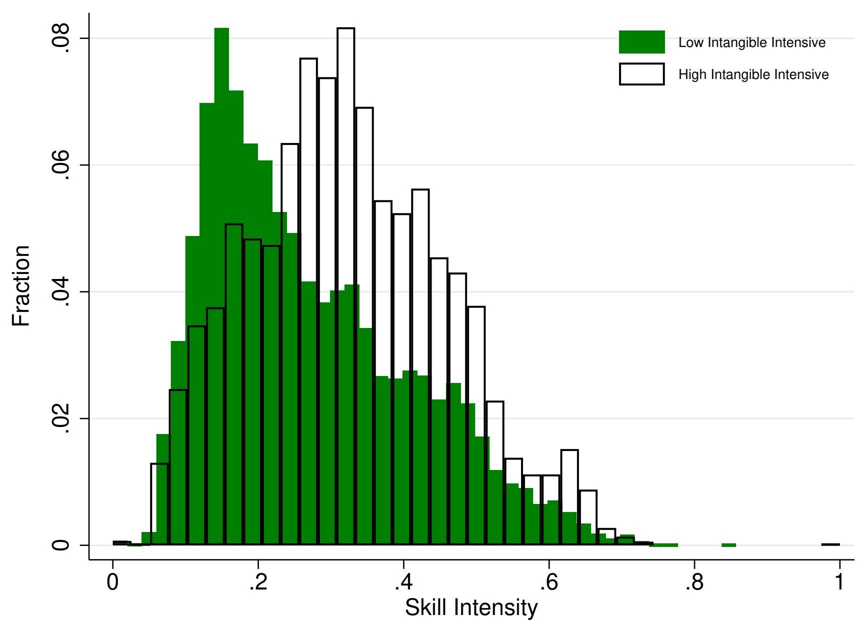
Note: This figure shows the kernel density of skill intensity for several selected years.

Figure B.7: Skill Intensity - Histogram by Firm Size



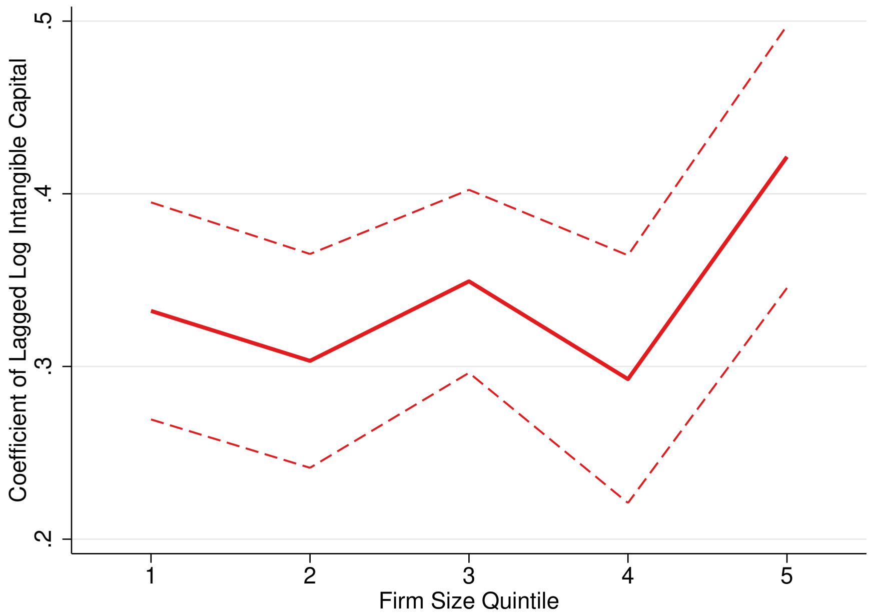
Note: This figure shows the histogram of skill intensity by small and large firms.

Figure B.8: Skill Intensity - Histogram by Intangible Ratio



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

Figure B.9: Quintile Regression



Note: This figure shows the coefficient of logarithm of one-year lagged intangible capital in the regression of Table A.7 within size quintiles.

C Synergy between Intangible Capital and Inventors

This section provides a complementarity analysis to our benchmark approach by analyzing the role of synergy between intangible capital and inventors on productivity dynamics. The advantage of having this complementarity approach is that we have access to individual-level disaggregated identifying variations in skill component at the firm- and inventor-level using USPTO patent and inventor data and merging it with Compustat, which provides us a laboratory to capture a more granular level of skill intensity and justify our benchmark mechanism.

C.1 Data

Patent Data. We analyze utility patents granted by the United States Patent and Trademark Office (USPTO). Our analysis relies on the registered names on the original patent applications to better capture the entities that performed the innovation activities. Each patent record provides information about the invention (e.g., technology classifications, citation of patents on which the current invention builds) and the inventors submitting the application.

We then merge the USPTO patent data with the Compustat firm sample using a crosswalk provided by Autor et al. (2016) which matches corporate patents granted by the USPTO between 1975 and March 2013 to Compustat firm identification numbers (GVKEY).[3] The algorithm relies on a web search engine to match the 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 the inventor mobility across different firms as follows. A particular inventor i moves from firm X to firm Y if at least one patent application authored or co-authored by inventor i has been submitted by firm X (source firm) prior to an application authored or co-authored by inventor i has been submitted by firm Y (destination firm). Hence, due to the construction of the USPTO patent data, we iden-

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

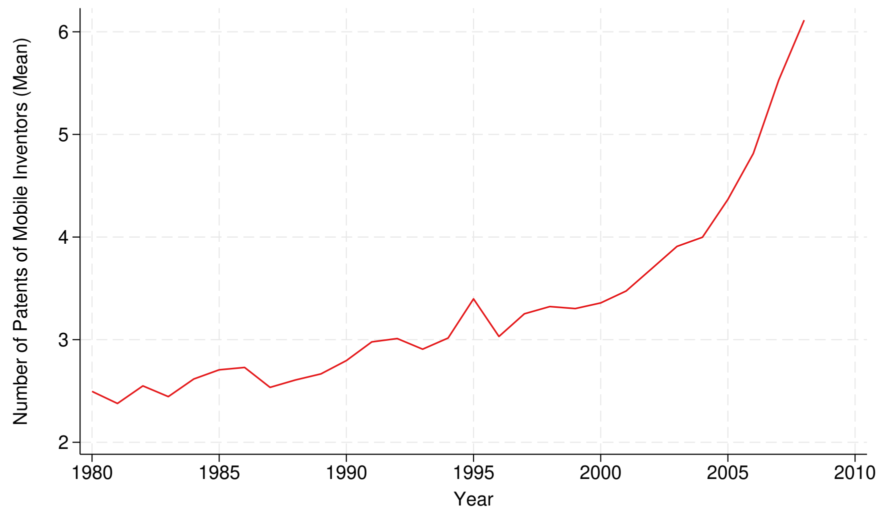
tify the timing of the mobility of inventor i from firm X to firm Y at the year when the patent application is submitted by inventor i at a firm Y.

We know that the time dimension to pin down when the inventor mobility occurs would be an issue because the earliest time we observe the mobile inventor engaging in a patent activity is the year of the earliest patent application submitted at the destination firm. However, the inventor mobility could occur before the year of the patent application at the destination firm. There could be substantial time needed for the mobile inventor to work together with other inventors at the destination firm before the patent application can be submitted. Hence, the ideal identification for the inventor mobility would be to observe precisely when the inventor moves from firm X to firm Y. However, unfortunately, we do not have that luxury due to the data limitation.

C.2 Stylized Facts

This section shows several stylized facts that the linkage between productivity and intangible capital would also potentially affect factor reallocation, such as inventor mobility. Our underlying conjecture is that small and medium-scale firm experiencing productivity slowdown would lose their skilled inventors to large-scale firms. In that regard, we show in Figure C.1 that inventors with a higher number of patents become more likely to move across firms over time. We can interpret this figure such that the skill requirement for inventor mobility has increased over time in the U.S. economy. Hence, we can argue that skilled inventors become a scarce input in the labor market.

Figure C.1: Patent Needed to Change a Company



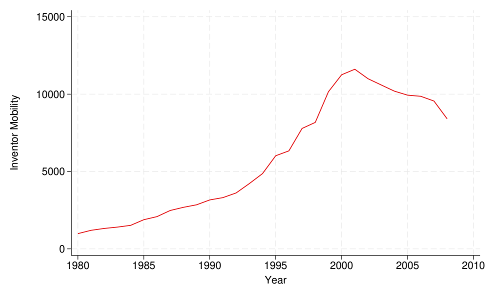
Note: This figure shows the average total patent of mobile inventors received at the (source) firm from which they leave.

Figure C.2a shows that while the total inventor mobility increases over time until the 2000s, the trend shows a declining pattern after the 2000s. Therefore, scarce skilled inventors become even more valuable for firms, given that they started to be less mobile after the 2000s.

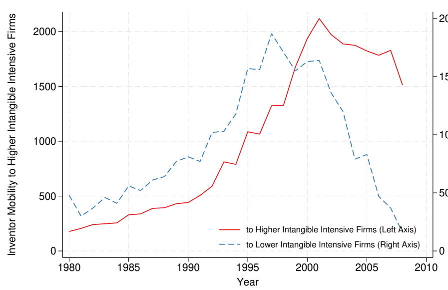
Given those phenomena, we argue that firms need to develop alternative ways to attract those scarce skilled inventors. We show that one of the alternative ways how firms poach and attract those inventors would be their effective intangible capital. We can think of firm-level intangible capital as R&D expenditures, organizational capital including employee training, restructuring organizational structure, and business culture. Given that that intangible capital can be potentially used to enhance inventors' personal and career development, firms with higher effective intangible capital would be more likely to poach and attract those scarce skilled inventors in the labor market.

We find that this is indeed the fact we observe in the U.S. economy. Figure C.2b and C.2c show that while inventor mobility to the firms with lower intangible capital and lower size has been declining, especially after the 2000s when we see a productivity slowdown and an increasing productivity dispersion, we do not see any decline in inventor mobility to the firms with higher size and higher intangible capital during that episode. Hence, we can argue that firms with high intangible capital are more able to attract the scarce skilled inventors when scarce skilled inventors become more valuable and there has been a declining trend in inventor mobility in the economy.

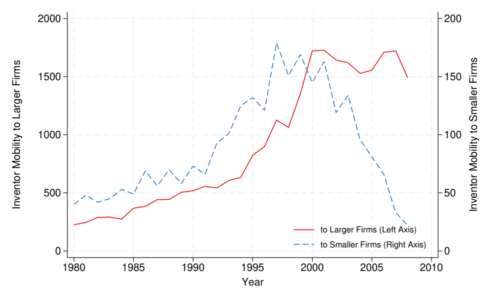
Figure C.2: Inventor Mobility and Intangible Capital



(a) Inventor Mobility



(b) Inventor Mobility by Intangible Capital

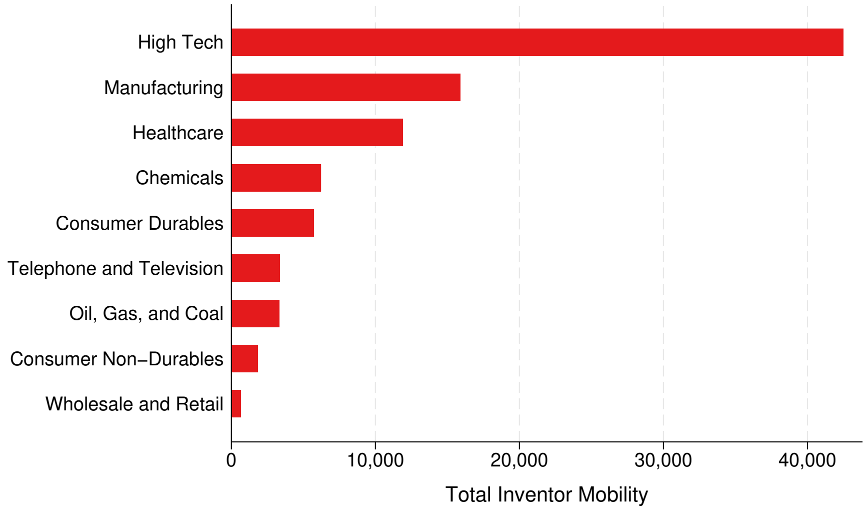


(c) Inventor Mobility by Firm Size

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.

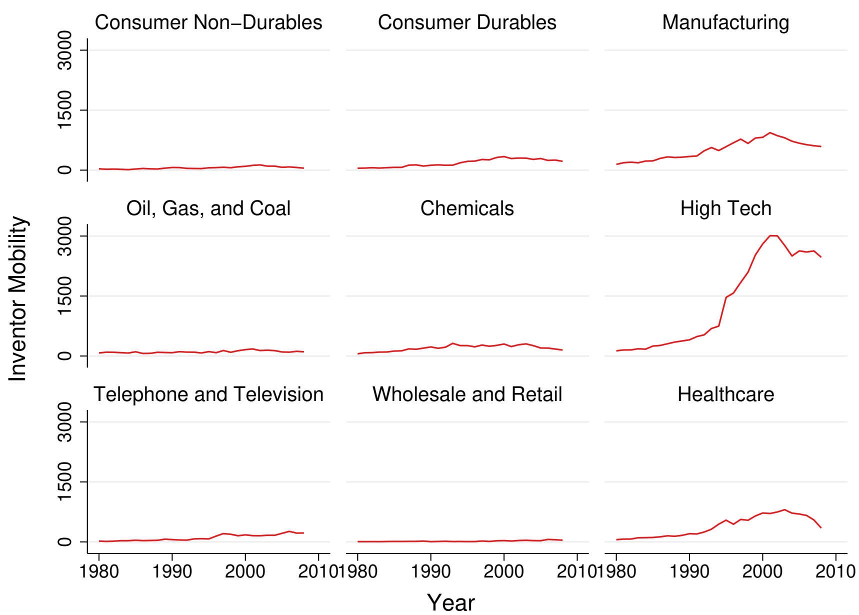
We also investigate the inventor mobility at the industry-level. Figure C.3 shows that we have a striking heterogeneity in the inventor mobility across industries and the most of the inventor mobility in the economy occurs in High Tech, Manufacturing, and Healthcare industries. Figure C.4 indicates that inventor mobility has an increasing trend until 2000s across different industries, whereas it has a declining trend afterwards.

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.

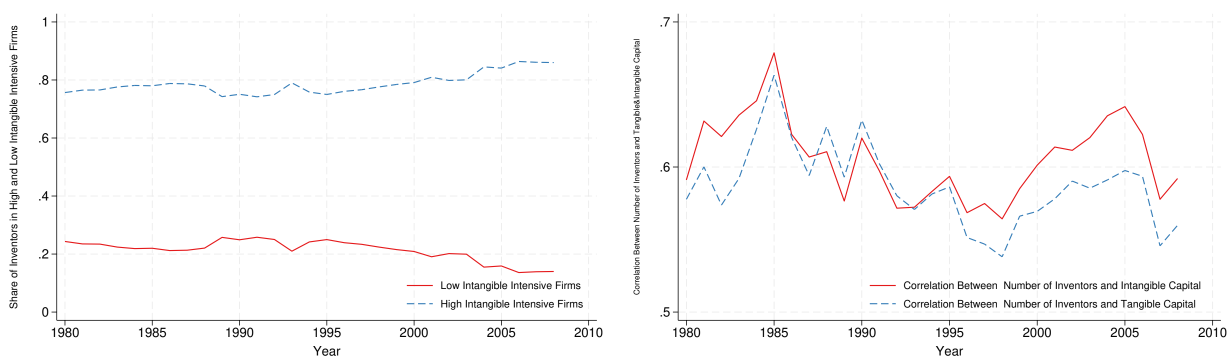
Figure C.4: Inventor Mobility by Fama-French Industries



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

Suppose we focus on the total number of inventors rather than only inventors who move. In that case, we also see a similar big-picture pattern that there is 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 intangible capital intensive firms. In other words, we find that the share of inventors working at firms whose intangible capital intensity is above the economy-wide average is around 80% almost all the time. Another fact in Figure C.5b shows 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 all the time. Hence, we argue that the fluctuations in the total stock of inventors are in line with the fluctuations in intangible capital rather than tangible capital.

Figure C.5: Intangible Capital Intensity for Inventors



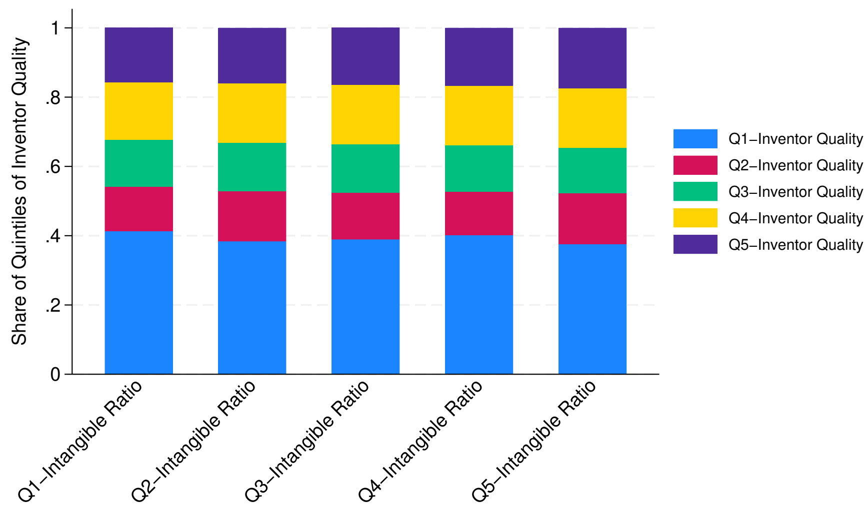
(a) Intangible Capital Intensity for Inventors

(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*).

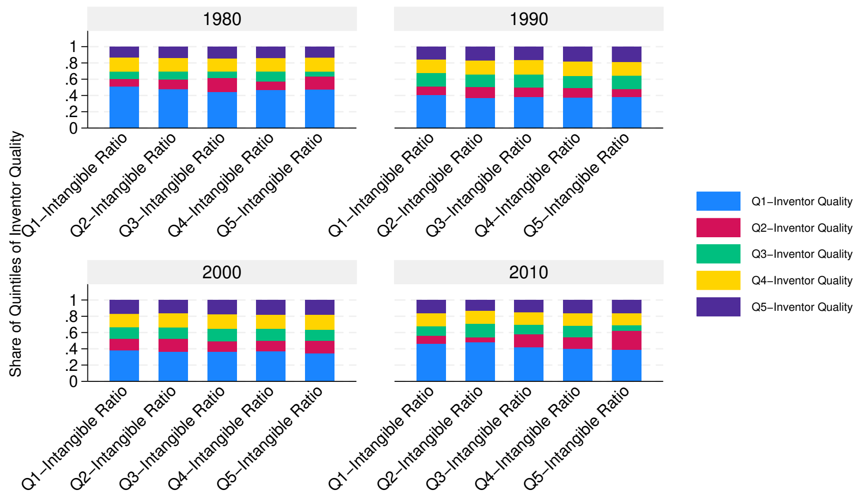
We match the inventor quality and intangible capital intensity at the firm level to bring more direct evidence. We first rank inventors based on their quality (5-year window citation per total patents) and construct the corresponding inventor quality quintiles. Then, we rank firms in terms of their intangible capital per asset and construct the corresponding intangible capital per asset quintile. Finally, we calculate the shares of the match between each possible pair of both quintiles. Figure C.6 indicates that as firms' intangible capital share increases, the share of higher quality inventors they also have increases. Hence, we can argue an assortative matching between inventor quality and intangible capital even when controlling the firm size. In other words, after controlling firm size, firms with higher intangible capital are more likely to meet higher quality inventors on average. This assortative matching is not just a particular time phenomenon as well. We show in Figure C.7 that the assortative matching between inventor quality and intangible capital is even the fact for different 10-year windows.

Figure C.6: The Share of Inventor Quality by Intangible 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 ratio quintile. y-axis denotes the corresponding share of each quintile of inventor quality within each quintile of intangible ratio.

Figure C.7: The Share of Inventor Quality by Intangible 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 ratio quintile. y-axis denotes the corresponding share of each quintile of inventor quality within each quintile of intangible ratio.

C.3 Empirical Analysis

In this section, we investigate how intangible capital affects the productivity of inventors.

C.3.1 Intangible Capital and Productivity of Inventors

The main goal in this section is to quantify how intangible capital and firm size affect inventors' productivity. Inventors are important drivers of productivity improvements of firms. When an inventor grants a patent to a firm, it will increase productivity and enable the firm to become more innovative. Therefore, our benchmark regression to pursue this direction and investigate how intangibles and firm size affect the productivity of inventors is as follows:

$$\Delta^{patent_{i,c}} = \beta_1 \Delta^{intangible_{i,c}} + \beta_2 \Delta^{asset_{i,c}} + \beta_3 X_{i,c} + u_i + u_t + u_s + \epsilon_{it} \quad (15)$$

$$\mathbb{1}^{patent_{i,c}} = \beta_1 \mathbb{1}^{intangible_{i,c}} + \beta_2 \mathbb{1}^{asset_{i,c}} + \beta_3 X_{i,c} + u_i + u_t + u_s + \epsilon_{it} \quad (16)$$

where subscripts $\{i, c, t, s\}$ index inventor, firm, year and sector, respectively. Our dependent variable in (15) is $\Delta^{patent_{i,c}}$ which denotes 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, and our dependent variable in (16) is $\mathbb{1}^{patent_{i,c}}$ as 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. For the specification (15), $\Delta^{intangible_{i,c}}$ 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. For the specification (16), $\mathbb{1}^{intangible_{i,c}}$ is a dummy variable with 1 if the inventor i moving to the firm c with higher intangible capital compared to the source firm the inventor i moves from. $\mathbb{1}^{asset_{i,c}}$ is a dummy variable with 1 if the inventor i moving to the firm c with higher asset compared to the source firm the inventor i moves from.

Our coefficients of interest are β_1 and β_2. Our firm-level control variables are denoted by the vector of $X_{i,c}$ which includes firm size and the level of intangible capital. Firm size is measured as the logarithm of the assets' logarithm, and intangible capital is the logarithm of intangible capital per worker at a firm c. We control for the intangible capital per worker because the average usage of intangible capital is an important determinant of patent creation. Due to the unobserved heterogeneity, we also include several fixed effects: inventor, year, and sector. As the productive inventors can benefit more from the intangible capital, we use the inventor fixed effects, u_i. Also, there are industrial differences to receive the patents. For instance, it may be more likely to grant a patent in computer, software, and electronic equipment, while it may be harder in the agricultural sector. Also, in Figure C.3 we show that the inventor mobility shows sectoral differences. Therefore, we also control for the sector fixed effects, u_s. Finally, over time it may be getting harder to realize innovation. We capture the time unobserved heterogeneity with u_t.

Table C.1 reports the results of the equation (15). We find that a unit increase of intangible capital (asset) in the difference between the destination and source firm of the inventor also increases the number of patents by around 0.91 (0.84). Thus, Table C.1 reflects that higher intangible capital and bigger firm size makes the inventors more productive.

Table C.1: The Effect of Intangible Capital and Firm Size on Productivity of Mobile Inventors

	$\Delta^{patent_{i,c}}$	$\Delta^{patent_{i,c}}$	$\Delta^{patent_{i,c}}$
$\Delta^{intangible_{i,c}}$	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 (15). 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.2 reports the results of the equation (16). The second column in Table 4 shows that inventors moving to bigger firms (firms with higher assets) are increasing their number of patents by 0.09 compared to their previous firms. Notice that in this column, we do not control for the intangible dummy variable. As we only include the dummy for intangible capital (column 1), we observe that inventors moving to the firm with higher intangible capital can generate 0.05 more patents than their previous firm. In the last column, we include both dummy variables for asset and intangible capital. In this case, when we control for the inventors moving to the firms with higher intangible capital, it becomes insignificant whether the inventor moves to bigger firms. Inventors moving to higher intangible capital firms still improve their number of patents by 1 even if we control the firm size. Therefore, those results indicate that the inventor's main driver (number of patents) is the intangible asset. Thus, Table C.2 reflects that the intangible capital makes the inventors more productive even when we control for the firm size.

Table C.2: The Effect of Intangible Capital and Firm Size on Productivity of Mobile Inventors

	$\mathbb{1}^{patent_{i,c}}$	$\mathbb{1}^{patent_{i,c}}$	$\mathbb{1}^{patent_{i,c}}$
$\mathbb{1}^{intangible_{i,c}}$	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 (16). The dependent variable is the total number of patents a mobile inventor is granted at the destination firm. $\mathbb{1}^{intangible_{i,c}}$ ($\mathbb{1}^{asset_{i,c}}$) 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. * $p < .10$, ** $p < .05$, *** $p < .01$.

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:

$$\Delta^{patent_{i,c}} = \beta_1[\mathbb{1}^{intangible_{i,c}} * \mathbb{1}^{asset_{i,c}}] + \beta_2 X_{c,t} + u_i + u_t + u_s + \epsilon_{it} \tag{17}$$

where $\Delta^{patent_{i,c}}$ which denotes 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. Our firm-level control variables are denoted by the vector of $X_{i,c}$ which includes the logarithm of firm-level assets and logarithm of firm-level intangible capital per worker. $\mathbb{1}^{intangible_{i,c}}$ is defined as a dummy variable with 1 for the inventor moving to the firm with higher intangible firm and 0 for the inventor moving to lower intangible capital. $\mathbb{1}^{asset_{i,c}}$ is also defined as a dummy variable with 1 for the inventor moving to the firm with higher assets and 0 for the inventor moving to lower assets. The coefficient of interest is β_1. Due to the unobserved heterogeneity concerns as in equation (15) and (16), we also include inventor u_i, year u_t and sector u_s fixed effects.

Table C.3 reports the estimation results of equation (17). In the second column, we observe that inventors moving to the firms with higher intangible and higher assets are generating 0.59 more patents than those moving to lower intangible and lower asset firms. When an inventor moves to higher intangible capital, given that he is moving to the low asset firm, he generates 1.26 more patents than the inventor moving to firms with lower intangible firms. However, given the inventors moving to lower intangible capital firms, the firm with higher assets has no significant effect on the number of patents received. It even lowers the number of patents when we do not control for the sector fixed effect as in column 1. Thus, Table C.3 indicates that inventors become more productive as they move to the bigger or higher intangible capital firm. The synergy between the asset and intangible capital makes the inventors more productive.

In Section 2, we have shown the rise in productivity dispersion and that intangible capital dispersion is positively correlated with productivity dispersion. Table C.3 shows us a potential reason why the productivity dispersion has been rising in favor of big firms in the U.S. economy. For small and large firms, intangible capital is an important determinant of granting a patent; but, inventors at bigger and higher intangible capital firms can produce more patents than the small ones. Those inventors are becoming more productive and granting higher patents for the firms they are working at. Thus, it would account for the productivity dispersion in favor of bigger firms in the U.S. economy.

Table C.3: The Effect of the Interaction between Intangible Capital and Firm Size on Productivity of Mobile Inventors

	$\Delta^{patent_{i,c}}$	$\Delta^{patent_{i,c}}$
$\mathbb{1}^{asset_{i,c}} = 0 * \mathbb{1}^{intangible_{i,c}} = 0$	0	0
	(.)	(.)
$\mathbb{1}^{asset_{i,c}} = 1 * \mathbb{1}^{intangible_{i,c}} = 0$	-0.226	-0.317
	(0.383)	(0.438)
$\mathbb{1}^{asset_{i,c}} = 0 * \mathbb{1}^{intangible_{i,c}} = 1$	0.983	1.269*
	(0.605)	(0.676)
$\mathbb{1}^{asset_{i,c}} = 1 * \mathbb{1}^{intangible_{i,c}} = 1$	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 (17). 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. * $p < .10$, ** $p < .05$, *** $p < .01$.