THE UNIVERSITY OF CHICAGO

ESSAYS ON THE ROLE OF INTANGIBLE CAPITAL IN FIRM DYNAMICS

A DISSERTATION SUBMITTED TO
THE FACULTY OF THE DIVISION OF THE SOCIAL SCIENCES
IN CANDIDACY FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

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CHICAGO, ILLINOIS
AUGUST 2022

To my wife, my parents, and all my family

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ACKNOWLEDGMENTS

I am greatly indebted to my advisor and thesis committee chair Harald Uhlig for his guidance and support during my Ph.D. process. He always provided constructive and informative feedback on my research papers, which helped me shape and develop the frontier research framework. He also shared his academic experience and insights on being productive and active in the academic environment, which was motivating and encouraging. I am also thankful to my advisors Ufuk Akcigit, Lars Peter Hansen, Greg Kaplan, and Thomas Winberry, for their valuable guidance, help, and support. I am grateful for their constructive comments and feedback, which helped shape this dissertation.

My doctoral study hugely benefitted from the support and suggestions from the great people. I would like to thank Ahmed Ahmed, Harun Alp, German Villegas Bauer, Oguz Bayraktar, Ibrahim Bicak, Serdar Birinci, Gorkem Bostanci, Thomas Bourany, Ari Boyarsky, John Grigsby, Reem Hashad, Furkan Karaca, Furkan Kilic, Ivan Kirov, Toshiaki Komatsu, Josh Morris-Levenson, Katherine McElroy, Hyejin Park, Jeremy Pearce, Shogher Ohannessian, Yusuf Ozkara, Younghun Shim, Hasan Tosun, Sait Tunc, and Yulia Zhestkova.

I am thankful to my dad Ramazan Gozen, my mom Hatice Gozen, and my sister Ayse Sena Gozen, who always provide me their endless love, guidance, and support. Thank you for supporting me and providing your positive energy in any instances during my life. My brother Ahmet Yavuz Gozen is always in my heart and lives in my memories; I continuously feel his love even though he is not with us anymore.

I am grateful to my wife, Ruveyda Gozen, who has always been with me through her love, patience, support, and encouragement, which gave me enormous strength and resilience against the stressful and challenging years of graduate school.

ABSTRACT

Intangible Capital Meets Skilled Labor: The Implications for U.S. Business Dynamism (with Yusuf Ozkara)

The U.S. economy has been experiencing a decline in aggregate productivity growth and an increase in productivity dispersion, which also co-moves with the rise of intangible capital. How would intangible capital lead to heterogeneous impacts on productivity patterns? To explore this question, we introduce a new channel in which intangible capital meets skilled labor to internalize 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, especially in intangible intensive sectors, ii) rising intangible capital concentration by large firms, iii) increasing number of skilled workers in large intangible firms, and iv) higher intangible-skill complementarity in large firms. Based on these motivating facts, we build an empirical framework to quantify the effects of the intangible capital - skilled labor complementarity on firm-level productivity dynamics. We find that complementarity brings higher productivity in large firms, whereas it has no effect on small firms. Hence, large firms' surge in intangible capital combined with skilled labor accounts for an increasing trend in productivity dispersion. We build a general equilibrium model that includes heterogeneous firms subject to adjustment costs investing in tangible and intangible capital, and hiring skilled and unskilled labor to discipline our reduced-form evidence. Consistent with the empirical insights, our model delivers that an increase in asset intangibility

increases the skilled premium and productivity dispersion by replacing unskilled labor with skilled labor. The model also provides predictions, that are empirically tested, on the implications of intangible capital in the linkage between firm-level investment dynamics and labor reallocation.

Intangible Capital and Competition in Ride Sharing: The Case of Lyft-Motivate Merger (with Hasan Tosun)

This study focuses on estimating the role of intangible capital on firms' competitiveness. We use Lyft's acquisition of Motivate, the biggest bike sharing company in the U.S. at the time, to evaluate the degree to which intangible capital affects the competition between Lyft and Uber. By acquiring Motivate, Lyft gained more consumer data as we interpret intangible capital, and bikes' presence on the streets potentially helped Lyft build stronger brand salience. We estimate the effect of the acquisition on Lyft's ridership by employing trip-level ride sharing data from New York City and using a difference-in-difference-in-differences model. We find that the acquisition helped Lyft increase its ridership by around 6%.

CHAPTER 1

INTANGIBLE CAPITAL MEETS SKILLED LABOR: THE IMPLICATIONS FOR U.S. BUSINESS DYNAMISM

1.1 Introduction

There is a vast range of evidence in the literature that the U.S. economy has been experiencing a decline in aggregate productivity growth and an increase in productivity dispersion (Andrews et al. (2016), Decker et al. (2018), Akcigit and Ates (2019)). Another related evidence is the increasing degree of skill-biased technological change in the U.S. economy (Acemoglu (1998), Krusell et al. (2000), Violante (2008)). One strand in the literature explains these phenomena 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 which see 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 underlying reasons behind declining U.S. business dynamism is still mixed.

In parallel, within the same episode, the U.S. economy has a dramatic increase in intangible capital (Corrado et al. (2009), Haskel and Westlake (2017)). This technological change can influence the firm dynamics in various aspects. The production function has shifted so that the share of intangible capital becomes as essential as tangible capital.

Based on these facts, in this chapter, we focus on the complementarity between intangible capital and skilled labor to study its role in the U.S. productivity dynamics. The underlying motivation is that intangible capital requires skilled labor to internalize its economic benefits, amplified with economies of scale. In that respect, we explore the following questions: Through which channels do firms effectively use their intangible capital for productivity gains? What are the contributions of skilled labor to the relationship between intangible capital and productivity? What would be a potential underlying heterogeneity why some firms could benefit from the complementarity between intangible capital and skilled labor but not the other ones? We address those questions to introduce a new channel to help us understand how the association between productivity slowdown, intangible capital, and skill components would account for the changing business dynamism in the U.S. economy.

We approach these questions based on our central argument that skilled labor is required to implement high-stakes intangible capital. Firms invest in intangible capital to increase productivity, but not simply develop software or advertise on spending. Firms need to employ skilled workers to utilize the high-stakes intangible capital and reach an efficient level of production capacity, which raises the complementarity between intangible capital and skilled labor. For instance, Amazon employs many Ph.D. researchers to analyze its crucial input of consumer data. Similarly, Microsoft hires many IT engineers to utilize its vast software investment. As a piece of anecdotal evidence, Table 1.1 reports the average intangible ratio and skill intensity for some large firms in the U.S. economy. We observe that these large frontier firms have high intangible ratio and skill intensity values, which are far above the economy average.

TABLE 1.1: Anecdotal Evidence

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 ratio and skill intensity for some large firms.

We examine the particular channel of intangible capital - skilled labor complementarity using both empirical and theoretical approaches. After documenting motivating stylized facts, our empirical analysis quantifies the effects of intangible capital-skilled labor complementarity on firm-level productivity. Next, we develop a theoretical framework to discuss the main channels through which an assortative matching between intangible capital and skilled labor affects firm-level investment choices and labor composition.

Using firm-level measures from Compustat and industry-level variables from Quarterly Workforce Indicators (QWI), we document several stylized facts which show the association between productivity dispersion, the role of intangible capital, and skilled labor. We find four main stylized facts: i) increasing productivity dispersion driven by large firms, especially in intangible intensive sectors, ii) rising intangible capital concentration by large firms, iii) increasing number of skilled workers in large and intangible firms, and iv) higher intangible-skill complementarity in large firms.

The next part in the empirical analysis develops a more systematic approach through the regression analysis, which explores the main insights captured by the stylized facts. First, we quantify the role of intangible capital in firm-level productivity. We find that intangible capital has a positive and dramatic contribution to the total factor productivity (TFP) more than tangible capital, suggesting that firms would have a higher incentive to internalize the effective intangible capital for productivity gains rather than tangible capital. Second, we estimate to which degree intangible capital influences firm-level skill intensity. Our empirical results suggest that for a one standard deviation increase in the ratio of intangible capital, skill intensity increases by up to 0.39 standard deviation depending on different fixed effects, which is amplified with firm size. In other words, larger firms with higher intangible capital have higher skill intensity. Third, we quantify the effect of intangibles and skilled workers on firm-level productivity. We show that firms with higher intangible and skill intensity have higher productivity, which is amplified with firm size. We find that one standard deviation increase in firm-level skill intensity increases the firm-level productivity by up to 2% and one standard deviation increase in firm-level intangible capital ratio increases the firm-level productivity by around 9%.

We also provide an additional set of analyses to our benchmark approach by analyzing the role of synergy between intangible capital and inventors on productivity dynamics. The advantage of having this complementary approach is that we use 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. This approach provides us a laboratory to capture a more granular level of skill intensity and justify our benchmark mechanism. We find that while inventor mobility to lower intangible capital 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 higher intangible capital during that episode. This fact indicates a potential complementarity between intangible capital and skilled inventors, aligning with our baseline framework. Motivated by this fact, we investigate how intangible capital affects inventors' productivity in different firm sizes. We find that inventors produce more patents as they move to the bigger and higher intangible capital firm, implying that the synergy between intangible capital and skilled inventors is higher in large firms.

To rationalize the reduced-form empirical evidence, we first sketch a simple model which motivates our empirical evidence of why firms with higher intangible capital benefit from skilled labor. We use the simplified, and modified model version by Acemoglu and Autor (2011) to argue through which channels there would be an assortative matching between intangible capital and skilled labor. In the model, the main channel through which the accumulation of intangible capital attracts skilled labor is disciplined by changing skill premia due to the change in the relative demand of skilled labor. The model delivers that an increase in the intangible capital intensity also increases the skilled premium, which is in line with our empirical evidence that higher intangible capital intensive sectors have higher skill intensity. We also bring an empirical test for the basic model prediction using the NBER-CES database to measure industry-level skill premium and unskilled-skilled labor ratio at the 4-digit NAICS. We find that an increase in the intangible-tangible ratio has a positive and significant impact on industry-level skill premium. Our regression coefficients align with the elasticity of substitution parameter between skilled and unskilled workers at the industry level derived in the literature.

Based on the insights from the motivating model, we construct a general equilibrium model of heterogeneous firms subject to investment adjustment costs investing in tangible and intangible capital and hiring skilled and unskilled labor. We include an idiosyncratic shock component in the degree of complementarity between intangible capital and skilled labor to capture heterogeneity in investment decisions. Moreover, we incorporate the productivity differences between intangible and tangible capital for the model to capture productivity dispersion, in line with the empirical evidence. Finally, we incorporate the component of adjustment costs to study the implications of the role of firm size.

Our model uses crucial insights by Chiavari and Goraya (2020), Krusell et al. (2000), Acemoglu (2002a), and Violante (2008). In that regard, our model has two essential building channels: i) an investment channel where there are heterogeneous firms that are subject to adjustment costs invest in tangible and intangible capital; and ii) a labor market channel where heterogeneous firms decide how much to hire skilled and unskilled labor, which generates the labor reallocation and skill premium. Our model brings several predictions, that are empirically tested, on the role of intangible capital in the linkage between investment dynamics and labor reallocation. Using both firm-level and industry-level data, we develop several empirical tests for our general equilibrium model predictions and find consistent evidence that the relative demand for skilled labor, and productivity dispersion increase with asset intangibility, which large firms drive. Our empirical tests suggest that large firms paying lower relative adjustment costs for intangible capital invest more in intangibles and hire highly skilled labor to benefit from the complementarity, increasing the equilibrium skill premium and productivity dispersion, which is in line with our empirical evidence.

Related Literature. Our chapter contributes to the literature in several ways. A particular 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 (2019)), 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 declining productivity slowdown disproportionately for small firms.

The second strand of the literature studies the dramatic increase in intangible capital ratio over time (Corrado et al. (2009); McGrattan and Prescott (2014); Eisfeldt and Papanikolaou (2014); Haskel and Westlake (2017); Peters and Taylor (2017);

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 even though there is 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 chapter, 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 its impact 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 assortative matching 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 to argue 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. The chapter has the following sections: Section 1.2 documents stylized facts on the association between productivity dynamics, intangible capital, and skilled labor. Section 1.3 provides information regarding the data and the measurements. Section 1.4 develops an empirical framework to study the implications of intangible capital in firm-level productivity and quantify the effects of complementarity between intangible capital and skilled labor on firm-level productivity. Section 1.5 sketches a motivating model which disciplines the empirical evidence on why and through which channel the synergy between intangible capital and skilled labor occurs. Section 1.6 extends the motivating model and develops a firm-level general equilibrium model to investigate the role of complementarity in the relation between investment dynamics and labor reallocation. Section 1.7 concludes by discussing future extensions.

1.2 Stylized Facts

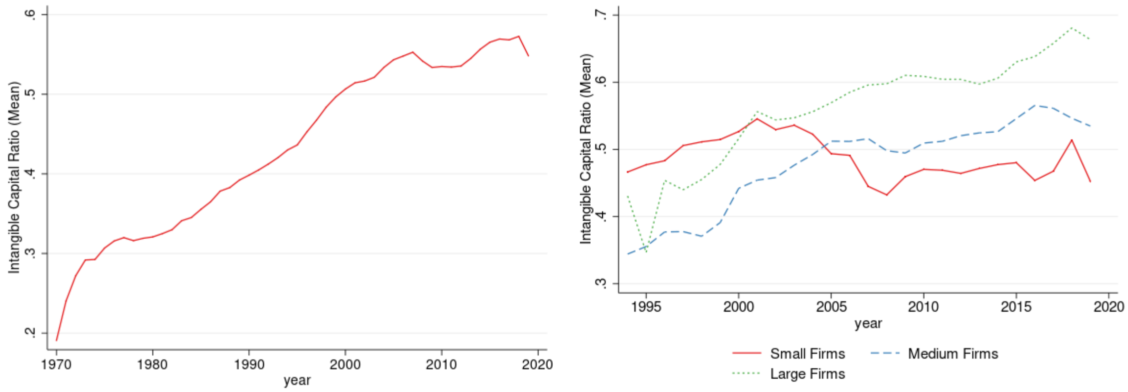
In this section, we document several stylized facts which show the association between productivity dispersion, the role of intangible capital, and skilled labor.

Fact 1: Intangible capital rises in the U.S. economy, which large firms drive.

Figure 1.1a shows the annual average of the intangible capital ratio over time. We observe that the intangible ratio rises from around 20% during 1970s to around 55% during 2010s. This graph implies that the corporate capital structure becomes more intangible capital heavy on average over time in the U.S. economy.

Figure 1.1b documents the annual average of the intangible ratio by quantiles in

Figure 1.1: Intangible Capital Ratio



(a) Intangible Capital Ratio

(b) Intangible Capital Ratio by Firm Size

Note: Panel (a) shows the annual average of intangible capital ratio for the Compustat publicly traded firms. Panel (b) shows the annual average of intangible ratio by firm size.

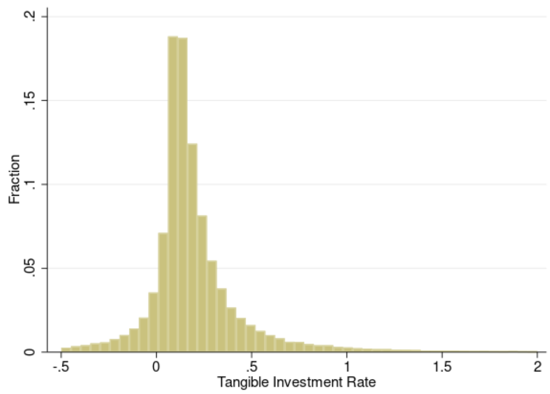
terms of firm size within each 3-digit NAICS and year. We observe that large firms dramatically increase the ratio over time, whereas small firms experience a decline in their trend, especially after the early 2000s. It indicates that the overall increase in intangible capital in the economy would be driven by large firms' accumulation of intangible capital.

Fact 2: Adjustment cost of intangible capital is lower for larger firms.

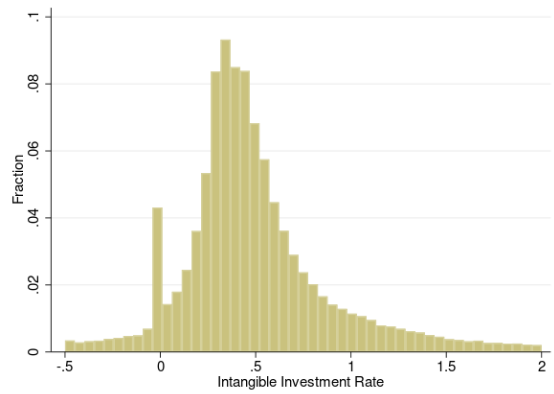
Given Fact 1, the next question is what can be potential reasons behind the disproportionate increase in intangible capital by larger firms? To address this question, we explore a cost channel of intangible capital and investigate whether we observe any heterogeneity in the cost structure of intangible capital. In that respect, as in Chiavari and Goraya (2020), we investigate the investment lumpiness to infer the underlying adjustment cost and analyze how it differs with firm size.

Figure 1.2 shows that there is a high amount of mass around zero for intangible investment rate, whereas we do not observe such evidence for tangible investment rate. It implies that the intangible investment rate has higher lumpiness and thus higher adjustment costs than the tangible investment rate.

Figure 1.2: Histogram - Investment Rates



(a) Tangible Investment Rate

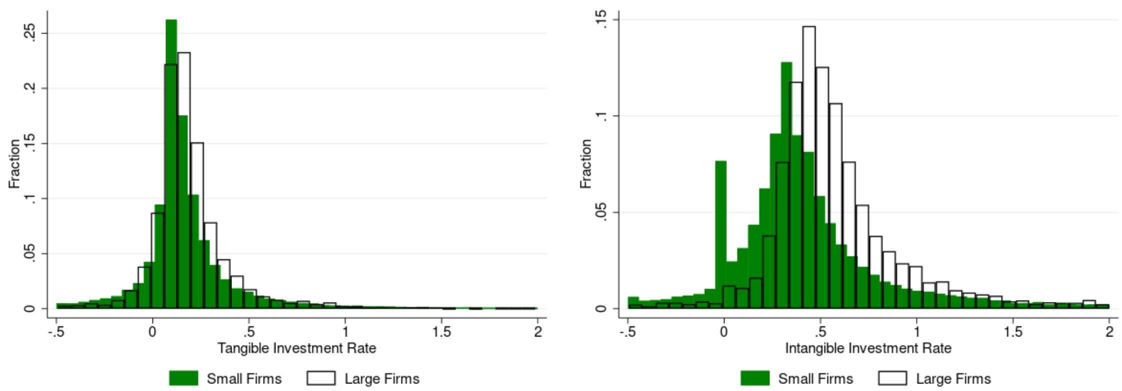


(b) Intangible Investment Rate

Note: This figure shows the histogram of tangible and intangible investment rate.

To distinguish the role of firm size in adjustment cost structure, we do a similar exercise but plot the corresponding histograms for small and large firms. Figure 1.3 documents that intangible investment rate has a higher mass around zero for smaller firms, whereas we do not see such a mass for tangible investment rate. It implies that the adjustment cost of intangible capital is higher for smaller firms. Hence, adjustment cost being cheaper for large firms would be a particular factor why we observe such a dramatic increase in intangible capital in larger firms.

Figure 1.3: Histogram by Firm Size - Investment Rates



(a) Tangible Investment Rate

(b) Intangible Investment Rate

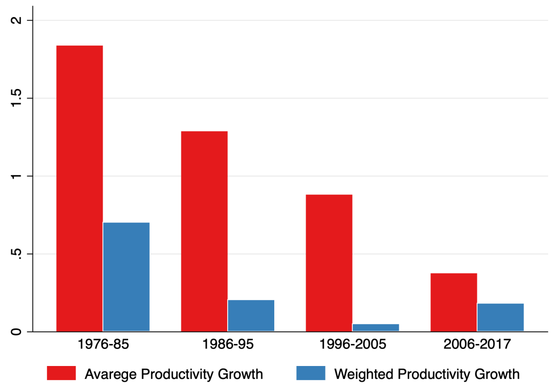
Note: This figure shows the histogram of tangible and intangible investment rate for small and large firms.

Fact 3: Productivity decline during the last two decades is driven by small firms.

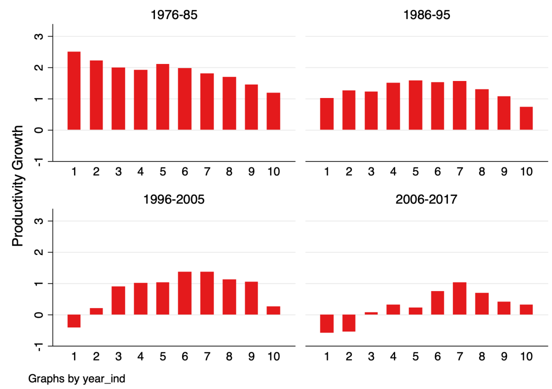
Figure 1.4a shows the simple and weighted average of productivity growth over 10-year windows. We first observe that there is an overall declining trend in productivity growth in the U.S. economy. Second, we show that the simple average of productivity growth declines faster after the early 2000s, which implies that the productivity growth of small firms would have a declining trend during this episode.

To emphasize the role of firm size in productivity growth, we plot the productivity growth rate of different firm size over a 10-year window in Figure 1.4b. The firm sizes are categorized by the sale of firms within a year. We label “10” to indicate the largest firms (top quantile), “1” to indicate the smallest firms

Figure 1.4: Productivity Growth



(a) Productivity Growth



(b) Productivity Growth by Size

Note: Panel (a) shows the 10-year window simple and weighted average of productivity growth rate. Panel (b) shows the 10-year window simple averages of productivity growth rate for each firm size quantile.

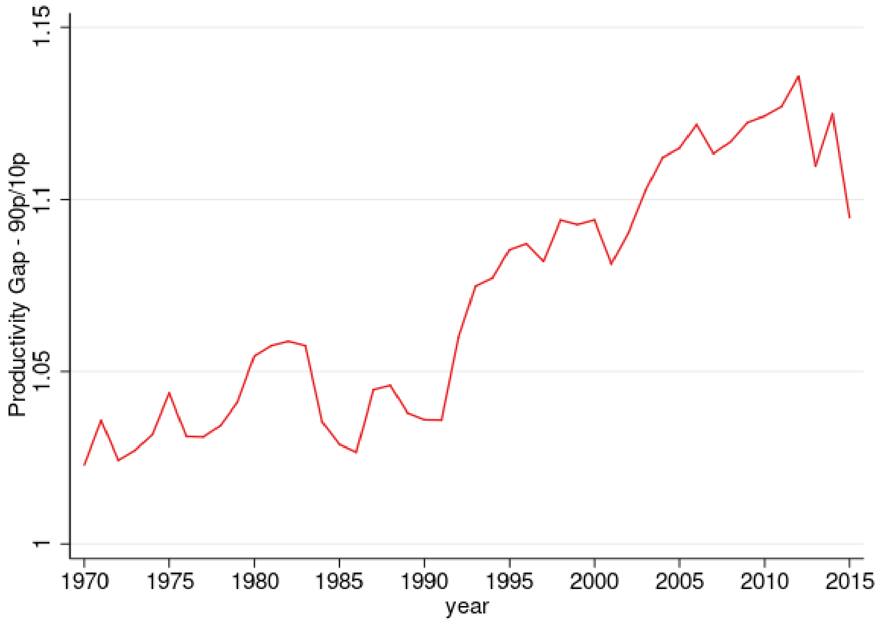
(bottom quantile). Figure 1.4b shows how the small firms' productivity growth and their contribution to the aggregate productivity declined over time.

Fact 4: Productivity dispersion has risen in favor of bigger firms.

Figure 1.5 shows the average productivity gap between the 90th percentile and 10th percentile of firm size distribution within each industry and year. We see that the productivity gap between large and small firms widens over time. It indicates that large firms in their industry seem to be one of the main drivers of productivity gains in the U.S. economy. In contrast, small firms show relatively stagnant productivity performance. This result indicates that the productivity dispersion between large and small firms has widened, especially after the 2000s.

In order to investigate further whether we indeed observe large frontier firms

Figure 1.5: Productivity Gap Between Large and Small Firms



Note: This figure shows the average productivity gap between 90th percentile and 10th percentile of firm size distribution within each industry and year.

are one of the main drivers for the productivity dispersion, Figure A8 decomposes the productivity gains of firms in their industry whether they i) are new leaders, ii) are incumbent leaders, iii) were leaders in the previous year but not now, and iv) are follower firms. We see that most of the productivity gains come from incumbent firms which have been leaders in their industry for several years. Hence, we can argue that incumbent leader firms are more likely to drive the current productivity dispersion in their industry.

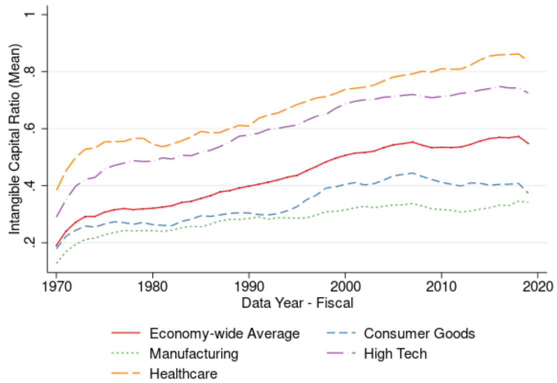
Regarding the last fact, Figure A9 documents to what extent incumbent leader firms are persistent in their position in their industry. We see that the persistency of incumbent leader firms has been increasing over time, especially after the 2000s, when we also show that the productivity dispersion has been widened. Moreover, the persistency of incumbent leader firms and the productivity dispersion between them and their followers go hand-in-hand (except a few years) over time. It suggests that the persistency of leader-incumbent firms can be a potential candidate for increasing productivity dispersion.

Fact 5: Sectoral heterogeneity in intangibles accounts for productivity dispersion.

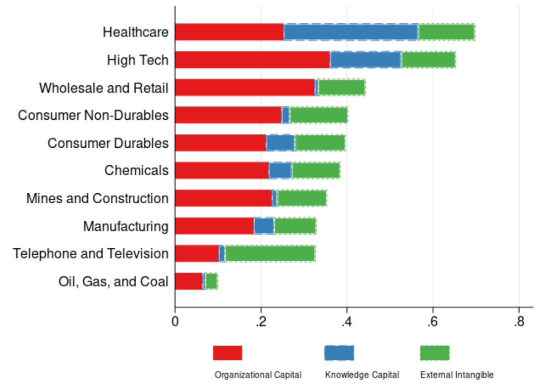
We first document that the trends in intangible capital show striking heterogeneity across different sectors. For instance, Figure 1.6a shows that even though there is a dramatic increase in the intangible ratio for selected sectors, the highest average intangible capital ratio is observed in Healthcare and High-tech sectors. In contrast, the average intangible ratio in Manufacturing and Consumer Goods sectors is below the economy-wide average intangible ratio. Looking at the components of intangible capital, we also observe a similar heterogeneity. Figure 1.6b documents that even though the share of organizational capital is bigger for almost all selected sectors, the knowledge capital constitutes an important share for the Healthcare, High-tech and Wholesale and Retail sectors.

We also find similar heterogeneity in productivity dispersion across different sectors. Figure 1.7 shows that productivity dispersion increases in the overall economy, which is line with the literature (Andrews et al. (2016), Decker et al. (2018), Akcigit and Ates (2019)). Moreover, since we aim to link the overall trend in productivity dispersion to intangible capital, we take two representative sectors: the Healthcare sector as a representative for highly intangible, and the

Figure 1.6: Sectoral Heterogeneity in Intangible Capital



(a) Intangible Capital Ratio



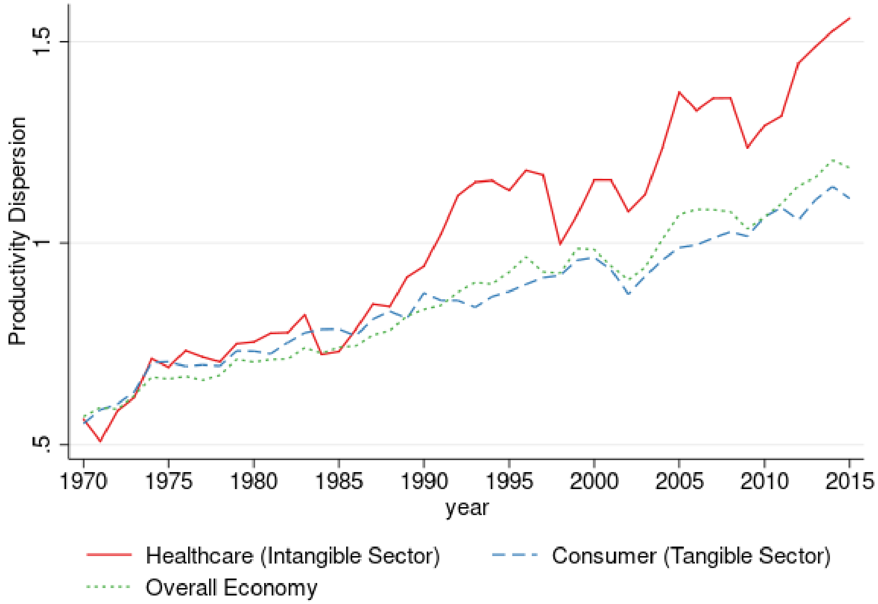
(b) Intangible Capital Components

Note: Panel (a) shows the annual average of intangible ratio, Panel (b) shows the pooled sample average of intangible capital components for Consumer Goods, Manufacturing, High Tech and Healthcare sectors.

Consumer sector as a representative for highly tangible. We observe that the Healthcare sector has a dramatic and sharp increase in productivity dispersion over time, whereas we do not find such evidence for the Consumer sector. It suggests that sectoral heterogeneity in intangible capital would be a key factor in the overall productivity dispersion. Our industry-level regression analysis in Table A3 also supports the stylized fact that intangible intensive industries have higher productivity dispersion, especially after the 2000s.

The next question is, what are the underlying sources behind the increase in productivity dispersion? Does it come from within- or between-group variations? To answer this question, we construct industry-level groups based on firm size: Small (S) and Large (L). Then, we decompose the industry-level productivity

Figure 1.7: Sectoral Productivity Dispersion



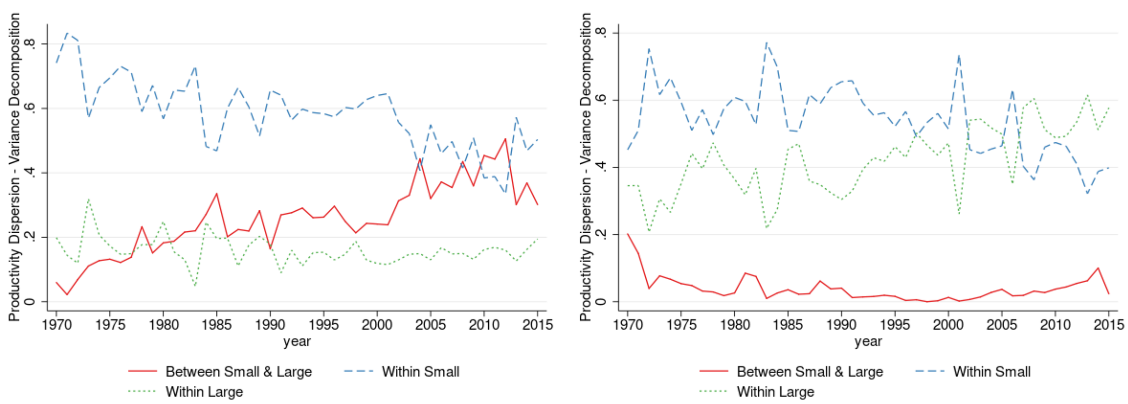
Note: This figures shows the productivity dispersion in the overall economy, Healthcare, and Consumer sectors. Productivity dispersion is measured based on the standard deviation of firm-level productivity within each industry and year.

dispersion into within- and between-group variations as follows:

$$\underbrace{Var(x_i)}_{\text{industry dispersion}} = \underbrace{[Var(x_i|i \in S) + Var(x_i|i \in L)]}_{\text{within-group}} + \underbrace{Var(\{\bar{x}_S, \bar{x}_L\})}_{\text{between-group}}$$

Figure 1.8 plots the contribution of each group to the total industry-level productivity dispersion within each year. We observe that the contribution of between-group variations across large and small firms dramatically increases at the Healthcare sector, especially after the 2000s. In contrast, we do not find such evidence for the Consumer sector. It implies that the productivity gap between large and small firms would be a key driver behind the overall increase in productivity dispersion in intangible intensive sectors. We also bring this fact to regression analysis and find in Table A4 that industries with higher intangible intensity have higher between-group variation after the 2000s.

Figure 1.8: Decomposition of Sectoral Productivity Dispersion

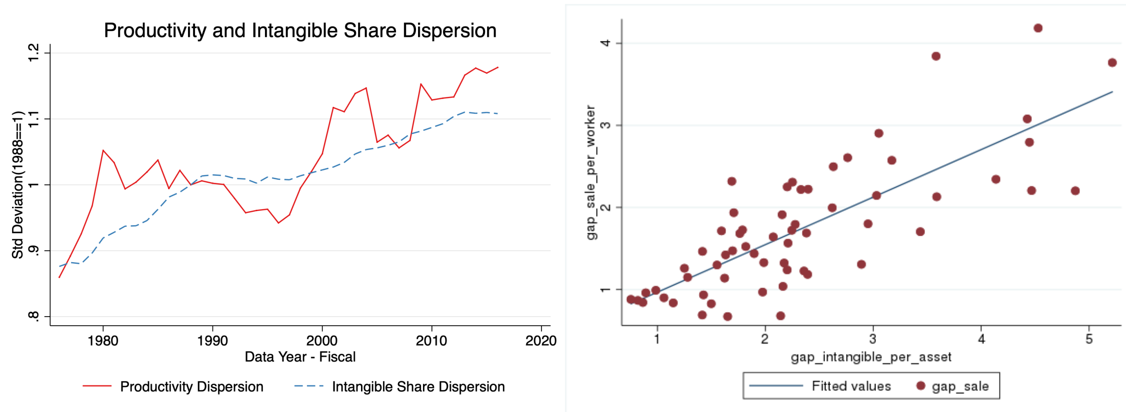


(a) Healthcare (Intangible Sector) (b) Consumer (Tangible Sector)

Note: This figures shows the contribution of within- and between-group variations to the industry-level productivity dispersion within for Healthcare, and Consumer sectors. Productivity dispersion is measured based on the standard deviation of firm-level productivity within each industry and year.

Given our observation that the productivity gaps between large and small firms are more pronounced in intangible intensive sectors, we focus on the association between productivity and intangible share dispersions in Figure 1.9a. We observe that the productivity dispersion widens with the intangible capital intensity. Moreover, Figure 1.9b shows the positive association between productivity dispersion and intangible intensity dispersion at the industry level. In other words, we observe that industries that have higher intangible capital ratio also have higher productivity dispersion on average.

Figure 1.9: Productivity and Intangible Share Dispersion



(a) Annual Average (b) Scatter plot

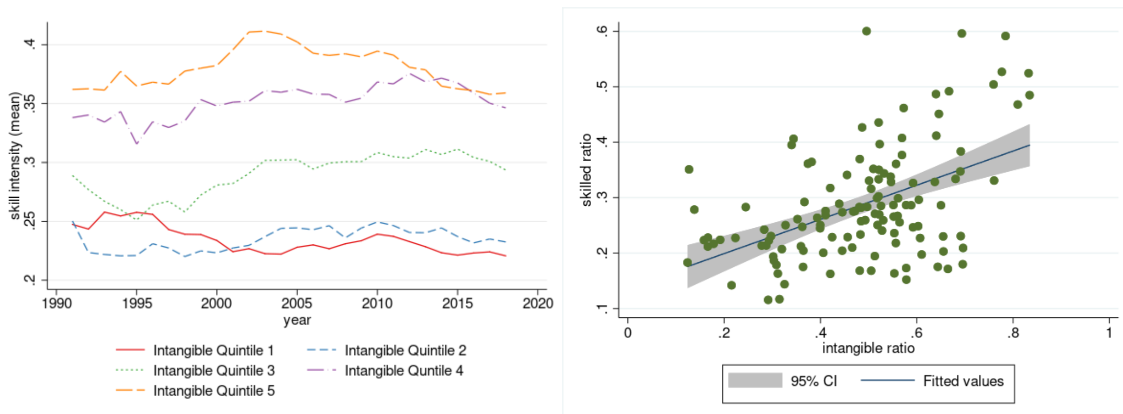
Note: Panel (a) shows the annual standard deviation of intangible share and productivity based on the base year of 1988. Panel (b) shows the scatter plot of 2-Digit SIC average gap of sales per worker and average gap of intangibles per total assets (between top %5 and others).

This evidence suggests that intangible intensive sectors would drive the increasing productivity dispersion in the overall economy. Hence, from now on, we focus on through which channel intangible capital leads to the heterogeneous pattern in the productivity dispersion across firms and industries. In particular, we investigate the particular channel of complementarity between intangible capital and skill intensity.

Fact 6: Intangible intensive firms and industries have higher skill 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, restructuring 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 workers.

Figure 1.10: Intangible Capital and Skill Intensity



(a) Skill Intensity by Intangible Quintile

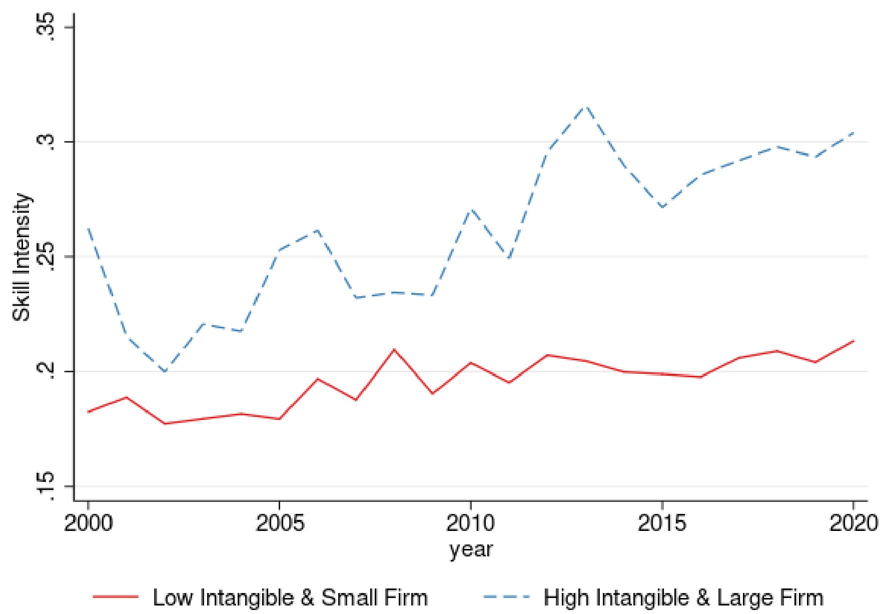
(b) Scatter Plot

Note: Panel (a) shows the annual average of skill intensity by intangible capital ratio quintiles. Panel (b) shows the scatter plot of 3-Digit SIC average intangible capital ratio and skill intensity.

Figure 1.10a shows supporting evidence for our hypothesis. Firms with higher intangible capital also have higher skill intensity, which is persistent over time. We do a similar exercise but at the industry level, and Figure 1.10b documents a strong and positive association between skill intensity and the intangible capital ratio at the industry-level. In other words, industries with higher intangible capital also have higher-skilled labor.

To understand the role of firm size in the relationship between intangible capital and skill intensity, Figure 1.11 plots the annual average of skill intensity for low intangible and small firms and high intangible and large firms. We find that the skill intensity is always higher for high intangible and large firms than low intangible and small firms. It increases dramatically in favor of the former firms. Hence, it is suggestive evidence that large firms with high intangibles have higher skill intensity on average.

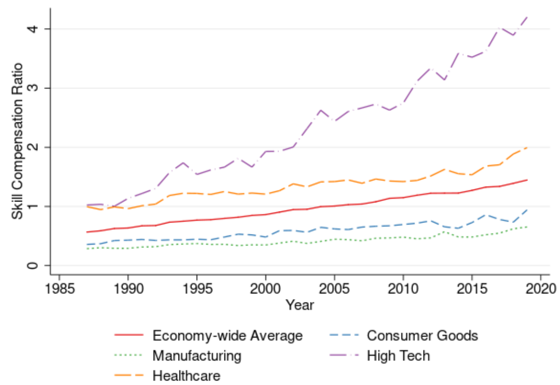
Figure 1.11: Skill Intensity by Intangible Capital and Firm Size



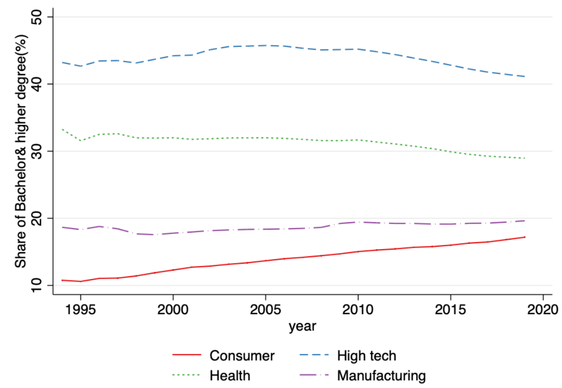
Note: This figure shows the skill intensity for low intangible small firms, and high intangible large firms.

To emphasize the relation between intangible capital and skill intensity, we group sectors based on the intangible capital intensity and show in Figure 1.12a and 1.12b that intangible intensive sectors (Health and High-tech) have higher skill premium and skill intensity than tangible intensive sectors (Manufacturing and Consumer Goods).

Figure 1.12: Skill Premium and Skill Intensity - Industry-level



(a) Skill Premium



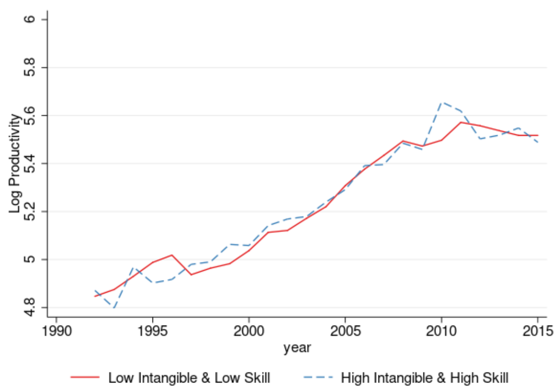
(b) Skill Intensity

Note: Panel (a) shows the skill premium (the ratio between high skilled and low skilled worker payrolls), Panel (b) shows the skill intensity for Consumer, Manufacturing, High Tech and Healthcare sectors.

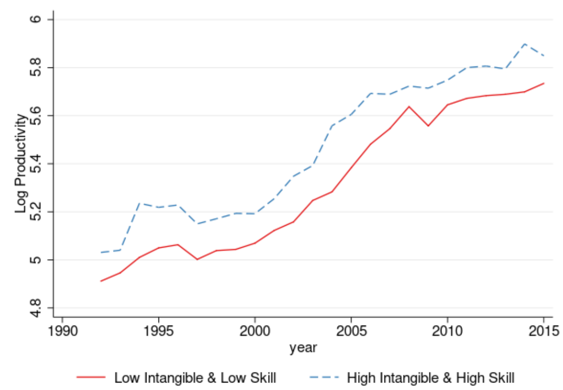
Fact 7: Large firms with high intangible and skill intensity have higher productivity.

To derive suggestive evidence on how the intangible capital-skill complementarity plays a role for productivity in different firm sizes, we plot the annual average of productivity-level for different groups of intangible and skilled labor in small and large firms. We construct each group based on the below and above the median of the corresponding variable within NAICS and year. Figure 1.13a and 1.13b suggest that the highest level of productivity occurs for high skill and high intangible 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 skill labor might not be sufficient to explain productivity dynamics in large firms. Hence, we need the complementarity between the two components to explain the firm-level productivity in large firms.

Figure 1.13: Productivity by Intangible, Skill Intensity and Firm Size



(a) Small Firms



(b) Large Firms

Note: Panel (a) shows the annual average of log productivity within each group of intangible capital and skill intensity for small firms, Panel (b) shows the same for large firms.

To sum up, our set of stylized facts show four related motivating evidence: i) intangible capital has risen in the U.S. economy, which is driven by large firms, especially in intangible intensive sectors, ii) productivity dispersion has risen in favor of bigger firms, which co-moves with intangible capital, iii) there is an increasing number of skilled workers in large and intangible firms, and iv) there is a strong and positive association between 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 impacts on the firm-level productivity dynamics in the U.S. economy.

1.3 Data

We use the U.S. Compustat database to measure firm-level intangible capital and firm-level related variables. 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 1975 to 2019. We follow the standard data cleaning process as in the literature and we drop financial sector (SIC 4900-4999), utilities sector (SIC 6000-6999), and government sector (SIC > 9000) from the data sample. In addition, we also drop if firms have missing or negative CAPX, assets/sales, R&D expenditures/SG&A expenses. We also drop if firms have total physical capital less than $5 million. We exclude firm observations if the variable of acquisitions is higher than 5% of total assets. Trimming is done by year.

Measurement of Intangible Capital. We measure intangible capital at the firm level with the methodology developed by Peters and Taylor (2017). Intangible capital consists of external and internal parts. External intangibles are the ones when a firm acquires or merges with another company. The intangible capital stock of an acquired/merged company is reported in Compustat as “intan" variable.

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 measure the knowledge capital by capitalizing R&D

expenditures:

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

where A_{it} represents the knowledge capital stock, $R\&D_{it}$ represents R&D expenditures, and $\delta_{R\&D}$ is the industry-level $R\&D$ depreciation rates along with the values estimated by Ewens et al. (2020). Our assumption is that A_{i0} has to be zero.

Similarly, we measure organizational capital by using Selling, General and Admininistrative expenses (SG&A). In particular, we capitalize SG&A expenses to proxy organizational capital:

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

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. Our assumption is that B_{i0} has to be zero.

Finally, we include the external intangible (G_{it}) to measured knowledge and organizational capital and measure total intangible capital as follows:

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

Table A1 shows the summary statistics for the ratio of intangible capital. Figure A1 documents the histogram analysis of the intangible capital ratio and we observe a sufficient degree of heterogeneity across firms. Figure A2 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 both firms and industries, which helps us implement our empirical specification.

Skill Intensity. Accessing to the database including firm-level skill components is challenging and 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 (for the details of the database construction see Abowd et al. (2009)). The data begins in the early 1990s and covers almost all states and industries in the U.S. economy.

To measure skill intensity, 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, 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 1.2: 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 firms similar but operating in different states and industries. Even if these two firms have similar scales, 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 1.2 shows an example in the sample of how we capture the variation in skill intensity across the industry, state, firm size, and year.

Table A2 reports the summary statistics for skill intensity, and Figure A3 shows the histogram of skill intensity in our sample. Figure A4 documents the histogram of skill intensity for some selected sectors, and we observe that intangible intensive sectors such as Healthcare and High tech have higher skill intensity compared to tangible intensive sectors 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 A5 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 A6 and A7 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.

1.4 Empirical Analysis

We explore the implications of intangible capital in firm-level productivity. Then, we quantify the effect of intangible capital on skilled labor. Finally, we estimate the impacts of the intangible capital-skill labor complementarity on firm-level productivity.

1.4.1 *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:

$$y_{it} = \beta_0 + \beta_1 l_{it} + \beta_2 tan_{it} + \beta_3 intan_{it} + \omega_{it} + \epsilon_{it} \tag{1.1}$$

where y_{it} is firm-level sales, l_{it} is firm-level total employment, 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 1975 to 2017. 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. In this framework, we are interested in capturing a measure of productivity (ω_{it}) based on a residual from the regression.

Table 1.3 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.

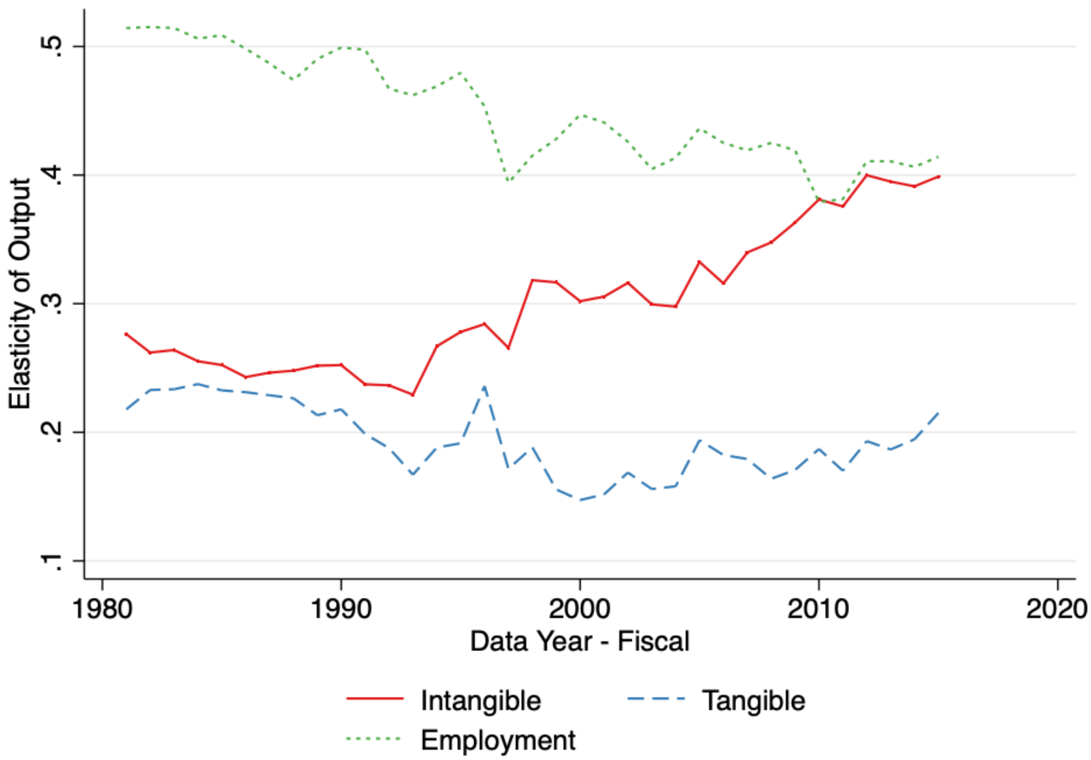
TABLE 1.3: Production Function Estimation

	Sale	Sale	Sale
Employment	0.622***	0.555***	0.51***
	(0.003)	(0.004)	(0.003)
Total Capital		0.369***	
		(0.004)	
Tangible Capital	0.223***		0.219***
	(0.007)		(0.009)
Intangible Capital			0.252***
			(0.001)
N	224775	224934	212830

Note: This table shows the production function estimation by Olley and Pakes (1996). Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

As a robustness check for the productivity estimation, we also implement 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). Implementing this robustness check, we also investigate how the share of each factor input in the production function changes over time. Figure 1.14 shows that the input share of intangible capital dramatically increases over time, whereas we observe a declining share of total employment in the production. It indicates that the importance of intangible capital in production technology has a significant increase over time.

Figure 1.14: Input Shares in the Production Function



Note: This figure shows the share of each input over time in the production function estimation.

After we measure the firm-level TFP based on Olley and Pakes (1996) framework, we analyze how marginal productivities of production factor inputs affect productivity. In that regard, we regress firm-level TFP on firm-level marginal productivity of labor, tangible and intangible capital. We find in Table 1.4 that the marginal productivity of labor and intangible capital has a positive and dramatic contribution to the TFP. In contrast, the marginal productivity of tangible capital has a negative contribution. Based on this evidence, we argue that firms would have a higher incentive to internalize the effective intangible capital for productivity gains than tangible capital.

TABLE 1.4: TFP and Marginal Productivity of Factor Inputs

	Productivity	Productivity	Productivity	Productivity
Log MPL	0.09***	0.068***	0.009***	0.009***
	(0.0005)	(0.0005)	(0.0006)	(0.0007)
Log MPK	-0.081***	-0.085***	-0.066***	-0.066***
	(0.0004)	(0.0006)	(0.0006)	(0.0006)
Log MPI	0.067***	0.055***	0.081***	0.081***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Firm FE	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Sector FE	No	No	No	Yes
Adjusted R^2	0.29	0.058	0.828	0.826
N	212830	212830	211638	204358

Note: This table shows the regression of TFP measured by the production function estimation by Olley and Pakes (1996) on the logarithms of marginal products of total employment (Log MPL), tangible capital (Log MPK) and intangible capital (Log MPI). Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

We also investigate how the marginal productivity of factor inputs affects the firm-level TFP growth. Similar to the evidence in Table 1.4, Table A5 shows that the marginal productivity of labor and intangible capital has a positive contribution to the TFP growth. In contrast, the marginal productivity of tangible capital has a negative impact. Based on this additional exercise, we confirm that intangible capital is more effective in firm-level TFP and TFP growth.

1.4.2 Intangible Capital and Skilled Labor

In this section, our main goal is to quantify the effects of intangible capital in skill intensity through the following regression specification:

$$y_{it} = \beta_0 + \beta_1 \textit{intangible ratio}_{it-1} + \Gamma' X_{it-1} + u_i + u_t + u_s + \epsilon_{it} \tag{1.2}$$

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-1} which includes firm size, age, and Tobin's Q. Firm size is measured as the logarithm of the assets firm holds. Due to the unobserved heterogeneity, we also include firm (u_i), 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 1.5 reports the results of the equation (1.2). We observe that an increase in intangible capital has a positive and significant effect on the number of skilled workers, i.e., one standard deviation increase in intangible capital ratio increases skill intensity by 0.08-0.39 standard deviation depending on the different fixed effects. This result suggests that there is a complementarity between intangible capital and skilled labor.

In Table A6 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%-0.36% depending on the different fixed effects. We also see that firm size is positive and significant for the number of skilled workers, i.e. one percent increase in firm size increases the number of skilled workers by 0.58%- 0.79% depending on the different fixed effects. It indicates that large firms are more likely to have a higher number of skilled workers.

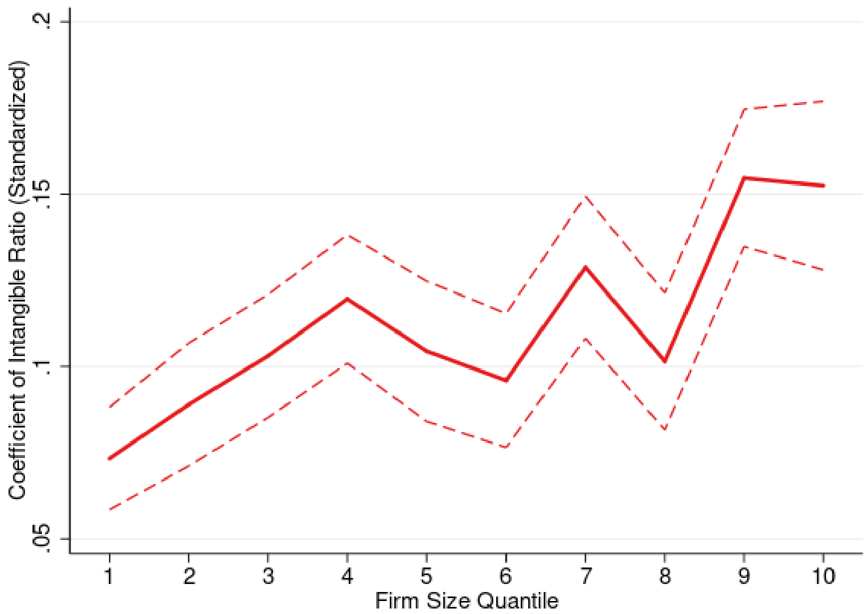
TABLE 1.5: Intangible Capital Ratio and Skill Intensity

	Skill Intensity	Skill Intensity	Skill Intensity	Skill Intensity	Skill Intensity
L.Intangible Ratio	0.39***	0.03***	0.008*	0.096***	0.008*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes
Year FE	No	No	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes
R^2	0.143	0.938	0.941	0.713	0.941
N	74332	73918	73918	74332	73918

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 are in parentheses. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

To investigate the role of firm size in the complementarity between intangible capital ratio and skill intensity, we construct firm size quantiles within each 3-digit NAICS industry and year. Then we run the regression equation (1.2) within each firm size quantile. Figure 1.15 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 quantiles, it gets much bigger as the firm size gets larger. We also implement a similar exercise but for the levels of variables in Figure A10 and we find a similar result that the positive effect of intangible on the number of skilled workers is higher at larger firms, i.e., the complementarity is amplified with firm size.

Figure 1.15: Quantile Regression - Complementarity Effect



Note: This figure pilots the coefficient of intangible capital ratio in the regression (1.2) within size quantiles.

1.4.3 *Intangible-Skilled Labor Complementarity and Productivity*

The previous section shows a complementarity between intangible capital and skilled labor, which is higher at larger firms. Given these results, in this section, we investigate how this complementarity affects firm-level productivity and whether the relationship is influenced by firm size. In order to analyze this direction, we pursue the following regression:

$$y_{it} = \beta_0 + \beta_1 \textit{skill intensity}_{it} + \beta_2 \textit{intangible ratio}_{it} + \Gamma' X_{it} + u_t + u_s + \epsilon_{it} \tag{1.3}$$

where the dependent variable is the firm-level log productivity for firm i at time t. The variable $\textit{skill intensity}_{it}$ denotes the firm-level skill intensity and $\textit{intangible ratio}_{it}$ represents firm-level intangible capital ratio. As in the previous regression model, X_{it} includes firm-level control variables such as firm size and Tobin's Q and we have year (u_t) and industry (u_s) fixed effects. We standardize skill intensity and intangible ratio so that the related units represents standard deviations relative to the corresponding means.

Table 1.6 documents that both skill intensity and intangible capital ratio have positive and significant effects on firm-level productivity. One standard deviation increase in firm-level skill intensity increases the firm-level productivity by around 1.6%-2%. One standard deviation increase in firm-level intangible capital ratio increases the firm-level productivity by around 9%. We also observe that an increase in firm size also positively and significantly affects productivity, i.e., a one percent increase in firm size increases productivity by around 0.1%. Moreover, age is a positive and significant component for productivity, i.e., established firms are more likely to have higher productivity on average.

TABLE 1.6: Intangible Capital, Skill Intensity and Productivity

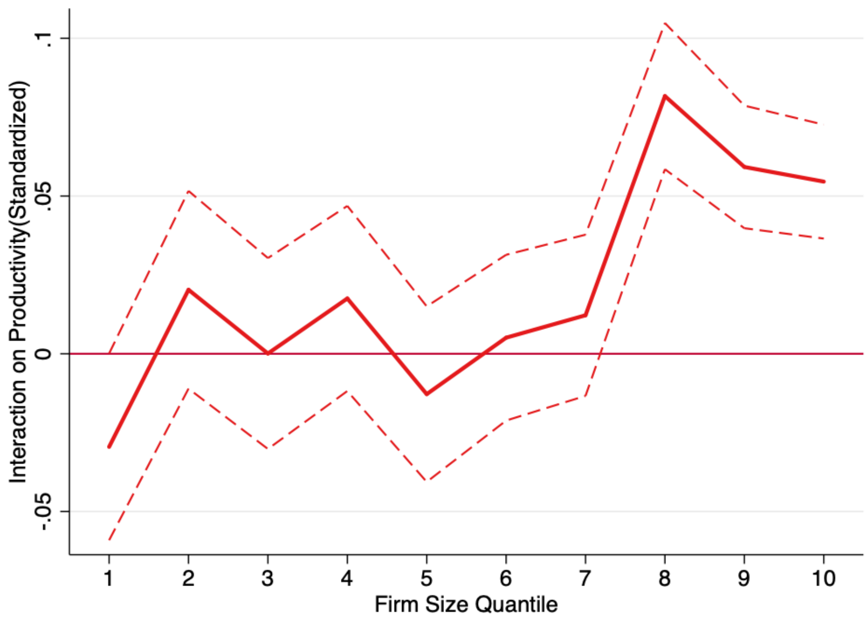
	Log Productivity	Log Productivity	Log Productivity
Skill Intensity	0.02**		0.016**
	(0.006)		(0.006)
Intangible Ratio		0.091***	0.09***
		(0.005)	(0.005)
Size	0.103***	0.109***	0.107***
	(0.001)	(0.001)	(0.001)
Age	0.003***	0.002***	0.002***
	(0.0006)	(0.0006)	(0.0006)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.46	0.462	0.462
N	80042	80037	79952

Note: This table shows the results of the regression specification (1.3). Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

To investigate whether the complementarity between intangible capital and skilled labor generates differential impacts on productivity for different firm sizes after we construct an interaction term between skilled ratio and intangible capital ratio, we include this term in the regression specification (1.3) and run this regression within each firm size quantile. We see in Figure 1.16 that the coefficient of the interaction term is almost zero and insignificant for the small size of firms.

In contrast, it becomes positive and significant for large firms. In other words, the complementarity between intangible capital and skilled labor has no impact on productivity for small firms, but it generates positive effects on productivity at larger firms. It implies that larger firms can internalize the economic effects of the complementarity and increase their productivity.

Figure 1.16: Quantile Regression - Productivity Effect



Note: This figure pilots the coefficient of interaction term between intangible capital and skill intensity in the regression (1.3) within size quantiles.

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 A.3. 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 internalize its economic benefits for innovation dynamics. In that regard, we argue that once inventors move to big firms with high intangibles, 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 low share in a firm. However, an analysis of the role of the interaction between intangible capital and inventors on productivity helps us understand several key mechanisms behind our baseline results.

1.5 Motivating Model

This section shows a motivating model that can discipline our empirical evidence of why firms with higher intangible capital benefit from skilled labor. We use the simplified, and modified model version by Acemoglu and Autor (2011) to argue through which channels there would be an assortative matching 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.

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:

$$Y(t) = \left[\left(K_T(t)L(t) \right)^{\rho} + \left(K_I(t)H(t) \right)^{\rho} \right]^{1/\rho} \tag{1.4}$$

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

$$w_L = \frac{\partial Y}{\partial L} = K_T^{\rho}\left[K_T^{\rho} + K_I^{\rho}\left(H/L\right)^{\rho}\right]^{(1-\rho)/\rho} \tag{1.5}$$

$$w_H = \frac{\partial Y}{\partial H} = K_I^{\rho}\left[K_T^{\rho}\left(H/L\right)^{-\rho} + K_I^{\rho}\right]^{(1-\rho)/\rho} \tag{1.6}$$

Combining the equations (1.5) and (1.6), we can derive the skill premium π as follows:

$$\pi = \frac{w_H}{w_L} = \left(\frac{K_I}{K_T}\right)^{\rho}\left(\frac{H}{L}\right)^{-(1-\rho)} \tag{1.7}$$

We can arrange the equation (1.7) to write down in logarithmic form as follows:

$$ln(\pi) = \left(\frac{\sigma-1}{\sigma}\right)ln\left(\frac{K_I}{K_T}\right) + \frac{1}{\sigma}ln\left(\frac{L}{H}\right) \tag{1.8}$$

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

$$\frac{\partial ln(\pi)}{\partial(K_I/K_T)} = \frac{\sigma-1}{\sigma} \tag{1.9}$$

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 (1.9), we also see that the skilled wage relative to the unskilled wage ($\frac{w_H}{w_L}$) also increases with $\frac{K_I}{K_T}$.

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 (1.9):

$$ln(\pi(t)) = \gamma_0 + \gamma_1 ln\left(\frac{K_I(t)}{K_T(t)}\right) + \gamma_2 ln\left(\frac{L(t)}{H(t)}\right) + \epsilon(t) \tag{1.10}$$

In order to assess whether our model passes the empirical test, we fit this empirical model (1.10) 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 (1.8). Table 1.7 shows the results that an increase in intangible-tangible ratio has a positive and significant impact 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 ($0.44 = 1/\sigma$) implies that the elasticity of substitution (σ) is ($1/0.44$) 2.27, which is very close to the average of the estimated elasticity of substitution as 2.2 based on the discussion by Havranek et al. (2020).

Besides these results imply that the empirical test validates our motivating model, another important takeaway is that our modeling framework provides much cleaner identification than Acemoglu and Autor (2011), which requires measuring the unobserved skill-specific TFP. However, our approach can predict the skill premium by measuring the intangible and tangible capital stocks that are indeed observable.

TABLE 1.7: Empirical Test of Motivating Model

	Log Skill Premium	Log Skill Premium
Log (Intangible/Tangible)	0.834***	0.557***
	(0.004)	(0.004)
Log (Unskilled/Skilled)	0.166***	0.443***
	(0.004)	(0.004)
Constant Term	Not Included	Included
N	15069	15069

Note: This table shows the results of the empirical model (1.10). Standard errors in parentheses. $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

After we have a motivating model which incorporates basic channels 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 logic of our two-sector motivating model. We will add an idiosyncratic productivity shock to capture underlying heterogeneity across firms. We will then incorporate adjustment costs for investment in tangible and intangible capital to feature the role of economies of scale because the literature suggests that the accumulation of intangible capital requires to incur higher upfront costs which favor bigger firm size (De Ridder (2019), Chiavari and Goraya (2020)).

1.6 Firm-level General Equilibrium Model

This section aims to develop a model of heterogeneous firms subject to adjustment costs investing in tangible and intangible capital, and hiring skilled and unskilled labor. Our goal in the model is to develop a conceptual framework that is able to provide some predictions on the implications of intangible capital in the linkage between investment dynamics and labor reallocation.

1.6.1 Model Environment

Our model has two essential building channels: i) an investment channel where there are heterogeneous firms that are subject to adjustment costs invest in tangible and intangible capital; and ii) a labor market channel where heterogeneous firms decide how much to hire skilled and unskilled labor.

In that respect, our model uses key insights based on the model developed by Chiavari and Goraya (2020). We extend their model in three distinct ways. First, we add the margin of skilled and unskilled labor into the model structure of Chiavari and Goraya (2020), which enables us to investigate the implications of intangible capital on labor reallocation. Second, we incorporate a labor market dimension to investigate the implications of intangible capital on skilled labor reallocation across firms of different sizes. Third, our model can study the impact of the complementarity between intangible capital and skilled labor on the relation between firm-level investment dynamics and labor reallocation.

Production firms. We specify the production technology in line with the spirit of Acemoglu (1998), Krusell et al. (2000), and Violante (2008). In that regard, heterogeneous firms invest in tangible (k_T)/intangible capital (k_I) and hire skilled (h)/unskilled (l) labor. Following the spirit of Chiavari and Goraya (2020) and Falato et al. (2020), we incorporate two different types of capital in the production technology: tangible and intangible. The production technology takes the following form:

$$y_t = (k_T)^{\alpha} \left[l^{\sigma} + \theta[\mu(e^z k_I)^{\rho} + (1-\mu)h^{\rho}]^{\frac{\sigma}{\rho}} \right]^{\frac{1-\alpha}{\sigma}} \tag{1.11}$$

where z is an augmented idiosyncratic technology shock to intangible capital, α is value-added share of tangible capital, σ is the elasticity of substitution between unskilled and skilled labor, ρ is the elasticity of substitution between intangible capital and skilled labor, μ denotes the importance of intangible capital in the capital-skilled labor complementarity, and θ governs the importance of the complementarity in the production technology. Given that the complementarity and asset intangibility is interrelated, we will use these two terms interchangeably. Time subscript t represents the current time period, and in order to make the interpretation convenient, we suppress time notation for t and have the notation of $'$ for the next period $t+1$. As in the basic motivating model we discussed in the previous section, we again assume complementarity between intangible capital stock and skilled workers.

As in Falato et al. (2020), the idiosyncratic technology shock follows an AR(1) process:

$$log z' = \rho_z log z + \varepsilon_z, \quad \varepsilon_z \sim N(0, \sigma_z^2) \tag{1.12}$$

To capture heterogeneity in intangibility, we incorporate an idiosyncratic shock in θ which governs the importance of complementarity in the production technology as follows:

$$\theta' = \rho_\theta \theta + \varepsilon_\theta, \quad \varepsilon_\theta \sim N(\mu_\theta, \sigma_\theta^2) \tag{1.13}$$

The law of motion for each capital is as follows:

$$k_T' = (1-\delta_T)k_T + x_T \tag{1.14}$$

$$k_I' = (1-\delta_I)k_I + x_I \tag{1.15}$$

where $\{\delta_T, \delta_I\}$ are depreciation rates for tangible and intangible capital and

$\{x_T, x_I\}$ denote the tangible and intangible capital investment respectively.

As in Chiavari and Goraya (2020), we assume that any adjustment in both tangible and intangible capital stock has a cost structure as follows:

$$C(x_T, x_I; k_T, k_I) = \frac{\varphi_T}{2}\left(\frac{x_T}{k_T}\right)^2 k_T + \frac{\varphi_I}{2}\left(\frac{x_I}{k_I}\right)^2 k_I + \mathbb{1}^T f_T + \mathbb{1}^I f_I \tag{1.16}$$

where $\mathbb{1}^T$ and $\mathbb{1}^I$ are indicator functions which take the value of 1 if the firm adjusts the tangible and intangible capital stock (i.e. if $x_T \neq 0$ and $x_I \neq 0$). The cost structure implies that when investing in new capital, the firm incurs a fixed cost (denoted by f_T and f_I respectively). The firm also incurs a convex cost which is positively related to the magnitude invested (x_T and x_I) and negatively related to the corresponding capital stock. This assumption aims to incorporate the role of economies of scale in the sense that firms with a higher stock of intangible or tangible capital pay lower adjustment costs for the corresponding capital stock.

1.6.2 Representative Household Problem

We follow the spirit of the household utility function from Chiavari and Goraya (2020). There are two types of representative households the one supplies skilled labor (h_t) by choosing over consumption c_t and how much to work, and the other supplies unskilled labor (l_t) by choosing over consumption c_t and how much to work.

The problem of the representative household supplying skilled labor is as follows:

$$\mathbb{E}_0 \sum_t^{\infty} \beta^t \left(c_t - \frac{h_t^{1+1/\phi}}{1+1/\phi} \right) \tag{1.17}$$

The problem of the representative household supplying unskilled labor is as follows:

$$\mathbb{E}_0 \sum_t^{\infty} \beta^t \left(c_t - \frac{l_t^{1+1/\phi}}{1+1/\phi} \right) \tag{1.18}$$

where β is the discount factor.

The role of the representative households is to provide elastic labor supply, which determines the equilibrium labor supply and wage relationship. Each firm pays w_h and w_l for skilled (h) and unskilled (l) labor respectively. In line with Chiavari and Goraya (2020), we assume that the output of each firm and the supply of tangible and intangible capital are infinitely elastic, and the prices of both capitals are normalized as 1. Given the representative household problem, as in Chiavari and Goraya (2020), the supply of skilled and unskilled labor is given by $H(w_h) = w_h^{\phi}$ and $L(w_l) = w_l^{\phi}$, where $\phi > 0$.

1.6.3 Firm Problem

The set of state variables are $\{z, \theta; k_T, k_I; w_h, w_l\}$. To make interpretation convenient, we represent the set of state variables as $\mathbf{s} \equiv \{z, \theta; k_T, k_I; w_h, w_l\}$. Given the set of state variables $\mathbf{s}$, we can write down the profit of a firm as follows:

$$\pi(\mathbf{s}) = \max_{h,l} \{y - w_h h - w_l l\} \tag{1.19}$$

where y is given by equation (1.11).

From now on, similar to Chiavari and Goraya (2020), we will have five value functions: i) $V(\mathbf{s})$ for the firm at the start-of-period, ii) $V_{TI}(\mathbf{s})$ for the firm investing in both tangible and intangible capital, iii) $V_T(\mathbf{s})$ for the firm investing in only tangible capital, iv) $V_I(\mathbf{s})$ for the firm investing in only intangible capital, and v) $V_w(\mathbf{s})$ for the firm not investing in any capital and waiting for the next period.

The corresponding value function at the start-of-period can be written as follows:

$$V(\mathbf{s}) = \pi(\mathbf{s}) + \max\{V_{TI}(\mathbf{s}), V_T(\mathbf{s}), V_I(\mathbf{s}), V_w(\mathbf{s})\} \tag{1.20}$$

where $V_{TI}(\mathbf{s})$ is the value function for investing in both tangible and intangible capital, which can be written as follows:

$$V_{TI}(\mathbf{s}) = \max_{k'_T, k'_I} -x_T - x_I - C(x_T, x_I; k_T, k_I) + \frac{1}{R}\mathbb{E}[V(\mathbf{s}')] \tag{1.21}$$

$V_T(\mathbf{s})$ is the value function for investing in only tangible capital, which can be written as follows:

$$V_T(\mathbf{s}) = \max_{k'_T} -x_T - C(x_T, 0; k_T, k_I) + \frac{1}{R}\mathbb{E}[V(z', k'_T, (1-\delta_I)k_I)] \tag{1.22}$$

$V_I(\mathbf{s})$ is the value function for investing in only intangible capital, which can be written as follows:

$$V_I(\mathbf{s}) = \max_{k'_I} -x_I - C(0, x_I; k_T, k_I) + \frac{1}{R}\mathbb{E}[V(z', (1-\delta_T)k_T, k'_I)] \tag{1.23}$$

$V_w(\mathbf{s})$ is the value function for not investing in any capital and waiting for the next period, which can be written as follows:

$$V_w(\mathbf{s}) = \frac{1}{R}\mathbb{E}[V(z', (1-\delta_T)k_T, (1-\delta_I)k_I)] \tag{1.24}$$

Timing The timeline of events during each time period can be summarized:

1. Firms observe idiosyncratic productivity shock to intangible capital and complementarity.

2. They decide how much to hire skilled and unskilled labor.

3. They decide whether to adjust tangible and intangible capital.

4. If they adjust, they choose how much to invest in tangible and intangible capital.

1.6.4 Equilibrium

Given the set of state variables $\mathbf{s} \equiv \{z, \theta; k_T, k_I; w_h, w_l\}$, an equilibrium is a set of value functions $\{V(\mathbf{s}), V_{TI}(\mathbf{s}), V_T(\mathbf{s}), V_I(\mathbf{s}), V_w(\mathbf{s})\}$; decision rules $\{k'_T(\mathbf{s}), k'_I(\mathbf{s}), h(\mathbf{s}), l(\mathbf{s})\}$; and measure of firms $\mu(\mathbf{s})$ such that

1. $V(\mathbf{s}), V_{TI}(\mathbf{s}), V_T(\mathbf{s}), V_I(\mathbf{s}), V_w(\mathbf{s}), k'_T(\mathbf{s}), k'_I(\mathbf{s}), h(\mathbf{s}), l(\mathbf{s})$ solve the equations (1.20), (1.21), (1.22), (1.23), and (1.24).

2. The labor market for unskilled and skilled workers clears: $\int l(\mathbf{s})\mu(\mathbf{s}) = L(w_l)$ and $\int h(\mathbf{s})\mu(\mathbf{s}) = H(w_h)$.

3. The measure of firms is consistent with the distribution and decision rules: $\mu(\mathbf{s}) = \int \int \mu(d\mathbf{s})\Gamma(dz'|z)$

1.6.5 Efficiency Conditions

Due to the nature of investment adjustment costs, as in Chiavari and Goraya (2020), we first investigate the extensive margin of intangible capital investment. Since the model features a non-convex adjustment cost, intangible investment is pinned down by the inaction region $[\underline{k_I}(\mathbf{s}), \overline{k_I}(\mathbf{s})]$. Each firm chooses to adjust if the current intangible capital stock is far away from the optimal level. In other words, if the current intangible capital stock is smaller than $\underline{k_I}$, the firm chooses to invest. If the current intangible capital stock is bigger than $\overline{k_I}$, the firm chooses to disinvest.

From now on, following the spirit from Chiavari and Goraya (2020) to emphasize the main mechanism, we focus on the case in which the firm decides to invest in both tangible and intangible capital. In that respect, we investigate the condition where the value function for investing in both tangible and intangible capital is bigger than the value function for waiting, i.e., $V(\mathbf{s}) \geq V_w(\mathbf{s})$. The intuition in that case also holds for other value functions we specify.

Intuitively, each firm chooses to adjust its tangible and intangible capital stock if the benefit of investing is bigger than the cost of adjustment. Therefore, we can characterize the decision based on the following relation:

$$\mathbb{E}\left[V\left(z', (1-\delta_T)k_T, k_I'\right) - V\left(z', (1-\delta_T)k_T, (1-\delta_I)k_I\right)\right] \geq x_I \frac{\varphi_I}{2}\left(\frac{x_I}{k_I}\right)^2 k_I + \mathbb{1}^I f_I \tag{1.25}$$

$$\mathbb{E}\left[V\left(z',k'_T,(1-\delta_I)k_I\right)-V\left(z',(1-\delta_T)k_T,(1-\delta_I)k_I\right)\right]\geq x_T\frac{\varphi_T}{2}\left(\frac{x_T}{k_T}\right)^2 k_T+\mathbb{1}^T f_T \tag{1.26}$$

As in Chiavari and Goraya (2020), if the firm chooses to adjust, how much to invest is pinned down by the intensive tangible and intangible capital investment margin. For the intensive margin, the efficiency conditions are summarized based on the marginal returns and marginal costs derived by the first-order conditions (FOCs) of the related value functions.

To interpret the derivations of the first order conditions (FOC), we first define the following term based on the production technology:

$$q(\mathbf{s})=\frac{1-\alpha}{\sigma}k'_T(\mathbf{s})^{\alpha}\left[l(\mathbf{s})^{\sigma}+\theta[\mu(e^z k'_I(\mathbf{s}))^{\rho}+(1-\mu)h(\mathbf{s})^{\rho}]^{\frac{\sigma}{\rho}}\right]^{\frac{1-\alpha-\sigma}{\sigma}} \tag{1.27}$$

Then, we can characterize the decision rules based on the following FOCs:

$$[k'_T(\mathbf{s})]:\mathbb{E}\left[\frac{\alpha y(\mathbf{s})}{k'_T(\mathbf{s})}-\frac{\partial C'_T}{\partial k'_T(\mathbf{s})}\right]=r+\delta_T+R\frac{\partial C_T}{\partial k'_T(\mathbf{s})} \tag{1.28}$$

$$[k'_I(\mathbf{s})]:\mathbb{E}\left[\theta[\mu k'_I(\mathbf{s})^{\rho}+(1-\mu)h(\mathbf{s})^{\rho}]^{\frac{\sigma-\rho}{\rho}}\frac{\sigma}{\rho}\mu k'_I(\mathbf{s})^{\rho-1}q(\mathbf{s})-\frac{\partial C'_I}{\partial k'_I(\mathbf{s})}\right]=r+\delta_I+R\frac{\partial C_I}{\partial k'_I(\mathbf{s})} \tag{1.29}$$

$$[l(\mathbf{s})]:\mathbb{E}\left[\sigma l(\mathbf{s})^{\sigma-1}q(\mathbf{s})\right]=w_l \tag{1.30}$$

$$[h(\mathbf{s})]:\mathbb{E}\left[\theta[\mu k'_I(\mathbf{s})^{\rho}+(1-\mu)h(\mathbf{s})^{\rho}]^{\frac{\sigma-\rho}{\rho}}\frac{\sigma}{\rho}(1-\mu)h(\mathbf{s})^{\rho-1}q(\mathbf{s})\right]=w_h \tag{1.31}$$

In order to provide an some insights regarding the corresponding efficiency conditions, we focus the equation (1.28) and (1.29), which equalize the marginal benefit (left-hand side of the corresponding equations) and the marginal cost (right-hand side of the corresponding equations) of tangible and intangible capital investment. As also indicated in Chiavari and Goraya (2020), due to the convex adjustment costs, the marginal benefit of each investment is reduced by the cost of changing capital stock in the current period. Given that the firm needs to rechange the capital stock in the next period by one unit because of the adjustment in the current period, the marginal cost is increased by the discounted value of the partial change in the adjustment cost next period.

Equation (1.30) and (1.31) give the efficiency conditions of the demand for unskilled and skilled labor, respectively, which equalize the marginal benefit (left-hand side of the corresponding equations) and the marginal cost (right-hand side of the corresponding equations) of hiring unskilled and skilled labor. The marginal benefit of each labor is the expected value of investing in additional capital that has a complementarity with labor, which is governed by the elasticity of substitution between skilled and unskilled labor. The marginal cost of each labor is the corresponding wage rate the firm should pay.

Notably, based on the efficiency conditions, we notice key implications of the complementarity on the linkage between tangible and intangible capital investment. As the complementarity increases (i.e., θ increases), investment in intangible capital has higher marginal benefit compared to investment in tangible capital due to the following two main channels. First, intangible capital investment experiences a relative increase in its marginal value, i.e., the difference between the marginal benefit of intangible and tangible investment increases with the complementarity based on equation (1.28) and (1.29). Second, based on equations (1.30) and (1.31), hiring skilled labor becomes relatively more favorable compared to unskilled labor as complementarity increases as it increases the degree of complementarity between intangible capital and skilled labor. Together, these two main channels indicate the importance of the complementarity in the linkage between the type of investment and labor demand.

If we arrange the equations (1.29), (1.30) and (1.31), we can also derive the equilibrium skill premium approximately as follows:

$$\pi = ln\left(\frac{w_h}{w_l}\right) \approx \mathbb{E}\left[\theta \frac{\sigma - \rho}{\rho} ln\left(\frac{k_I'(\mathbf{s})}{h(\mathbf{s})}\right) + (1-\sigma) ln\left(\frac{l(\mathbf{s})}{h(\mathbf{s})}\right)\right] \tag{1.32}$$

We have several observations from equation (1.32). First of all, in line with the prediction by Krusell et al. (2000), and Violante (2008), if $\sigma > \rho$, i.e., the elasticity of substitution between skilled and unskilled labor is bigger than the elasticity of substitution between skilled labor and intangible capital, we show that the relative demand for skilled labor increases with intangible capital. This equation also indicates that an increase in complementarity also increases the skilled premium. It replaces unskilled workers with skilled labor and increases the wage rate of skilled labor more than unskilled labor.

1.6.6 Complementarity and Labor Reallocation

This section characterizes the main channels through which the complementarity influences the investment decision and labor reallocation. The model enables us to discover the critical sources of heterogeneous labor demand which varies across firms that have different degrees of the complementarity. In that respect, we study the effect of an increase in complementarity.

Proposition 1. *The relative marginal adjustment cost of intangible capital investment decreases with the degree of complementarity*

$$\frac{\partial\left[\mathbb{E}\left[\frac{\partial C_I'}{\partial k_I'(\mathbf{s})} - \frac{\partial C_T'}{\partial k_T'(\mathbf{s})}\right]\right]}{\partial\theta} \leq 0 \tag{1.33}$$

Proposition 1 implies that as complementarity increases, the intangible capital adjustment becomes much cheaper than tangible investment adjustment. The intuition is that investing in intangible capital becomes more favorable with a higher degree of complementarity (as we discussed for equations (1.28), and (1.29)) and hence firms have more incentive to adjust their intangible capital rather than tangible capital, which makes the adjustment of intangible investment more profitable than the adjustment of tangible investment.

Having an empirical test for Prediction 1 requires measuring firm-level adjustment costs of intangible and tangible investment. We bring an empirical test by following a regression specification from Peters and Taylor (2017). Based on the standard q-theory, Peters and Taylor (2017) argues that the regressing intangible and tangible investment rates on Tobin's Q measures would provide inference for the adjustment costs. More precisely, the inverse of the coefficient of Tobin's Q in this regression gives an approximate estimate for each particular adjustment cost (for the detailed discussion, see Peters and Taylor (2017)). We follow this identification methodology and correct a potential bias in the measurement of intangible capital with higher-order cumulant estimator using the method of Erickson et al. (2014) which implements a two-step generalized method of moments (GMM) and minimum distance estimators. We then regress the intangible investment rate on the lagged values of firm-level Tobin's Q with firm and year fixed effects.

TABLE 1.8: Inference on Adjustment Cost - Firm-level Regression

	Intangible Investment Rate	Tangible Investment Rate
Tobin Q	0.069***	0.165***
	(0.001)	(0.005)
Firm FE	Yes	Yes
Year FE	Yes	Yes
R^2	0.232	0.45
N	130618	128383

This table shows the results of the regression of the intangible and tangible investment rate on the lagged values of Tobin's Q with firm and year fixed effects. Standard errors in parentheses. $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Given the inverse of the coefficients, Table 1.8 shows that the adjustment cost of intangible capital is much higher than tangible capital on average. Given that one component in our measurement of intangible capital is R&D, this result is in line with several empirical and theoretical discussions on how R&D has higher adjustment cost than tangible capital (Grabowski (1968), Hall et al. (1986), Himmelberg and Petersen (1994), Hall (2002), Brown et al. (2009)). Our framework extends these discussions and has a broader perspective of intangible capital rather than only R&D.

To test Proposition 1, we first run a similar regression at the sector level. Table 1.9 shows that the adjustment cost of intangible capital becomes lower as industry-level asset intangibility increases. We find that intangible intensive industries, such as Healthcare and High-tech, have lower adjustment costs of intangible investment than tangible intensive industries, such as Consumer Goods and Manufacturing.

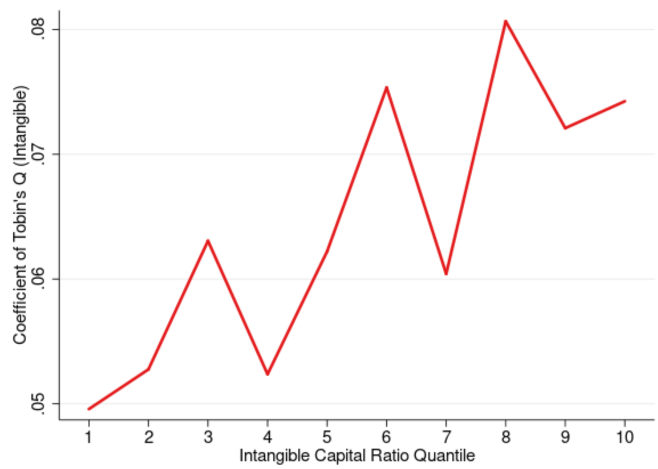
TABLE 1.9: Inference on Adjustment Cost - Sector-level Regression

	Healthcare	High-Tech	Consumer	Manufacturing	Others
	Intangible Rate	Intangible Rate	Intangible Rate	Intangible Rate	Intangible Rate
Tobin Q	0.088^{***}	0.059^{***}	0.047^{***}	0.018^{***}	0.051^{***}
	(0.003)	(0.002)	(0.003)	(0.001)	(0.001)
	Tangible Rate	Tangible Rate	Tangible Rate	Tangible Rate	Tangible Rate
Tobin Q	0.085^{***}	0.024^{***}	0.0513^{***}	0.113^{***}	-0.019
	(0.006)	(0.0009)	(0.003)	(0.006)	(0.014)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.738	0.716	0.689	0.742	0.832
N	15961	29011	13861	33366	36894

Note: This table shows the results of the regression of the intangible and tangible investment rate on the lagged values of Tobin's Q. Standard errors in parentheses. $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

We then run a quantile regression based on the firm-level intangible capital to investigate the role of asset intangibility on adjustment cost. Figure 1.17 documents that the coefficient of Total Q increases for higher quantiles. Given that the approximate adjustment cost is inversely related to the coefficient (Peters and Taylor (2017)), the adjustment cost of intangible capital decreases with asset intangibility, in line with Proposition 1.

Figure 1.17: Empirical Test of Proposition 1



Note: This figure documents the coefficient of Tobin's Q based on the quantile regression of intangible investment rate on the lagged values of Tobin's Q. Quantiles are based on the firm-level intangible capital ratio.

Proposition 2. *The decline in relative marginal adjustment cost of intangible capital investment due to increase in the degree of complementarity is amplified with firm size*

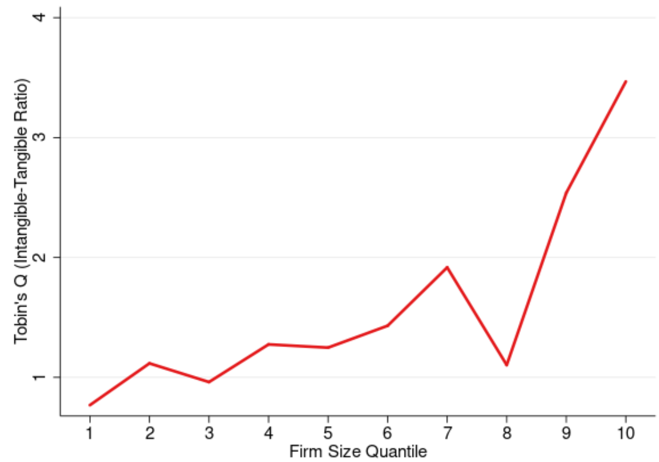
$$\frac{\partial^2 \left[\mathbb{E} \left[\frac{\partial C_I'}{\partial k_I'(\mathbf{s})} - \frac{\partial C_T'}{\partial k_T'(\mathbf{s})} \right] \right]}{\partial \theta \partial k} \leq 0 \tag{1.34}$$

where $k = k_I + k_T$. Proposition 2 suggests that as firm size increases, the adjustment in intangible capital becomes much cheaper when the firm draws a favorable shock in complementarity. The intuition is that since firms have more incentive to invest in intangible capital by incurring adjustment costs (as we discussed in Proposition 1) with a higher degree of complementarity, large firms are more able to pay the adjustment cost because the adjustment is negatively related to firm size. This prediction is in line with our empirical evidence that bigger firms invest more in intangible capital investment.

Similar to the empirical test for Proposition 1, we develop a test for Proposition 2 based on the regression specification by Peters and Taylor (2017). We construct firm-level quantiles of a total asset (size) and regress the tangible and intangible investment rate on the lagged values of firm-level Total Q with firm and year fixed effects within each quantile. According to our Prediction 2, we need to focus on how the relative adjustments between intangible and tangible capital change with firm size.

Figure 1.18 reports the ratio of the coefficient of Tobin's Q in the regressions of intangible and tangible investment rates. We find that the ratio of the coefficients increases with firm size, even more for higher quantiles of the size distribution. It indicates that the relative adjustment cost of intangible investment becomes higher for smaller firms, i.e., the adjustment in intangible capital is more costly than tangible capital in smaller firms. As a side note, even though we do not study the channel of financial constraints in this chapter, this result is also in line with several discussions that smaller firms facing severe financial constraints

Figure 1.18: Empirical Test of Proposition 2



Note: This figure reports the ratio of the coefficient of Tobin's Q in the regressions of intangible and tangible investment rate on lagged Tobin's Q with firm and year fixed effects.

adjust their intangible capital less frequently than tangible capital given the fact that asset intangibility leads higher degree of financial constraints (Almeida and Campello (2007)). On the other hand, the result suggests that large firms pay lower adjustment costs for intangible capital than tangible capital. Hence, we can argue that as firm size increases, the adjustment in intangible capital becomes more favorable than tangible capital. This evidence supports our Prediction 2.

Proposition 3. *Given the wage rates fixed, the relative demand for skilled labor increases with the average degree of complementarity and firm size*

$$\frac{\partial^2 \mathbb{E}\Big[h(\mathbf{s})/l(\mathbf{s})\Big]}{\partial \mathbb{E}[\theta]\partial \mathbb{E}[k]} \geq 0 \tag{1.35}$$

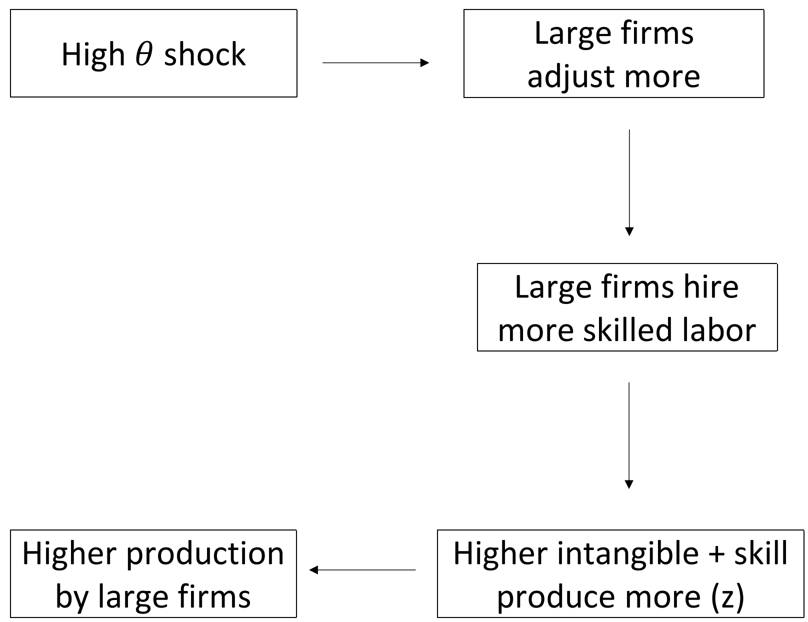
Derived from the insight from equation (1.32), Proposition 3 implies that the degree of complementarity increases, large firms having a higher incentive to invest more in intangible capital are encouraged to hire skilled labor instead of unskilled labor given the complementarity between intangible capital and skilled labor. The intuition is that large firms are more willing to adjust intangible capital (as we discussed in Proposition 2). They have a higher incentive to operate profitably by investing more in intangible capital, which requires higher skilled labor input in the production function. It suggests that in equilibrium, there would be an assortative matching between intangible capital and skilled labor. This prediction is in line with our empirical evidence in Table 1.5 that large firms investing more in intangible capital investment hire skilled labor.

Proposition 4. *The equilibrium production dispersion increases with the average degree of complementarity*

$$\frac{\partial \mathbb{E}\Big[Var[y(\mathbf{s})]\Big]}{\partial \mathbb{E}[\theta]} \geq 0 \tag{1.36}$$

The intuition is that, as we also depict the mechanism in Figure 1.19, given that the relative adjustment cost of intangibles decreases with firm size (Proposition 2), large firms hit by positive complementarity shock (θ) adjust intangibles less costly. Then, given the complementarity in the production function, large firms hire more skilled labor to complement with higher intangible capital. Hence, given that intangible capital is more productive than tangible capital (governed by z shock), large firms with higher intangible capital and skilled labor produce more than small firms in the equilibrium, i.e., production moves towards large firms. Therefore, production dispersion between large and small firms widens in the equilibrium, consistent with our benchmark empirical evidence.

Figure 1.19: Model Mechanism - Proposition 4



Note: This figure shows the main mechanism of Proposition 4.

As a to-do list, we aim to develop a quantitative analysis for the model to match empirical moments of the heterogeneous investment and labor demand decisions in response to dramatic changes in the asset intangibility we observe in the empirical evidence. In that regard, we plan to implement several counterfactual exercises to answer the following questions of what happens to i) skill premium, ii) labor reallocation, iii) entry and exit rates, iv) productivity dispersion across firms with different intangible capital intensity if (separately) a) persistency in productivity of intangible capital increases relative to tangible capital, b) adjustment cost of investing in intangible capital changes, and c) elasticity of substitution between skilled and unskilled labor increases.

1.7 Conclusion

In this chapter, we study how the accumulation of intangible capital affects U.S. business dynamism, particularly increasing productivity dispersion. To explain firm-level heterogeneity in productivity dynamics, we study a channel on the complementarity between intangible capital and skilled labor.

As motivating evidence, we document four main stylized facts: i) increasing productivity dispersion driven by large firms, especially in intangible intensive sectors, ii) rising intangible capital concentration by large firms, iii) increasing number of skilled workers in large and intangible firms, and iv) higher intangible-skill complementarity in large firms.

This set of stylized facts yields us to quantify the effects of intangible capital - skilled labor complementarity on productivity in different firm sizes. We find that one standard deviation increase in firm-level skill intensity increases the firm-level productivity by around 1.6%-2% and one standard deviation increase in firm-level intangible capital ratio increases the firm-level productivity by around 9%. This empirical evidence suggests that firms with higher intangible and skill intensity have higher productivity, which is amplified with firm size.

In order to discipline our empirical evidence, we first sketch a simple motivating model and then a full-fledged firm-level general equilibrium model in which there are heterogeneous firms, subject to investment adjustment costs, invest in tangible and intangible capital, and hire skilled workers and unskilled labor. Our model provides predictions, that are empirically tested, on the implications of intangible capital in the linkage between investment dynamics and labor reallocation. Using both firm-level and industry-level data, we develop several empirical tests for the model predictions. We find consistent evidence that the relative demand for skilled labor and productivity dispersion increase with asset intangibility, which large firms drive.

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 chapter suggests that the channel of intangible capital investment constitutes a critical form of technological change. It has key implications on firm-level productivity dynamics that are 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 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.

We plan to extend our analysis in both empirical and theoretical directions. For the empirical part, we aim to extend our analysis by having access to firm-level data to observe a detailed level of skill and occupation decomposition. Moreover, we plan to develop an empirical specification of how the complementarity between intangible capital and skilled labor affects other firm dynamics such as sales and profitability growth, 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 of what happens to skill premium and labor reallocation across firms if there is a change in intangible capital intensity.

CHAPTER 2

INTANGIBLE CAPITAL AND COMPETITION IN RIDE SHARING: THE CASE OF LYFT-MOTIVATE MERGER

2.1 Introduction

The effects of mergers and acquisitions (M&A) on competition has been commonly debated in the related literature and several policy discussions. This chapter approaches this debate from a different and novel perspective by taking into account the structural transformation in the economy which is shaped by the rise of intangible capital. We investigate the following questions: Do firms leverage intangible capital acquired during M&A transactions to enhance their competitive power? Does intangible capital help the acquirer firm in M&A transactions increase intra-firm spillover? Does intangible capital acquired after M&As have significant impacts on the dynamics of industry competition? We attempt to address these questions by developing a novel and causal empirical framework. We use the case of Lyft's acquisition of Motivate, the biggest bike-sharing company in the U.S. at the time, and apply difference-in-difference-in-differences (DDD) model to evaluate the degree to which intangible capital affects the competition between Lyft and Uber.

These questions are important because we observe structural transformation towards intangible capital in the U.S. economy. The intangible capital (e.g. information technology, knowledge, human, and organizational capital, user data, brand equity) share in total capital has been rising from 20% during 1970s up to

70% during 2010s (Falato et al. (2020)). We argue that the incentives for many U.S. companies to engage in M&A transactions would be dramatically shaped by the phenomena of increasing intangible capital in the U.S. economy. More explicitly, in contrast to the traditional merger analysis focusing on the role of accumulating and effectively utilizing tangible capital (e.g. plants, properties, equipment and structures) acquired in M&A transactions, we suggest that the acquirer firm would instead target intangible capital of the acquired firm to internalize its economic competencies in the business model because the former firm would try to keep pace with the evolving economy towards knowledge economy.

Intangible capital is composed of several different components and each component would provide distinct benefits to the acquirer firm. In our context, there are three main conceptual channels how intangible capital accumulated through M&As in the ride-sharing industry would bring different advantages to the acquirer firm. First, given that access to the ride-sharing service is based on the usage of app, M&As providing new app integration would be convenient for the customers, which provides a positive network externality driven by intangible capital. Second, M&As would help the acquirer firm increase brand salience in the marketplace. For instance, in our context of the study, Lyft potentially increased its brand salience in the daily life in NYC after its acquisition of Motivate. In that way, Lyft's bikes which are noticed by bike customers more can also influence their decision when they choose a ride-sharing service in favor of Lyft rather than Uber. Given the highly similar nature of the service provided by the firms in ride-sharing industry, brand salience constitutes a significant factor in determining the market shares. Third, M&As would provide integrated rich level of user data across different production units which can spill over the efficiency gains within the firm boundary. In our case, Lyft was able to integrate both bike-sharing and ride-sharing apps into a single app which enables the customers to choose any transportation mode Lyft provides. In return, Lyft gains an advantage to operationalize the user data interchangeably between its bike-sharing and ride-sharing services. However, due to data limitations, we are not able to distinguish all these three distinct channels of intangible capital. Hence, our empirical results proxy some potential combination of these three candidate channels and we argue that the acquirer firms internalize at least one of the three channels to enhance their competitive power in the industry. Since the data limitation prevents us to distinctly analyze each of these channels, we need to study an industry which has an underlying nature of business operations combining all of these three channels at the same time. Hence, we select ride-sharing industry as a good candidate for such an industry because its intangible capital heavy business nature is likely to benefit all the three channels of intangible capital we have described.

Employing the rich variation in various databases such as bike-sharing and ride-sharing trips in New York City, we apply difference-in-difference-in-differences (DDD) model to estimate the causal impact of the acquisition on competition in ride-sharing market. We find that after the acquisition Lyft increases its rides by 6% compared to Uber; even more on weekends. Moreover, we find that the positive effect reaches its peak during rush hours on weekdays, which indicates that increasing intensity of using ride-sharing during the rush hours enables Lyft to internalize the effects of the acquisition because increasing brand salience through bikes is more likely to attract customers which use ride-sharing more frequent during rush hours within the weekdays. We also investigate whether the exposure to brand salience and user data can be heterogeneous based on the number of bike stations. In that regard, we find that the treatment effect in taxi-zones with more than 5 bike stations is higher than the one in taxi-zones with less than 5 bike stations. We interpret this result that the exposure to more bike stations enabling higher Lyft brand salience would increase the intensity of the treatment such that Lyft would gain more ride-trips compared to Uber.

Related Literature. This chapter contributes to the literature in distinct ways. The first strand of the literature is related to the merger evaluation using program evaluation methods. There is an extensive series of papers which study the effects of merger activities for different industries such as gasoline (Hastings (2010), Hosken et al. (2011), Taylor et al. (2010), Simpson and Taylor (2008)), parking (Choné and Linnemer (2012)), hospitals (Vita and Sacher (2001)), Brickley and Van Horn (2002), Tenn (2011), Lewis and Pflum (2017), Cooper et al. (2019)), beer (Frake (2017)), and airlines (Bamberger et al. (2004), Kwoka and Shumilkina (2010)). Our contribution in this strand of the literature is two-fold. First, we analyze the merger evaluation by investigating ride-sharing market as another key industry for which the literature has not focused on yet. Second, we provide a novel methodological contribution by designing a causal approach based on DDD estimation strategy which is rarely implemented in the literature due to the lack of appropriate variation in the data. We use the advantage of having our rich-level of ride-sharing data which provides a sufficient variation and hence enables us to implement DDD estimation strategy.

The second strand we touch upon is about competition in sharing platforms. For instance, Cao et al. (2018) categorize market expansion and market stealing of incumbent firms to study the effects of entry of bike-sharing firms on entry and exit dynamics of the bike-sharing platform. Nikzad (2017) studies the effects of competition on the ride-sharing through equilibrium welfare and wage analysis. Jiang et al. (2018) analyzes the degree of competition and accessibility in ride-sharing markets in San Francisco and New York City based on statistical techniques. Our contribution is to consider both ride-sharing and bike-sharing operations to measure how M&As could create market advantage for the acquirer firm depending on the production technology becoming more intangible capital heavy.

Our chapter also contributes to the literature which emphasizes the role of intangible capital on firm dynamics. Given that we observe an increasing share of intangible capital (Corrado et al. (2009); McGrattan and Prescott (2014); Eisfeldt and Papanikolaou (2014); Haskel and Westlake (2017); Peters and Taylor (2017); McGrattan (2020)), there are several papers which measure the effect of intangible capital on different firm dynamics such as productivity growth (Corrado et al. (2017)) and firm behavior (De Ridder (2019)). Atalay et al. (2014) argue that the use of intangible capital enhances intra-firm spillover, which is one of the closest papers to our main story. We investigate how the intra-firm spillover provided by intangible capital affect firms' competitiveness. Our contribution is to emphasize that the motivation of acquirer firms in M&As would be to use the intangible capital accumulated through M&As as a leverage to enhance its competitive advantage. In that regard, to the best of our knowledge, we provide the first attempt to investigate the role of intangible capital in merger evaluation.

Layout. The remainder of the chapter is structured as follows. Section 2.2 discusses some motivating facts on the rise of intangible capital and competition in the ride-sharing industry. Section 2.3 introduces the rich-level of data we use in our study. Section 2.4 includes a detailed discussion how we construct a causal empirical method based on DDD and shows the main empirical results. We conclude by discussing some potential future work.

2.2 Motivating Facts

U.S. economy has been experiencing a technological progress and transition to an intangible capital intensive economy including information technology, knowledge, human and organizational capital, user data, and brand equity. Figure B1 documents that the share of intangible capital in total capital in the U.S. economy has been rising from 20% during 1970s up to 70% during 2010s. This secular trend is also valid in the ride-sharing platforms. For instance, Figure B2 shows that the intangible capital ratio of Lyft and Uber is dramatically high and more importantly their ratio is higher than the average economy-wide intangible ratio during the corresponding years shown in Figure B1.

The natural question would be on how we relate the accumulation of intangible capital to the M&A dynamics in the ride-sharing platforms. We argue that acquirer firms would use the intangible capital accumulated through M&A transactions to leverage its competitive advantage against the rival firms. In that respect, the degree of competition in the ride-sharing market would be a key determinant how the accumulation of intangible capital creates an advantage for the acquirer firms. In line with this argument, we indeed find a stylized fact that there is a fierce competition (especially between Uber and Lyft) in the ride-sharing platform, which is increasing over the last years. Figure B4 shows that even though Uber takes a big portion of the market share, Lyft starts to grab a significant amount of the market share from Uber, which indicates that Lyft tries to gain a competitive advantage over Uber over time. We see that Lyft has more than doubled its market share from 11.5% to almost 25% over last 5 years, whereas Uber lost its market share from 87.5% to around 75% over the last 5 years. It indicates that even though the ride-sharing market is very concentrated in the sense that there are only two big operating firms, competition between the two becomes fierce over time.

We also decompose the market share of Lyft in ride-sharing over time at the taxi-zones with and without bike stations to have a smell check before DDD estimation whether Lyft performs a different pattern at taxi-zones with bike stations (corresponding to the treatment group in our empirical model) and zones without bike stations (corresponding to the control group in our empirical model). Figure B5 shows that Lyft increases its market share of ride-trips at the taxi-zones with bike stations towards the end of 2018 when the acquisition actually happened, whereas its market share does not show a similar dramatic increase at the taxi-zones without bike stations during the same period.

We now bring another fact which motivates us further to investigate the relationship between intangible capital accumulated through M&A's and the competitive advantage in the marketplace. Figure B6 shows the raw correlation between the number of i) Lyft bike-trips vs. Lyft ride-trips, ii) Lyft ride-trips vs. Uber ride-trips and iii) Lyft bike-trips vs. Uber ride-trips in each hour in a day. As expected, we find that the correlation between Lyft ride-trips and Uber ride-trips is dramatically high during all hours in a day, which indicates a high degree level of competition between the two firms. Moreover, we also see that the correlation between Lyft bike-trips and Lyft ride-trips increases during rush hours in a day, which would indicate that Lyft would take advantage of its bike operation. This result makes sense because bike-trips can be potentially a substitute for ride-trips during rush hours. We also see an increasing correlation between Lyft bike-trips and Uber ride-trips during rush hours, which can be interpreted as people using the option of bike-trips as a substitute for ride-trips during rush hours would also spill over the network externality to the rival firms' ride-trips, but this is out of our scope in this chapter.

2.3 Data

In this section, the first part introduces the ride sharing and bike sharing data, shows some summary statistics and the variation of each dataset across different taxi zones. The second part discusses the measurement of firm-level intangible capital through which we motivate that sharing platforms have intangible capital heavy businesses.

2.3.1 Ride Share and Bike Share Data

We use trip-level ride sharing data from New York City, provided by NYC Taxi and Limousine Commission (TLC). The dataset contains 662,519,590 ride sharing trips (the sum of Lyft and Uber ride-trips) taken during the period between January 2016 and December 2019. We can observe when each trip started and ended, pick-up location and the ride sharing firm. For the time period after January 2017 we can also observe the drop-off location. During this time period, we observe more than 453,000 ride sharing trips on average per day. Figure B3 shows the ride-trip counts and Figure B4 shows the market shares of Lyft and Uber over time.

The pick-up and drop-off locations are in taxi-zone level, which is a collection of census tracts. It is used by TLC to report the taxi and ride sharing data for de-identification purposes. Although the actual data point has the exact location of the pick-ups and drop-offs, TLC reports only the taxi zone that those locations belong to. For the purposes of this paper, we aggregate the trips by hour of day, date, pick-up location and operator firm. The resulting dataset has the trip counts by the pick-up location for each firm during the period between 2016 and 2019 for each hour of day.

We also use bike sharing data provided by Motivate, the bike share operator in New York City. This dataset contains trip-level bike sharing data from 2013 to 2019. We use this dataset to identify where the active bike stations are located, and figure out which taxi zones have active bike stations. We label a taxi-zone as "with-bike taxi zone" if there is at least one active bike share station in the taxi zone, and "without-bike taxi zone" otherwise. Table B1 shows the number of taxi zones, and the market shares of Uber and Lyft for each category.

Figure 2.1 shows a map of taxi zones based on the categories for which i) we exclude taxi-zones that do not have any ride-trips and taxi-zones that are in airports, ii) taxi-zones that do not have any bike stations, iii) taxi-zones that have at least one bike station. This figure shows that we have sufficiently enough taxi-zones that are in treatment groups (taxi-zones with at least one bike station) and control groups (taxi-zones without any bike station) to implement our DDD specification. Figure B7 is a map of taxi zones, where the colors represent the total ride share trips per square mile originating from each taxi zone. It shows that Manhattan has the highest number of ride share trips per square mile. Figure B8 shows where the with-bike and without-bike taxi zones are. All with-bike zones are either in Manhattan, or in parts of Queens and Brooklyn that are closest to Manhattan.

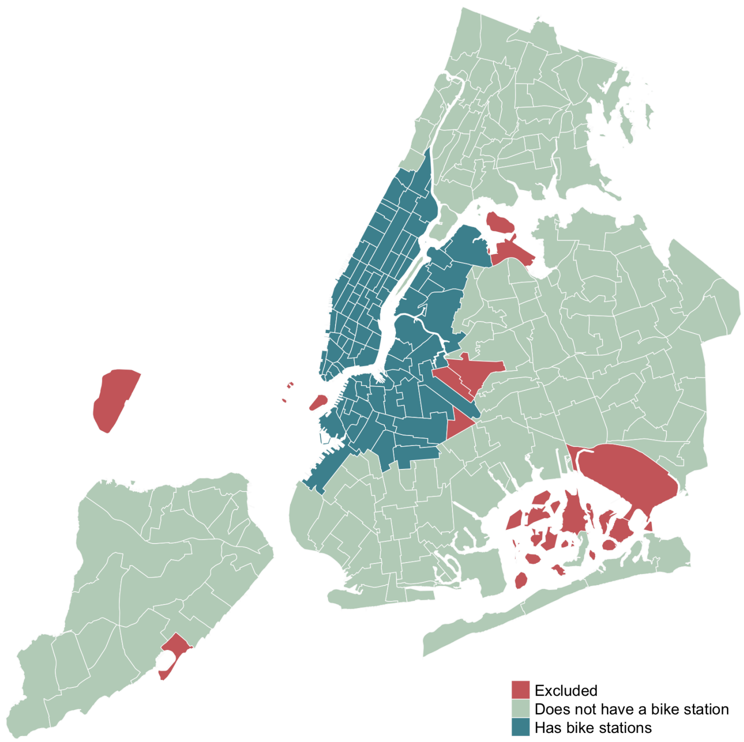
Figure B9 shows the average ride sharing trips for each hour during each day of week. We observe that day of week and time of day seems to have a strong effect on the number of ride share trips. Therefore, we expect that the acquisition might have differential impacts on trip counts depending on the time of day and day of week.

2.3.2 *Measurement of Intangible Capital*

We measure intangible capital with the perpetual inventory method developed by Peters and Taylor (2017).

According to the measurement approach developed by Peters and Taylor

Figure 2.1: Zone Categories, New York City



Note: This figures shows a map of taxi zones based on the categories for which i) we exclude taxi-zones that do not have any ride-trips and taxi-zones that are in airports, ii) taxi-zones that do not have any bike stations, iii) taxi-zones that have at least one bike station.

(2017) (see also related studies on different measurement approaches of intangible capital, including Lev and Radhakrishnan (2005), Eisfeldt and Papanikolaou (2014), Ewens et al. (2019))), we can categorize intangible capital into three components: (i) knowledge capital, (ii) organizational capital, and (iii) externally acquired intangible capital.

We proxy knowledge capital based on capitalized R&D expenditures:

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

where A_{it} represents knowledge capital, $R\&D_{it}$ represents R&D expenditures for each firm i during the year t, and $\delta_{R\&D} = 15\%$ (Hall et al. (2000)). Our assumption is that A_{i0} has to be zero.

In order to proxy organizational capital, we capitalize Selling, General, and Administrative Expenses (SG&A) which is defined by GAAP as firms' operating expenses unrelated to the cost of goods sold. Some examples include advertising and marketing expenses and provisions for employee bonuses. We follow the related literature that α fraction of SG&A represents an organizational capital investment and use the perpetual inventory method as follows:

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

where $\delta_{SG\&A} = 20\%$ (Lev and Radhakrishnan (2005), Eisfeldt and Papanikolaou (2014)). To the best of our knowledge, the only estimate of α comes from Hulten and Hao (2008), who estimate $\alpha = 0.3$. Our assumption is that B_{i0} has to be zero.

We also include externally acquired intangible capital assets (G_{it}) to the measured R&D (A_{it}) and organizational capital (B_{it}), and measure total intangible capital (INT_{it}) as follows:

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

2.4 Empirical Analysis

Our goal is to estimate the causal impact of Lyft's acquisition of Motivate on the competition in ride share industry in New York City, using a difference-in-difference-in-differences (DDD) estimation. We use December 2018, the first month after Lyft completed the acquisition of Motivate, as the starting point of the treatment. We assume that only the taxi zones where there is at least one bike share station are treated.

2.4.1 Empirical Model

The unit of observation in the dataset is the number of trips by a particular company for a given calendar day in a taxi zone. We implement the following DDD specification:

$$\begin{aligned} log(n_{itf}) = {} & \beta_0 + \beta_1 Firm_f + \beta_2 Year_{y(t)} + \beta_3 Zone_i \\ & + \theta_1 Month_{m(t)} \\ & + \delta_0 YearFirm_{y(t)f} + \delta_1 ZoneFirm_{if} + \delta_2 ZoneYear_{iy(t)} \\ & + \delta_3 D_{itf} + \epsilon_{itf} \end{aligned} \tag{2.1}$$

where n_{itf} represents the number of ride-sharing trips originating from zone i on day t and operated by firm f. In addition, D_{itf} is a dummy variable taking the value of 1 if i) zone i has at least one bike station, ii) date $t \geq$ 2018-11-30, and

iii) f= Lyft. $\{Firm_f, Zone_i, Month_{m(t)}, Year_{y(t)}\}$ are firm, taxi zone, month and year fixed effects, respectively. $\{YearFirm_{y(t)f}, ZoneFirm_{if}, ZoneYear_{iy(t)}\}$ are year-firm, zone-firm, and zone-year fixed effects. This specification implies that we estimate a separate treatment effect for each day of week. The standard errors are clustered at zone level. Our main coefficient of interest is δ_3.

There are two sources of new customers for Lyft due to the treatment. The first is that customers switch from Uber to Lyft, denoted as SfU, and the second is the new Lyft customers who would not use ride-sharing otherwise, denoted as NLC. The treatment might also affect the number of new Uber customers, denoted as NUC. Table 2.1 depicts the summary of how our DDD estimator works in a two-by-two setting (Cunningham (2021)).

TABLE 2.1: Summary of the Identification of DDD estimator

Firm	Zone	Period	Outcome	D1	D2	D3
		After	$L+T+L_t+A_t$			
	A		+SfU + NLC	$T+L_t+A_t$		
		Before	L	+ SfU + NLC		
Lyft					$A_t-B_t+SfU+LNC$	
		After	$L+T+L_t+B_t$			
	B			$T+L_t+B_t$		
		Before	L			
						$2\times SfU$
		After	$U+T+U_t+A_t$			+ NLC - NUC
	A		- SfU + NUC	$T+U_t+A_t$		
		Before	U	- SfU + NUC		
Uber					$A_t-B_t-SfU+NUC$	
		After	$U+T+U_t+B_t$			
	B			$T+U_t+B_t$		
		Before	U			

The first difference (D1 column in Table 2.1) takes the firm (Uber and Lyft) fixed effect out before and after the acquisition date. The second difference (D2 column in Table 2.1) takes the sector-specific time effect and firm-specific (Uber and Lyft) time effect out. Finally, the third difference (D3 column in Table 2.1) takes zone-specific time effects out. As a result, we have the remaining estimate of $\delta_3 = 2 * SfU + NLC - UNC$, which we interpret as the causal impact of the acquisition on the relative change in number of Lyft ride-trips. We would ideally want to estimate $SfU + NLC$ instead as it is the treatment effect on Lyft. In the current setting, customers who switch from Uber will be double counted as a result of using Uber as the control group, since Uber is affected by the treatment as well. Therefore, the parameter estimate from the DDD estimation will capture SfU twice. Additionally, it will also capture the additional change in Uber ridership due to the change in new customers as a result of the treatment. Therefore, we cannot interpret δ_3 as the treatment effect, since $\delta_3 = 2SfU + NLC - NUC$. Since we have year-zone specific fixed effects, we cannot capture NLC or NUC separately, hence we cannot identify SfU, which makes estimating our target, $SfU + NLC$, not attainable. However, we can still estimate a lower bound for the treatment effect.

We first assume that the treatment effect on the total number of new ride share customers is non-negative, i.e. $NLC + NUC \geq 0$. This assumption implies that the acquisition does not shrink the ride share market. Then,

$$SfU + NLC \geq SfU + \frac{NLC - NUC}{2} = \frac{\delta_3}{2} \tag{2.2}$$

Hence, dividing the DDD estimate by two would give us a lower bound for the treatment effect estimate. We also correct for the standard error of the DDD estimate accordingly.

2.4.2 *Identification Assumptions*

We have several identification assumptions for our DDD estimation. First, we assume that there are only three common trends which are sector, Lyft-specific and Uber-specific time trends. We also assume that there is no extra treatment by Lyft to the with-bike zones after the acquisition. This assumption is crucial because other potential subsequent Lyft policies after the acquisition would interact with the effect of the acquisition per se, which would make our DDD estimate biased. Another assumption we have is that there is no compositional changes in zone demographics before and after the acquisition. One potential concern would be to have a mobility of people sorting on several zone-specific characteristics which can correlate with the underlying determinants why people choose bike trips. We also assume a standard condition that there is no spatial autocorrelation in errors. Another key assumption generally made in the related literature is that we hold Stable Unit Treatment Value Assumption (SUTVA) in the sense that there is no interference and there is only a single treatment effect across units. Other technical assumptions we bring to identify our DDD estimate are that outcomes are additive, treatment occurs only if there is a bike station is within taxi zone boundaries, and finally, treatment is binary.

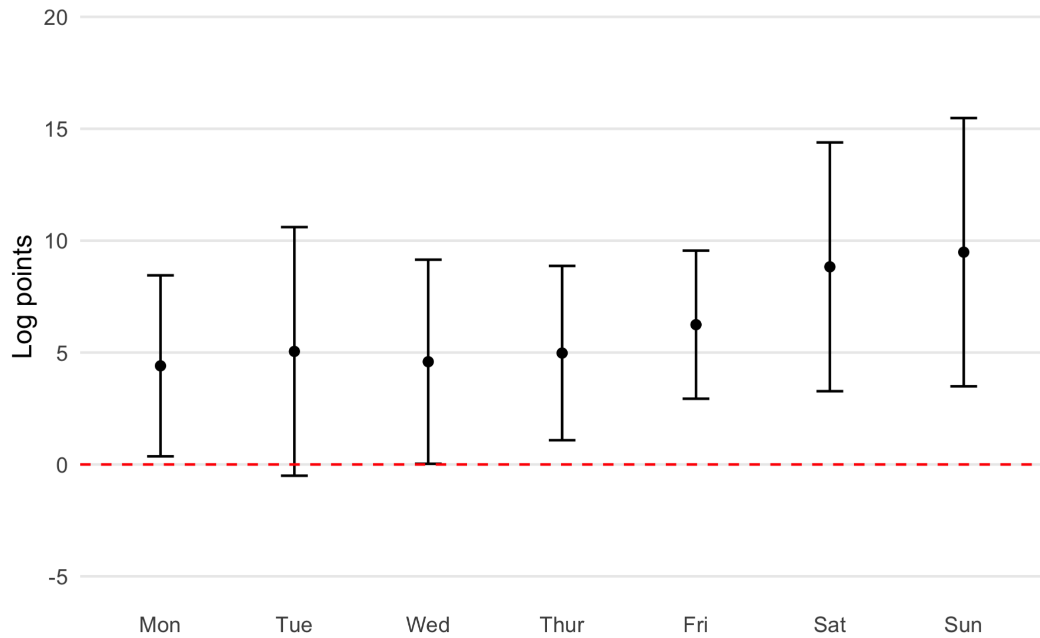
2.4.3 Empirical Results

Figure 2.2 documents the DDD estimate of the regression equation (2.1) by each day. After controlling several fixed effects, we see that the coefficient of DDD causal estimate (δ_3) is statistically significant and positive in almost all the days (except Tuesday), i.e. after the acquisition Lyft was able to increase its ride-trips compared to Uber during almost all the days. We find that Lyft increases its ride-trips by around 6% compared to Uber after the acquisition. Moreover, we see that this positive impact of the acquisition on Lyft ride-trips reaches its peak during the weekends.

In order to motivate why standard difference-in-differences (DD) specification is not suitable for our estimation strategy and hence we select the DDD model, we run our benchmark equation (2.1) but for DD model, i.e. we exclude year-firm, zone-firm, and zone-year fixed effects. Figure 2.3 shows that if we would implement DD model instead, the empirical estimates would give us opposite and inconsistent results compared to our baseline DDD model. In that respect, we verify the importance of unobservable characterictics driven by possible combinations of year-firm, zone-firm, and zone-year categories, which are absorbed through our corresponding fixed effects in DDD model.

The next step is to investigate whether the DDD causal estimate shows a heterogeneous pattern across hours and days of the week. When we analyze the DDD estimates across different hours and days of the week, we observe different patterns between weekdays and weekends. Figure 2.4 shows that the DDD causal

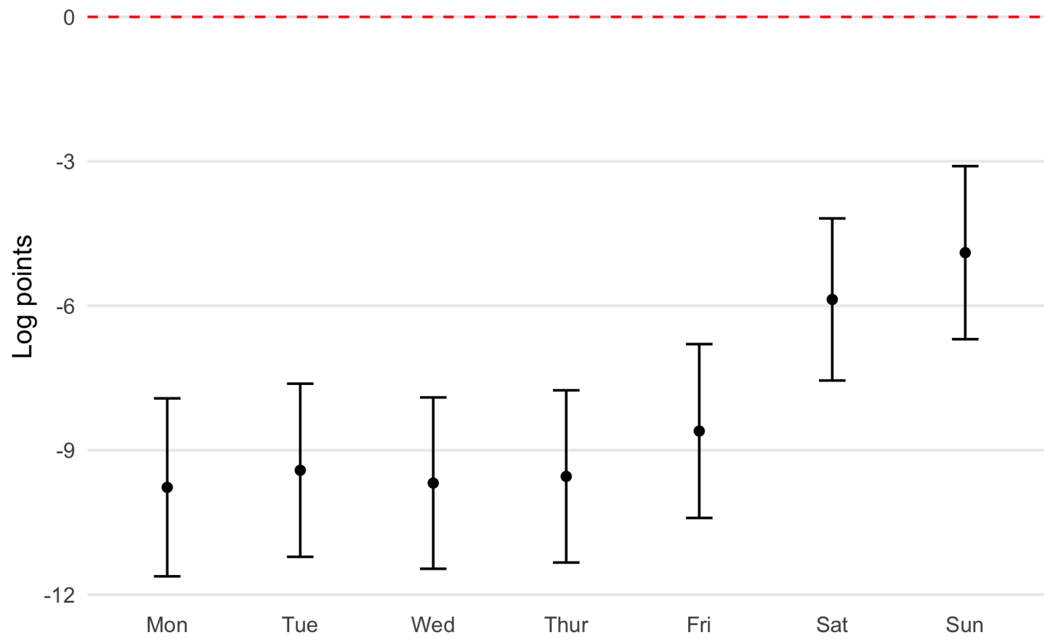
Figure 2.2: DDD Estimate - By Day



Note: This figure documents the DDD estimate of the regression equation (2.1) by each day, which is divided by two according to the equation (2.2). Point estimates represent the DDD estimates for each corresponding day. Standard errors are clustered at the zone level. Confidence intervals are at 95%.

estimate is statistically and economically significant and positive during almost all hours and days within a week. Moreover, we find that the positive effect reaches its peak during rush hours on weekdays, whereas the effect is even higher during weekends along with the evidence that the higher effect during weekends is almost uniformly distributed across hours. We interpret this result in two ways. First, increasing intensity of using ride-sharing during the rush hours would enable Lyft to internalize the effects of the acquisition because increasing brand salience through bikes is more likely to attract customers which use ride

Figure 2.3: DD Estimate - By Day

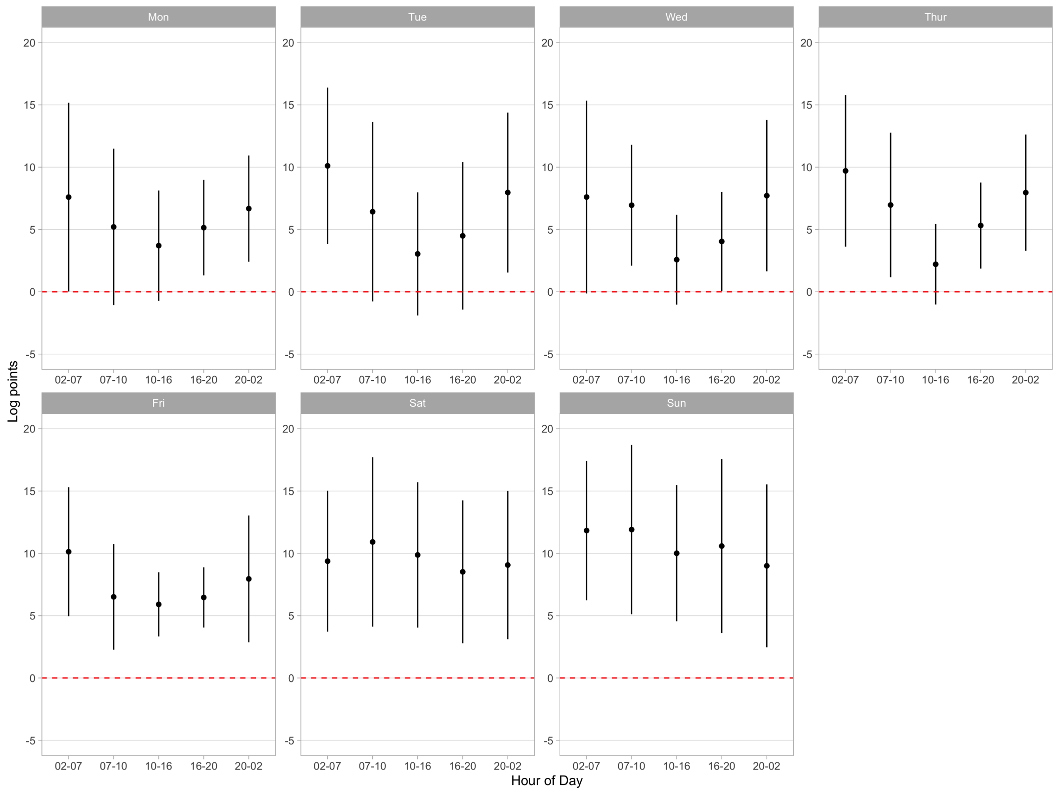


Note: This figure documents the DD estimate by each day, calculated through the modified version of regression equation (2.1) for DD model. The estimates are divided by two according to the equation (2.2). Point estimates represent the DD estimates for each corresponding day. Standard errors are clustered at the zone level. Confidence intervals are at 95%.

sharing more frequent during rush hours within weekdays. Second, given that customers are likely to use ride and bike sharing for leisure activities during weekends more compared to during weekdays, the intensity of using ride sharing is more uniformly distributed across hours during weekends, which enhances Lyft's opportunity to benefit its brand salience through bikes for attracting the customers to ride sharing at higher frequency of time during weekends.

We also investigate whether the exposure to brand salience and user data

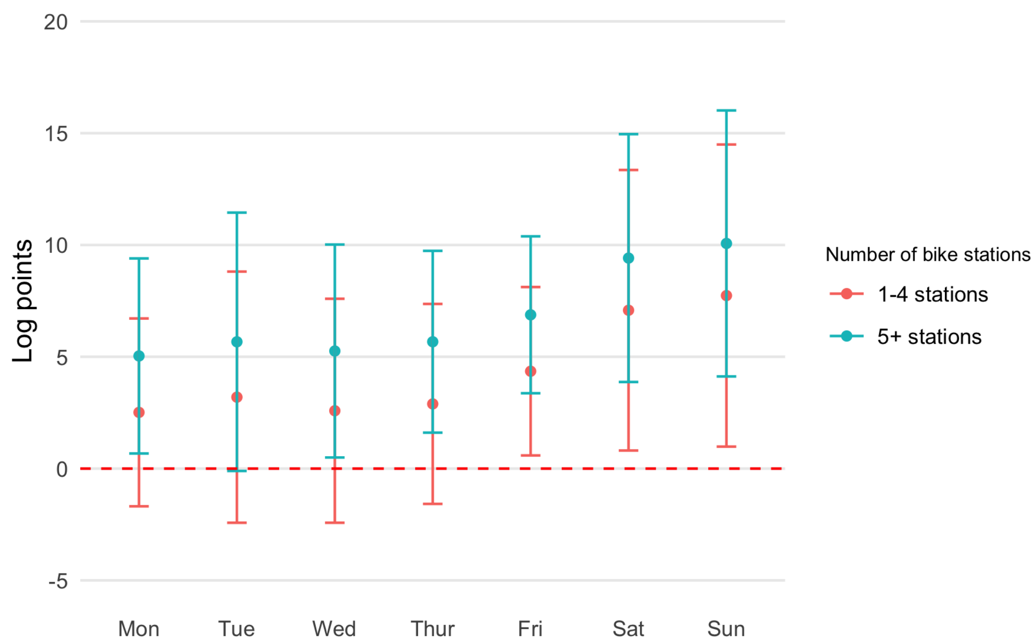
Figure 2.4: DDD Estimate - By Day and Hour



Note: This figure documents the DDD estimate of the regression equation (2.1) by each day and hour, which is divided by two according to the equation (2.2). Point estimates represent the DDD estimates for each corresponding day-hour pair. Standard errors are clustered at the zone level. Confidence intervals are at 95%.

can be heterogeneous based on the number of bike stations. Hence, we run our benchmark DDD regression in equation (2.1) for taxi-zones with less than 5 bike stations and taxi-zones with more than 5 bike stations to capture the intensity of treatment. Figure 2.5 shows that the treatment effect in taxi-zones with more than 5 bike stations is higher than the one in taxi-zones with 5 bike stations during all days. Moreover, we see that the treatment effect in taxi-zones with more than 5

Figure 2.5: DDD Estimate - Treatment Intensity



Note: This figure documents the DDD estimate of the regression equation (2.1) by each day for taxi-zones with less than 5 bike stations and taxi-zones with more than 5 bike stations. The estimates are divided by two according to the equation (2.2). Point estimates represent the DDD estimates for each corresponding day. Standard errors are clustered at the zone level. Confidence intervals are at 95%.

bike stations is statistically significant during all days, whereas it is not statistically significant for taxi-zones with less than 5 bike stations. This figure indicates that the exposure to more bike stations enabling higher Lyft brand salience would increase the intensity of the treatment and hence Lyft would gain more ride-trips compared to Uber. We aim to do a statistical test whether the two treatment effects are statistically different, which is in progress.

2.4.4 *Test of Parallel Trends*

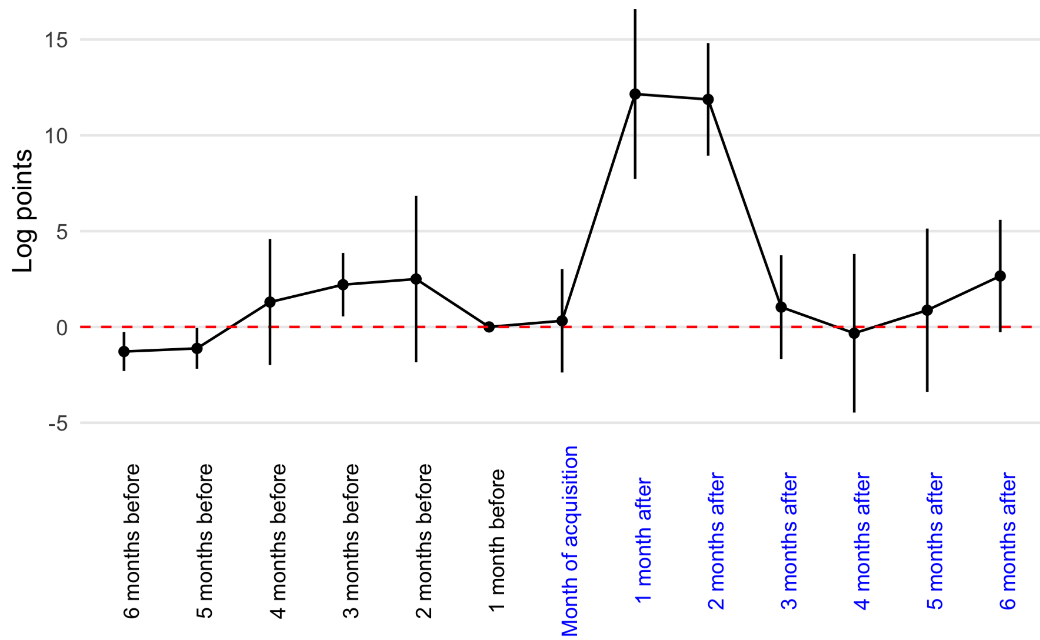
One of our identification assumptions is to have parallel trends between treatment and control groups, as a standard assumption in the estimation of treatment effects. We perform a placebo test to check our parallel trend assumption by adjusting our benchmark regression specification (2.1) as follows:

$$\begin{aligned} log(n_{itf}) = &\beta_0 + \beta_1 Firm_f + \beta_2 Year_{y(t)} + \beta_3 Zone_i \\ &+ \theta_1 Month_{m(t)} \\ &+ \delta_0 YearFirm_{y(t)f} + \delta_1 ZoneFirm_{if} + \delta_2 ZoneYear_{iy(t)} \\ &+ \sum_{\tau=-6}^{6} \delta_{3,\tau} \mathbb{1}\{EventMonth_{itf} = \tau\} + \epsilon_{itf} \end{aligned} \tag{2.3}$$

where $\mathbb{1}\{EventMonth_{itf} = \tau\}$ is defined as a dummy variable which takes the value of 1 if the treatment event would take place before (for $\tau \in [-6,0)$) and after (for $\tau \in (0,6]$) the month of the Lyft's acquisition. By construction, since there is no pre-period trend between control and treatment groups during the month of the acquisition (for $\tau = 0$), $\delta_{3,0} = 0$. Other variables are same as before in equation (2.1).

The motivation of the test of parallel trends is verify the assumption that the dependent variable in the regression which is the number of ride sharing trips ($log(n_{itf})$) would be same between treatment and control groups if there would be no Lyft's acquisition. Figure 2.6 shows the evidence that our parallel trend assumption holds, i.e. there is no pre-existing trend between treatment and control groups. Moreover, we see that the coefficient estimate becomes statistically

Figure 2.6: Test of Parallel Trends



Note: This figures shows the estimates of the treatment effect ($\delta_{3,\tau}$) in the placebo regression specification (2.3) for the test of parallel trends. $\tau \in [-6, 6]$ represents the months before and after the Lyft's acquisition month. By construction, $\delta_{3,0} = 0$ which corresponds to the estimate of the treatment effect during the month of the acquisition (τ =0). Standard errors are clustered at the zone level. Confidence intervals are at 95%.

significant during 1 month and 2 months after the month of acquisition, which is in line with our benchmark DDD estimation strategy.

2.5 Conclusion

This study focuses on the role of intangible capital in Mergers and Acquisitions (M&A) evaluation for industry competition by using the ride and bike sharing markets in which intangible capital brings the features of synergy and network externality to the acquirer of the acquisition. We investigate whether acquirer sharing platforms in M&A transactions leverage intangible capital to enhance their competitive advantage. To handle this question, we use the case of bike-sharing platforms and in particular Lyft's acquisition of Motivate, the biggest bike sharing company in the U.S. at the time. Employing the rich variation in the dataset of bike-sharing and ride-sharing trips, we apply difference-in-difference-in-differences (DDD) model to estimate the causal impact of the acquisition on competition in ride-sharing market. We find that after the acquisition Lyft increases its rides by 6% compared to Uber; even more on weekends. We interpret this result that intangible capital accumulated through the merger enhances Lyft's opportunity to benefit its brand salience through bikes by attracting their bike customers to ride sharing.

We have several steps for the future work. First, we aim to estimate the heterogeneous treatment effects in which the causal impact of the acquisition would differ across several demographics such as income, age, education, employment and residential population. Hence, we would potentially investigate which part of the society would help Lyft internalize its intangible capital for the competitive advantage. Second, we plan to design a empirical framework for continuous treatment in which we would extend binary treatment into continuous treatment. The motivation is to quantify whether the exposure to brand salience and user data can be heterogeneous based on the number of bike stations.

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APPENDIX A

APPENDIX TO INTANGIBLE CAPITAL MEETS SKILLED LABOR: THE IMPLICATIONS FOR U.S. BUSINESS DYNAMISM

A.1 Tables

TABLE A1: Summary Statistics - Intangible Capital Ratio

	Mean	Sd	P25	P50	P75	Min	Max	Count
Intangible Ratio	.446	.292	.184	.486	.7	0	1	202315

Note: This table shows the summary statistics of measured intangible capital ratio.

TABLE A2: Summary Statistics - Skill Intensity

	Mean	Sd	P25	P50	P75	Min	Max	Count
Skill Intensity	.298	.154	.171	.271	.401	.025	.875	87811

Note: This table provides the summary statistics of skill intensity.

TABLE A3: Productivity Dispersion and Intangible Capital - Industry-level Analysis

	Period < 2000	Period ≥ 2000
	Productivity Dispersion	Productivity Dispersion
Intangible Ratio	0.076*	0.12**
	(0.031)	(0.041)
Controls	Yes	Yes
Industry FE	Yes	Yes
R^2	0.566	0.644
N	10818	9419

Note: Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE A4: Between-group Productivity Variation and Intangible Capital - Industry-level Analysis

	Period < 2000	Period ≥ 2000
	Between Group Share	Between Group Share
Intangible Ratio	-0.317**	0.394*
	(0.114)	(0.155)
Controls	Yes	Yes
Industry FE	Yes	Yes
R^2	0.532	0.547
N	3671	3271

Note: Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE A5: TFP Growth and Marginal Productivity of Factor Inputs

	Productivity Growth	Productivity Growth	Productivity Growth	Productivity Growth
Log MPL	-0.006***	-0.018***	-0.024***	-0.024***
	(0.0002)	(0.0005)	(0.0006)	(0.0007)
Log MPK	0.0006**	-0.003***	-0.001**	-0.001
	(0.0002)	(0.0005)	(0.0005)	(0.0006)
Log MPI	0.008***	0.027***	0.03***	0.03***
	(0.0001)	(0.0004)	(0.0004)	(0.0004)
Firm FE	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Sector FE	No	No	No	Yes
Adjusted R^2	0.0112	-0.0808	0.0260	0.0279
N	187574	187574	185686	180307

Note: This table shows the regression of the annual growth of TFP measured by the production function estimation by Olley and Pakes (1996) on the logarithms of marginal products of total employment (Log MPL), tangible capital (Log MPK) and intangible capital (Log MPI). Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

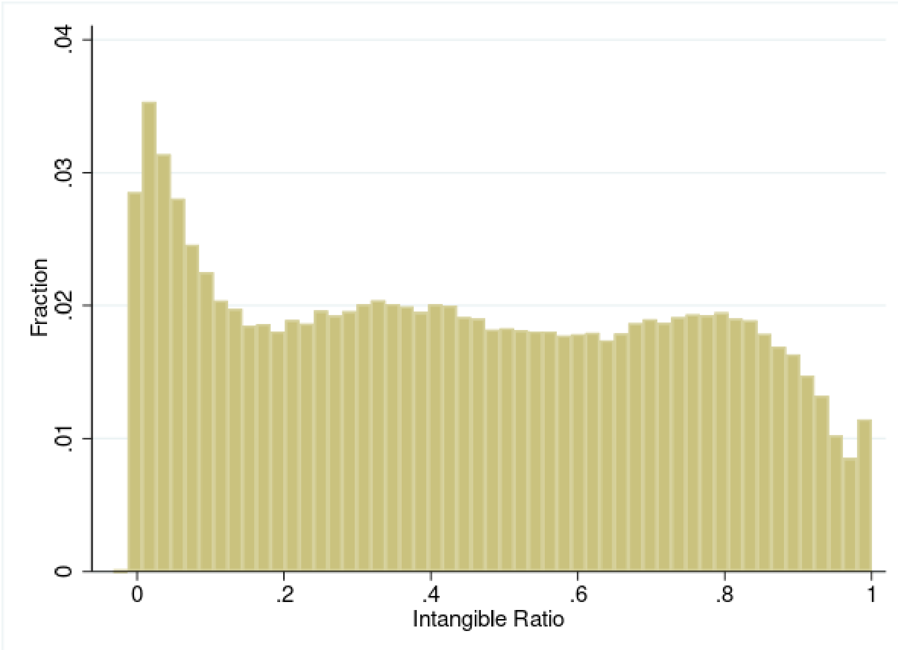
TABLE A6: Intangible Capital and Skilled Workers

	Skilled Workers	Skilled Workers	Skilled Workers	Skilled Workers
Intangible Capital	0.325***	0.106***	0.361***	0.151***
	(0.003)	(0.004)	(0.003)	(0.003)
Size	0.594***	0.792***	0.580***	0.766***
	(0.003)	(0.004)	(0.003)	(0.004)
Age	-0.023***	-0.019***	0.017***	0.011***
	(0.0007)	(0.0005)	(0.0008)	(0.0006)
Industry FE	No	No	Yes	Yes
Year FE	No	Yes	No	Yes
R^2	0.741	0.863	0.765	0.875
N	71049	71029	71049	71029

Note: This table shows the regression of the number of skilled workers on intangible capital and control variables. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

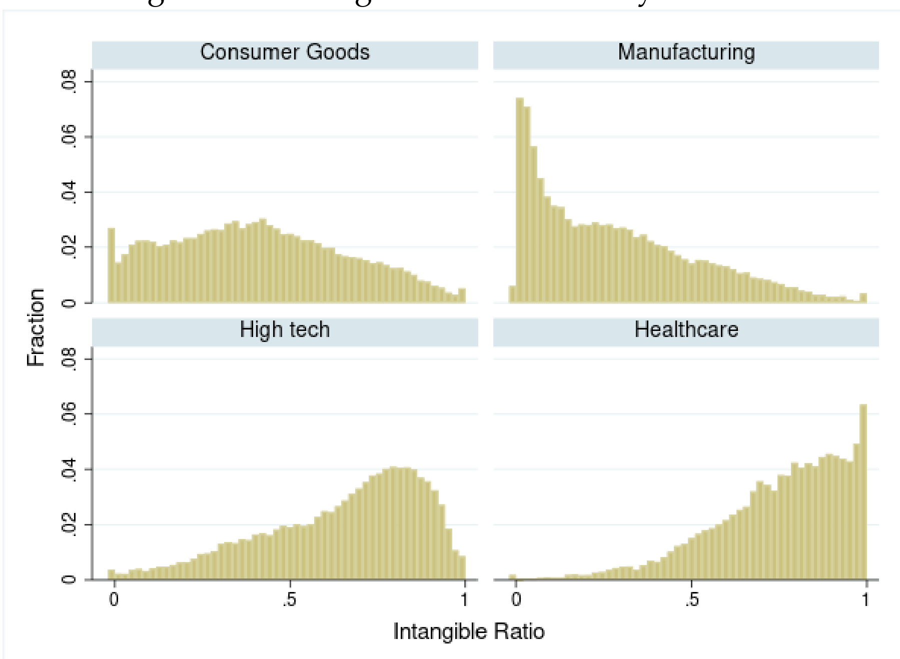
A.2 Figures

Figure A1: Intangible Ratio - Histogram



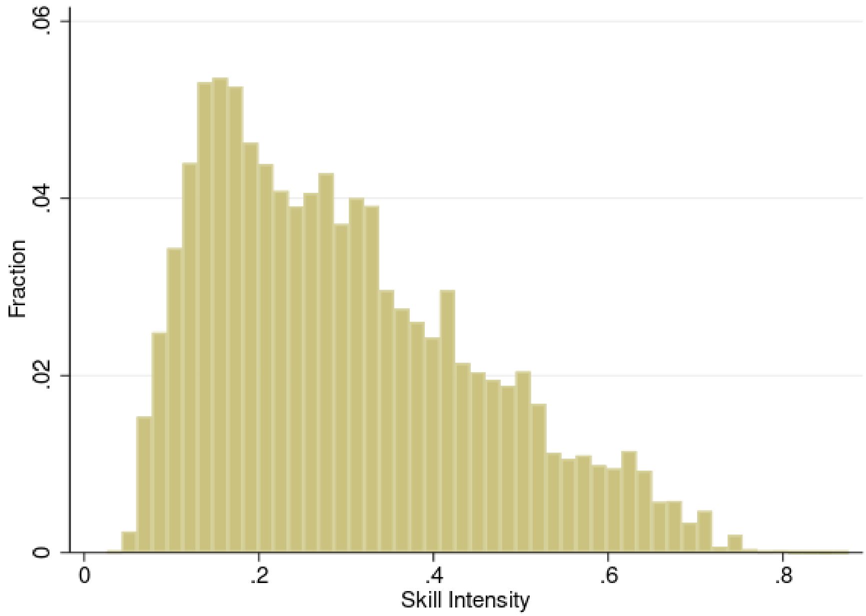
Note: This figure documents the histogram of intangible capital ratio.

Figure A2: Intangible Ratio - Industry Variation



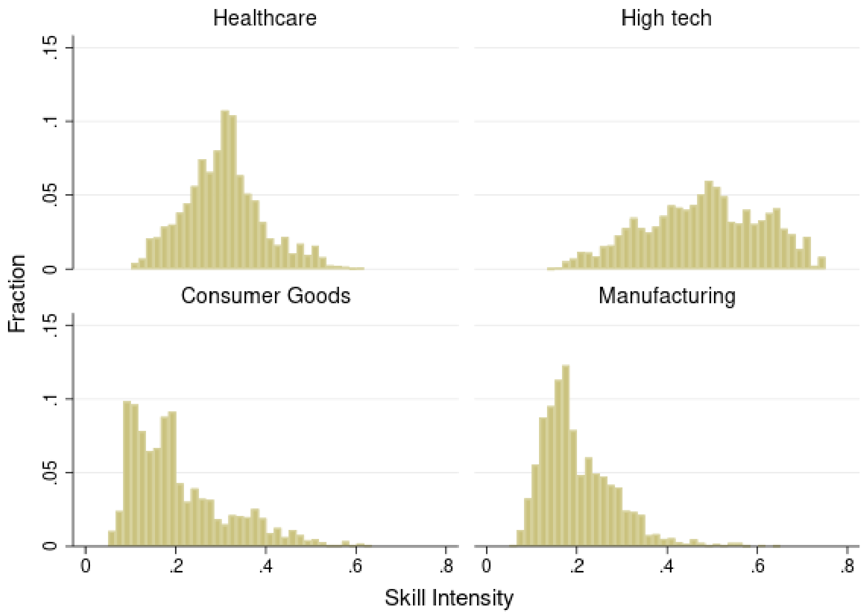
Note: This figure shows the histogram of intangible ratio for some selected industries.

Figure A3: Skill Intensity - Histogram



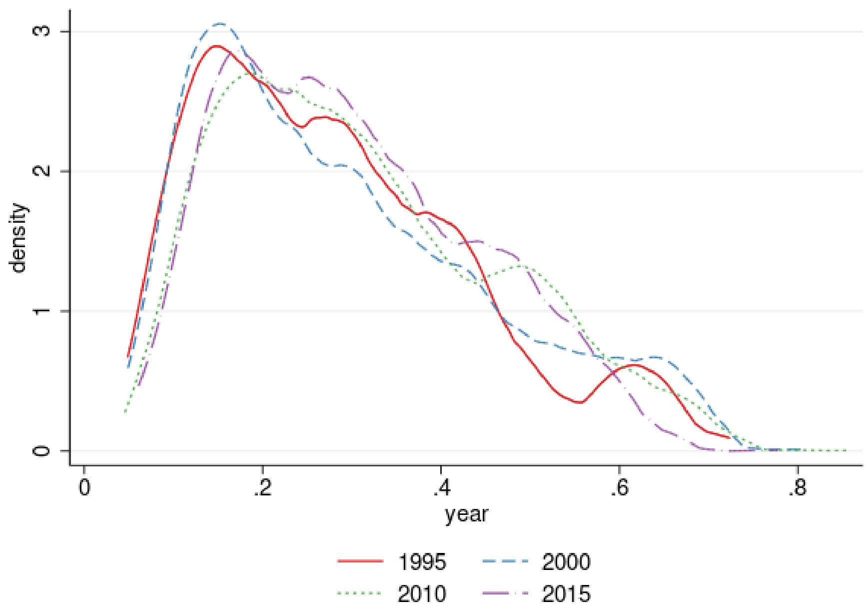
Note: This figure shows the histogram of skill intensity.

Figure A4: Skill Intensity - Industry Variation



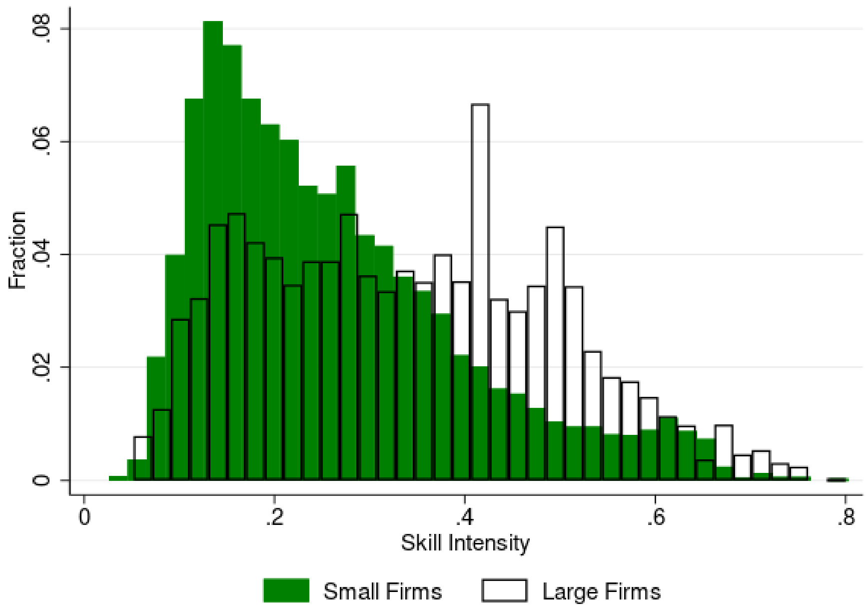
Note: This figure shows the histogram of skill intensity for some selected industries.

Figure A5: Skill Intensity - Kernel Density



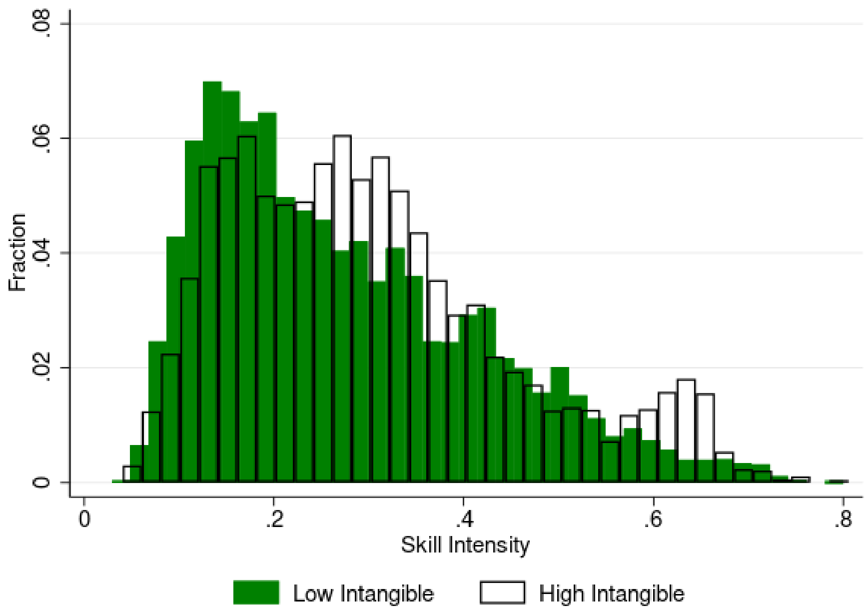
Note: This figure shows the kernel density of skill intensity for several selected years.

Figure A6: Skill Intensity - Histogram by Firm Size



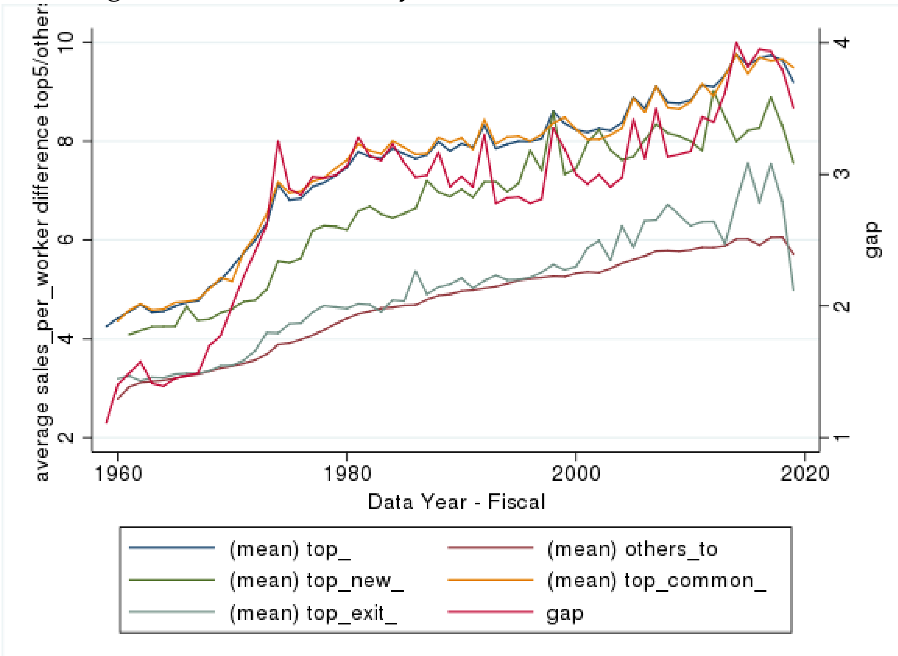
Note: This figure shows the histogram of skill intensity by small and large firms.

Figure A7: Skill Intensity - Histogram by Intangible Ratio



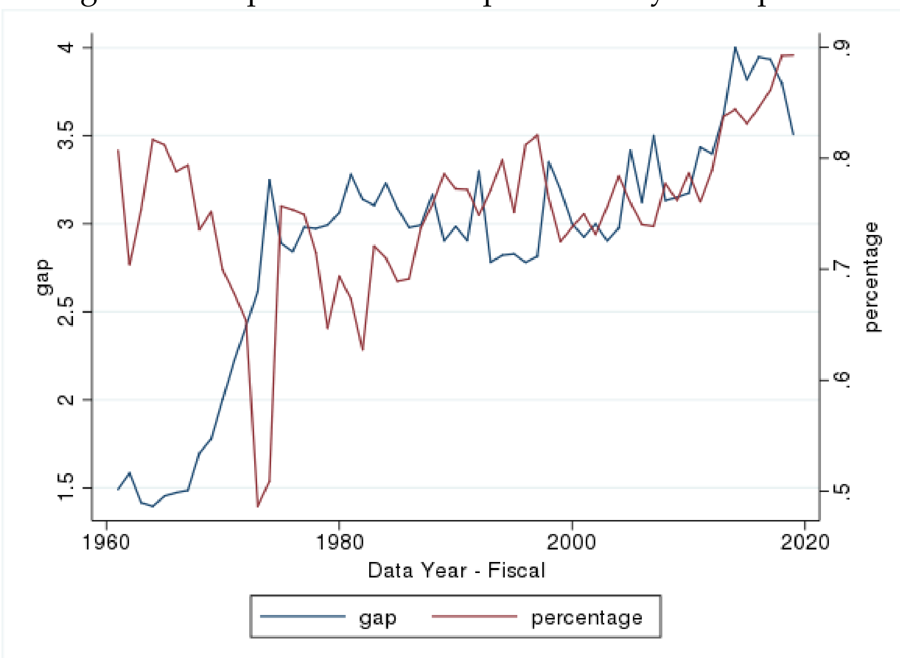
Note: This figure shows the histogram of skill intensity by low and high intangible intensive firms.

Figure A8: Productivity of Leader and Follower Firms



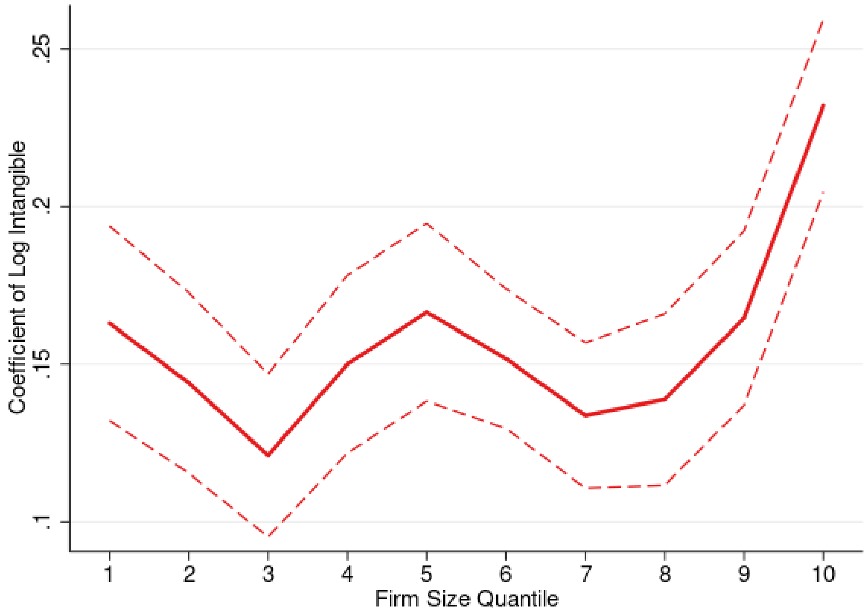
This figure shows the annual average of log of productivity (sales per worker) for firms that are among the following classifications: Top_Common: Firms that are in the top 5% in terms of total sales in the consecutive two years, Top_New: Firms that are in the top 5% in terms of total sales in the current year but were not in the previous year, Top_Exit: Firms that were in the top 5% in terms of total sales in the previous year, but are not in the current year.

Figure A9: Top %5 - Leadership Persistency for Top Firms



Note: This figure shows the leadership persistency, which is measured as the percentage of top %5 firms (based on sales per worker) at time t that are also classified as leader firms at time $t+1$.

Figure A10: Quantile Regression - Complementarity Effect (Level)



Note: This figure shows the coefficient of intangible capital in the regression of Table A6 within size quantiles.

A.3 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.

A.3.1 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).[1] The algorithm relies on a web search engine to match the company name variations found on patents to the corresponding firm records.

1. For details of the matching algorithm, see the David Dorn's data page.

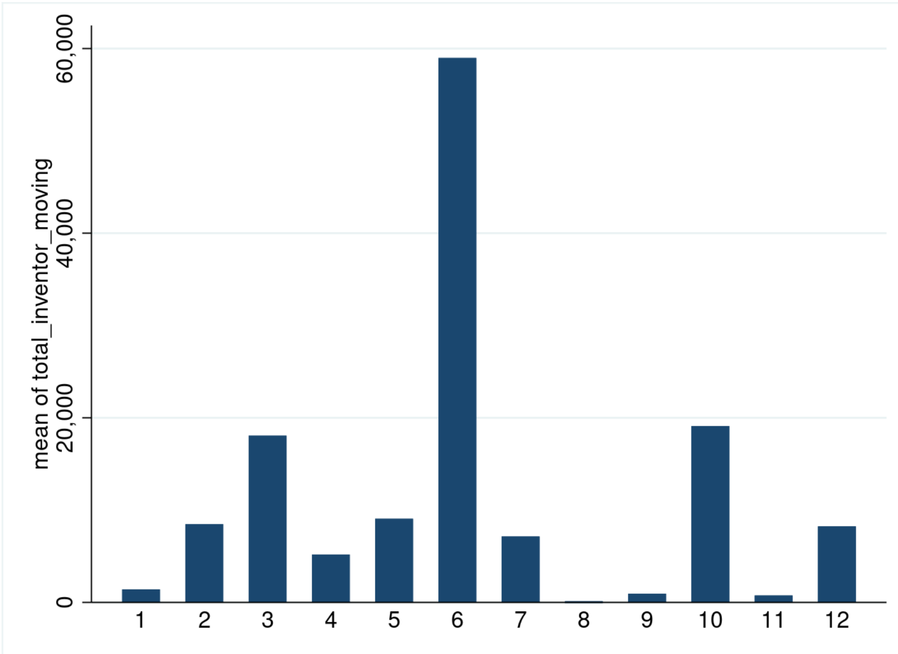
The matching results uniquely link assignee identification numbers from patent data to public firms' permanent identification numbers (i.e., "GVKEY") in the Compustat database.

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 identify 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.

Figure A11 shows the total number of mobile inventors for Fama-French 12 industries. We observe that the highest degree of inventor mobility is realized

Figure A11: Total Number of Mobile Inventors



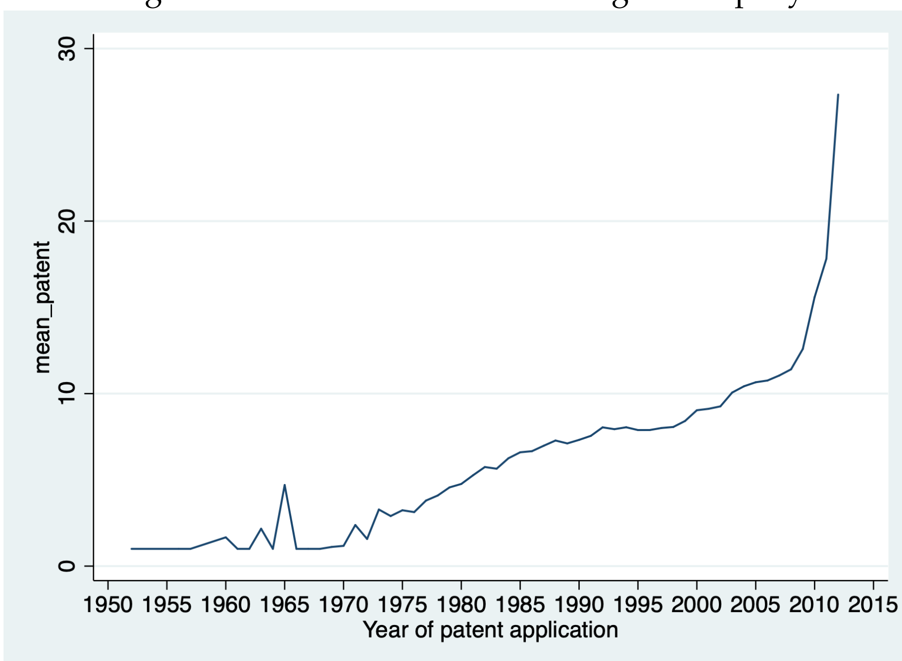
Note: This figure shows the total number of mobile inventors throughout our sample for Fama-French 12 industries. We label each Fama-French 12 industries as follows: 1 "Consumer Non-Durables", 2 "Consumer Durables" , 3 "Manufacturing", 4 "Oil, Gas, and Coal", 5 "Chemicals", 6 "Computers, Software, and Electronic Equipment", 7 "Telephone and Television", 8 "Utilities", 9 "Wholesale, Retail", 10 "Healthcare", 11 "Finance", 12 "Other".

at "Computers, Software, and Electronic Equipment" and "Healthcare" industries, which also have higher intangible capital intensity than the economy-wide average.

A.3.2 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 A12 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, skilled inventors become a scarce input in the labor market.

Figure A12: 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 A13a 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 A13b shows that while inventor mobility to lower intangible capital 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 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 the declining trend in inventor mobility in the economy.

Suppose we focus on the total number of inventors rather than only inventors who move. In that case, we also see a strong and positive association between the firm-level total number of skilled inventors and intangible capital. Figure A14a 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 higher than 50% almost all the time. Another fact in Figure A14b shows that the correlation between the

Figure A13: Inventor Mobility and Intangible Capital

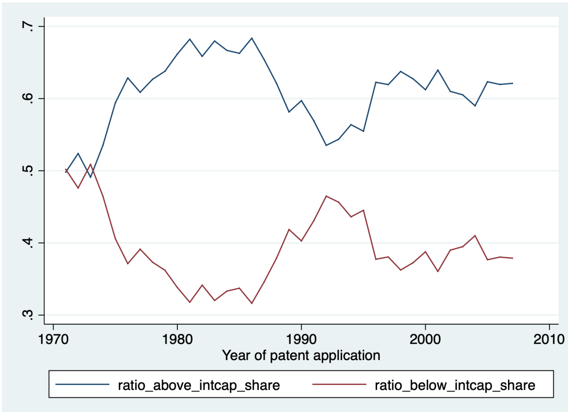
(a) Inventor Mobility (b) Inventor Mobility by Intangible Capital

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

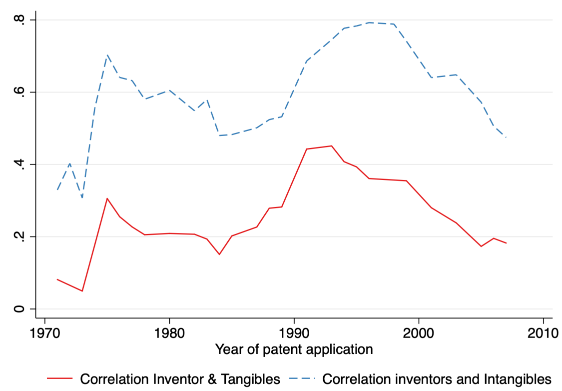
firm-level total stock of inventors and intangible capital is always higher than the correlation between the firm-level total stock of inventors and tangible capital all the time. Hence, we argue that the fluctuations in the total stock of inventors are in line with the fluctuations in intangible capital rather than tangible capital.

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 (3-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 A15 indicates that as firms' intangible capital share increases, the share of higher quality inventors they also have increases. Hence, we can argue a

Figure A14: Intangible Capital Intensity for Inventors



(a) Intangible Capital Intensity for Inventors

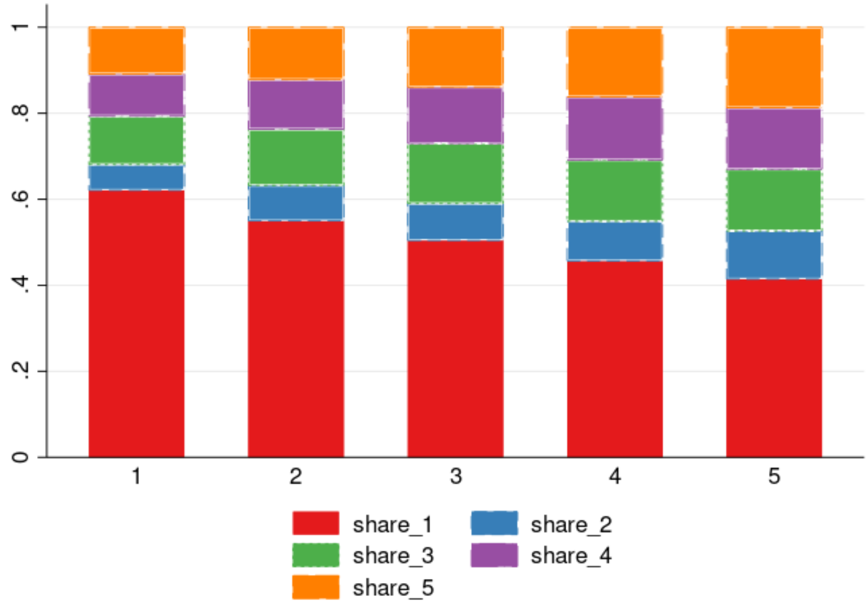


(b) Correlation

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 (red line) and the correlation between the firm-level number of inventors and intangible capital (blue dashed line). The correlations are computed between the number of total inventors working at a firm and this firm's tangible capital and intangible capital in each year.

strong 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 A16 that the assortative matching between inventor quality and intangible capital is even the fact for different 10-year windows.

Figure A15: The Share of Inventor Quality by Intangible per Asset (Quintiles)



Note: This figure shows the match between all potential quintiles of inventor quality and intangible capital intensity at the firm level. Inventor quality is based on the annual $\frac{\text{3-year window citation}}{\text{total patent}}$. x-axis denotes each intangible per asset quintile. y-axis denotes the corresponding share of each quintile of inventor quality within each quintile of intangible capital per asset.

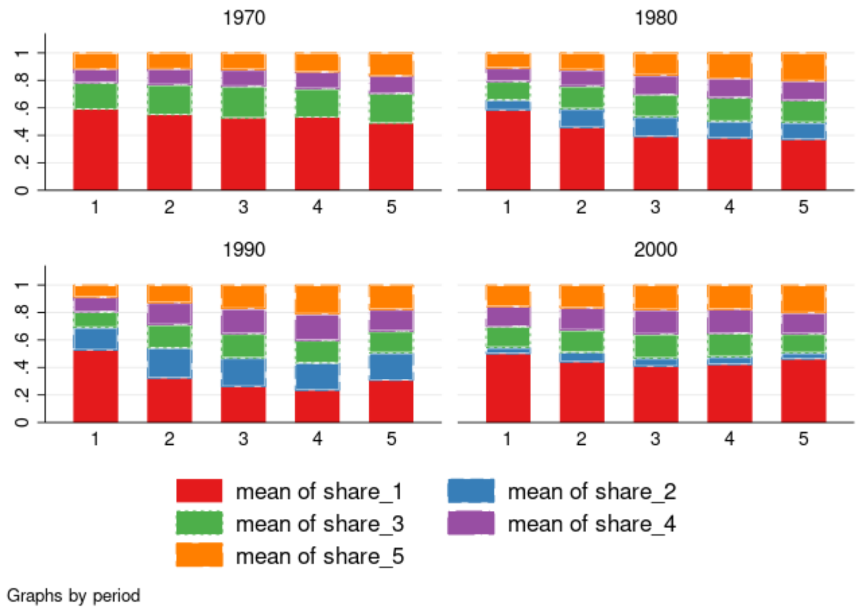
A.3.3 Empirical Analysis

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

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

Figure A16: The Share of Inventor Quality by Intangible per Asset (Quintiles) - 10-year window



Note: This figure shows the match between all potential quintiles of inventor quality and intangible capital intensity at the firm-level within 10-year window. For instance, the sub-part of the figure called "1970" denotes an average of the particular match for the years between 1970-1979. The inventor quality is based on the annual $\frac{\text{3-year window citation}}{\text{total patent}}$. x-axis denotes each intangible per asset quintile. y-axis denotes the corresponding share of each quintile of inventor quality within each quintile of intangible capital per asset.

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:

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

where subscripts $\{i, c, t, s\}$ index inventor, firm, year and sector, respectively. Our dependent variable is the total number of patent inventors i is granted at a firm c. $\mathbb{1}^{intangible_{i,c}}$ 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 A11 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 1.5 reports the results of the equation (A.1). The second column in Table 1.5 shows that inventors moving to bigger firms (firms with higher assets) are increasing their number of patents by 0.6 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 1.14 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. We also observe that the level of intangible capital also matters. As the intangible capital per worker increases by 1%, inventors produce 0.6 more patents. The effect of bigger firms (log of assets) is around one-third of it, 0.2. Thus, Table A7 reflects that the intangible capital makes the inventors more productive even when we control for the firm size.

TABLE A7: The Effect of Intangible Capital and Firm Size on Productivity of Mobile Inventors

	Number of Patent	Number of Patent	Number of Patent
$\mathbb{1}^{intangible_{i,c}}$	1.14***		0.995***
	(0.072)		(0.147)
$\mathbb{1}^{asset_{i,c}}$		0.631***	-0.148
		(0.067)	(0.148)
Size	0.242***	0.197***	0.162***
	(0.026)	(0.024)	(0.025)
Log Intangible per Worker	0.660***	0.585***	0.594***
	(0.057)	(0.051)	(0.054)
Inventor FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
R^2	0.502	0.491	0.489
N	270689	185638	171569

Note: This table shows the results of the regression specification (A.1). 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. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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:

$$patent_{i,c} = \beta_1[\mathbb{I}^{intangible_{i,c}} * \mathbb{I}^{asset_{i,c}}] + \beta_2 X_{c,t} + u_i + u_t + u_s + \epsilon_{it} \tag{A.2}$$

where $patent_{i,c}$ is the number of patents received by inventor i at firm c. 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. $\mathbb{I}^{intangible_{i,c}}$ 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. $\mathbb{I}^{asset_{i,c}}$ 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 (A.1), we also include inventor u_i, year u_t and sector u_s fixed effects.

Table A8 reports the estimation results of equation (A.2). In the second column, we observe that inventors moving to the firms with higher intangible and higher assets are generating 0.8 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 0.4 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 A8 indicates that inventors become more productive as they move to the bigger and higher intangible capital firm. The synergy between the asset and intangible capital makes the inventors more productive. If they move to a smaller but higher intangible firm, they are still more productive (granting 0.4 more patents) but not as productive as big firms (0.8 more patents).

In Section 1.2, we have shown the rise in productivity dispersion and that intangible capital dispersion is positively correlated with productivity dispersion. Table A8 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. The other supporting fact is that among the inventors moving to bigger assets or higher intangible capital firms, 80% of them move to both bigger and higher intangible capital firms. Only 8.8% moves to a bigger but smaller intangible capital firm while 10.8% goes to the smaller but higher intangible capital firm. This fact shows that 90% of the inventors prefer to work at bigger and higher intangible capital firms. Those inventors are becoming more productive and granting higher patents for the firms they are working at. Thus, it raises the productivity dispersion in favor of bigger firms in the U.S. economy.

TABLE A8: The Effect of the Interaction between Intangible Capital and Firm Size on Productivity of Mobile Inventors

	Number of Patent	Number of Patent
$\mathbb{I}^{asset_{i,c}} = 0 * \mathbb{I}^{intangible_{i,c}} = 0$	0	0
	(.)	(.)
$\mathbb{I}^{asset_{i,c}} = 1 * \mathbb{I}^{intangible_{i,c}} = 0$	-0.485**	0.088
	(0.18)	(0.181)
$\mathbb{I}^{asset_{i,c}} = 0 * \mathbb{I}^{intangible_{i,c}} = 1$	0.601***	0.425**
	(0.161)	(0.162)
$\mathbb{I}^{asset_{i,c}} = 1 * \mathbb{I}^{intangible_{i,c}} = 1$	0.918***	0.854***
	(0.092)	(0.092)
Size	0.123***	0.168***
	(0.03)	(0.03)
Log Intangible per Worker	0.348***	0.587***
	(0.063)	(0.064)
Inventor FE	Yes	Yes
Year FE	Yes	Yes
Industry FE	No	Yes
R^2	0.465	0.471
N	121778	121778

Note: This table shows the results of the regression specification (A.2). The dependent variable is the total number of patents a mobile inventor is granted at the destination firm. $\mathbb{I}^{intangible_{i,c}}$ ($\mathbb{I}^{asset_{i,c}}$) 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. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

APPENDIX B

APPENDIX TO INTANGIBLE CAPITAL AND COMPETITION IN RIDE SHARING: THE CASE OF LYFT-MOTIVATE MERGER

B.1 Tables

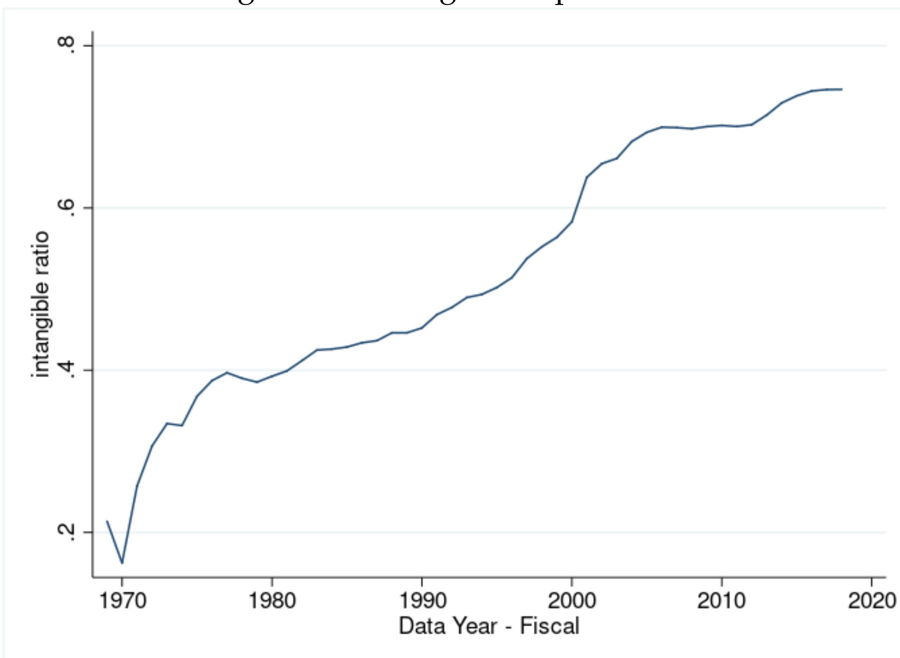
TABLE B1: Share of Ride-trips by Zone Category

Zone Category	Number of taxi zones	Share of Lyft trips	Share of Uber trips
Without Bike	161	0.329	0.352
With Bike	96	0.671	0.648

Note: This figure shows the number of taxi zones, and the market shares of Uber and Lyft for each category.

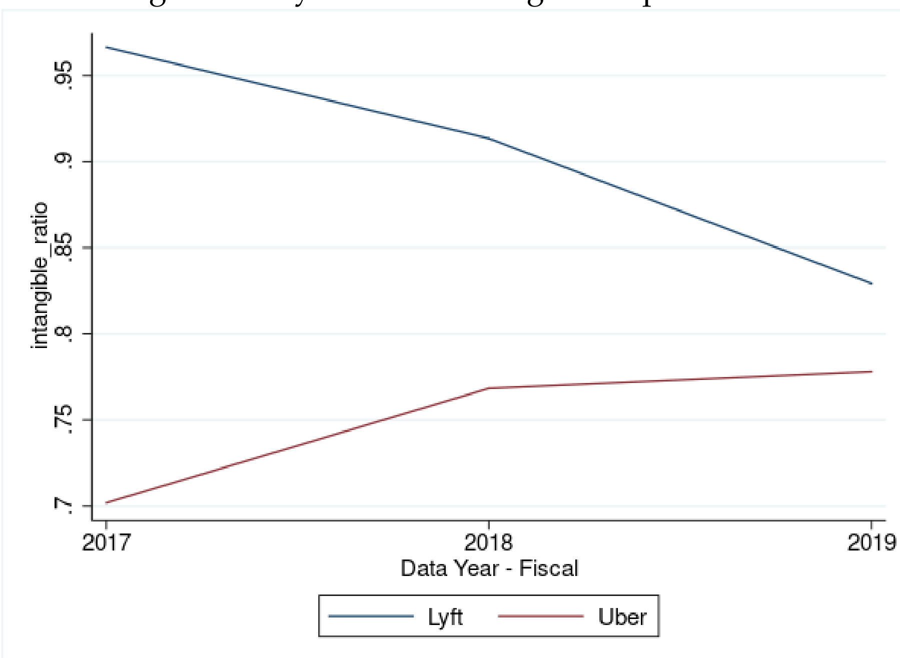
B.2 Figures

Figure B1: Intangible Capital Ratio



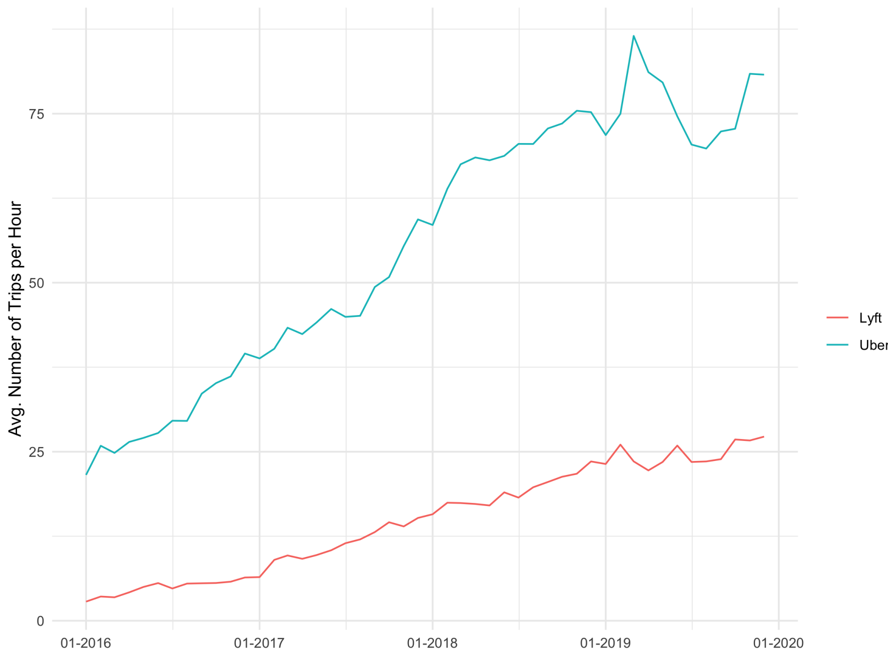
Note: This figure documents the annual average of intangible capital ratio in the Compustat data sample.

Figure B2: Lyft & Uber Intangible Capital Ratio



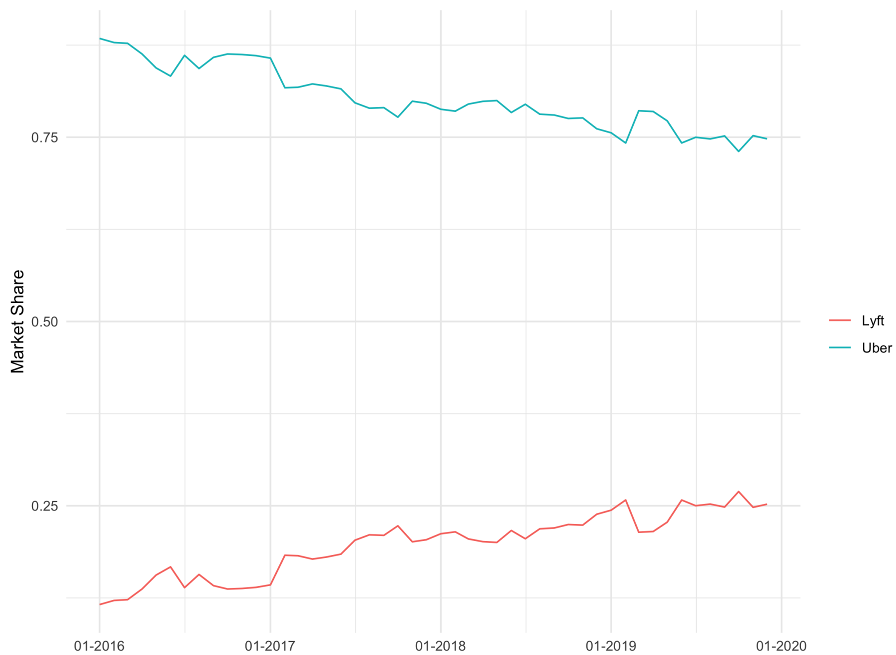
Note: This figure documents the annual intangible capital ratio of Lyft and Uber.

Figure B3: Average Number of Ride-trips Per Hour



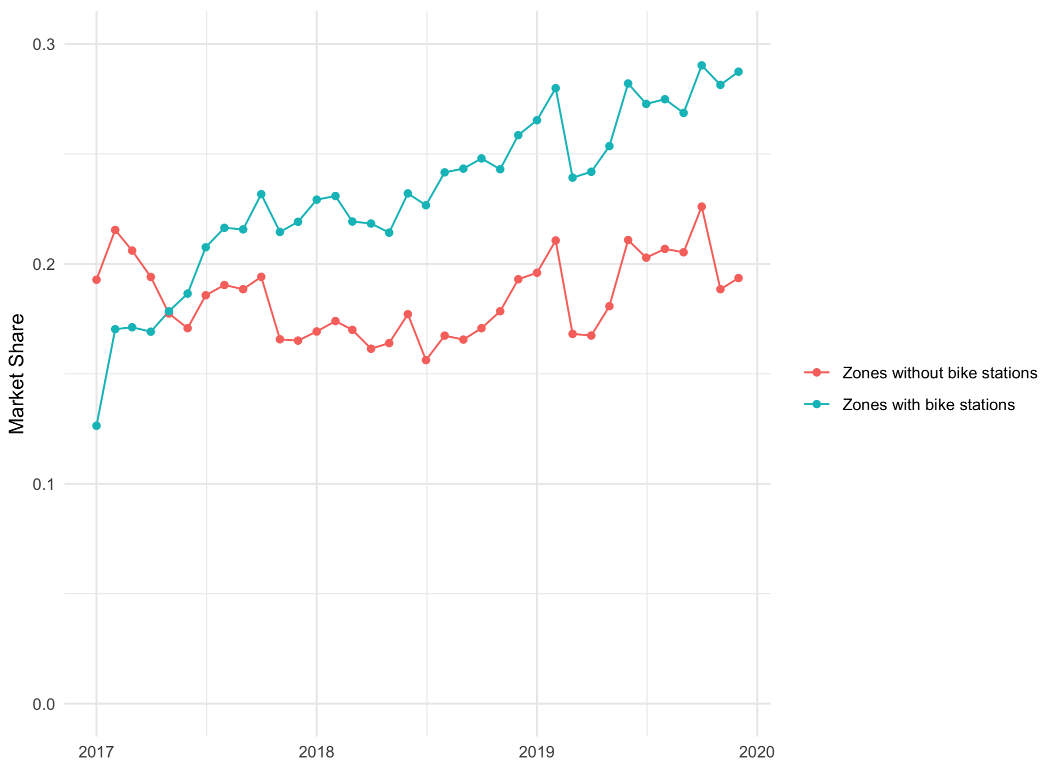
Note: This figure shows the average number of ride-trips per hour for Lyft and Uber.

Figure B4: Market Shares of Ride-trips



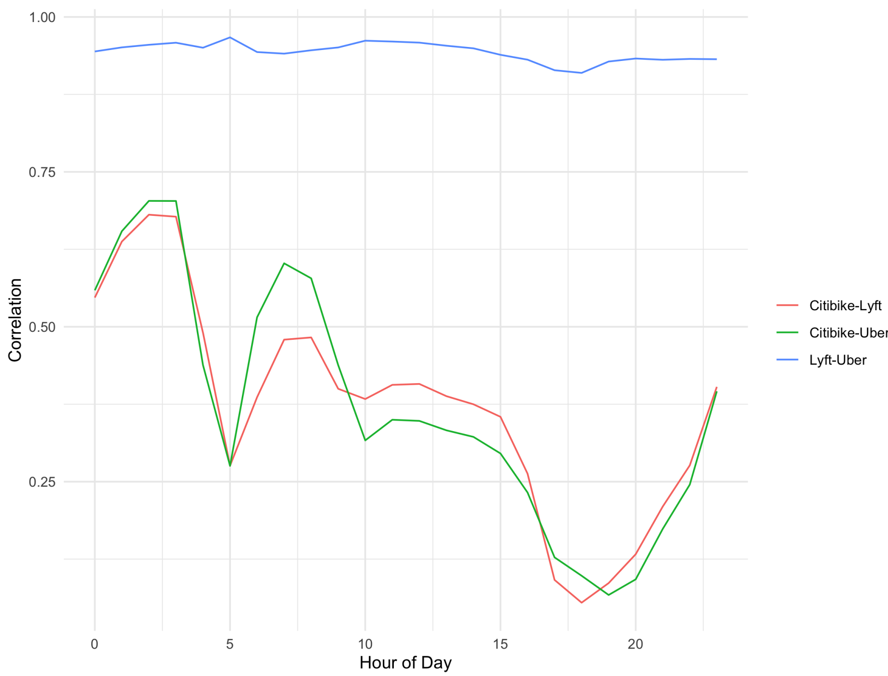
Note: This figure shows the market shares of Uber and Lyft in ride-sharing over time.

Figure B5: Lyft's Market Share at Taxi-zones with and without Bike Stations



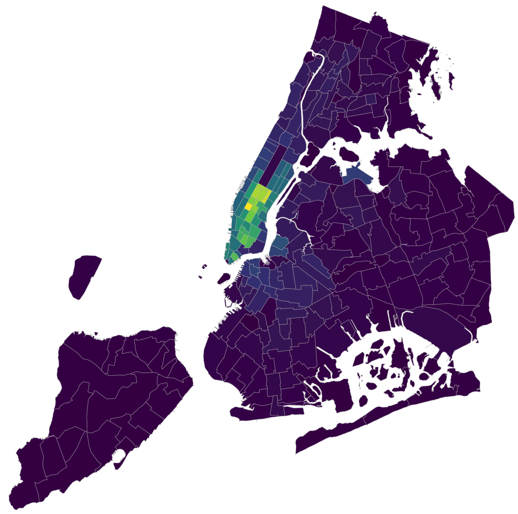
Note: This figure shows the market share of Lyft in ride-sharing over time at taxi-zones with and without bike stations.

Figure B6: Correlation of Number Trips Across Firms - By Hour



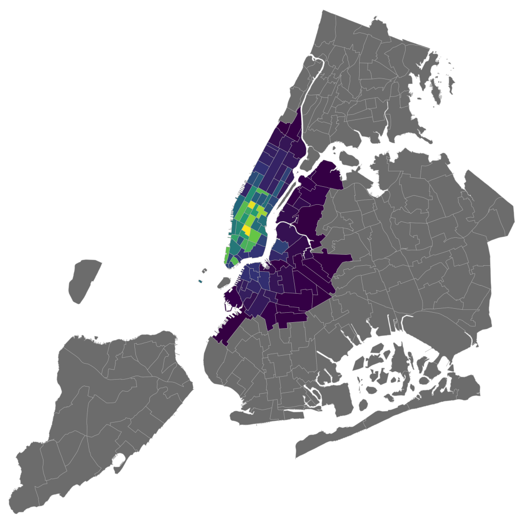
Note: This figure shows the raw correlation between the number of trips i) Lyft bike vs. Lyft ride, ii) Lyft ride vs. Uber ride and iii) Lyft bike vs. Uber ride in each hour in a day.

Figure B7: Ride-share Heatmap, New York City



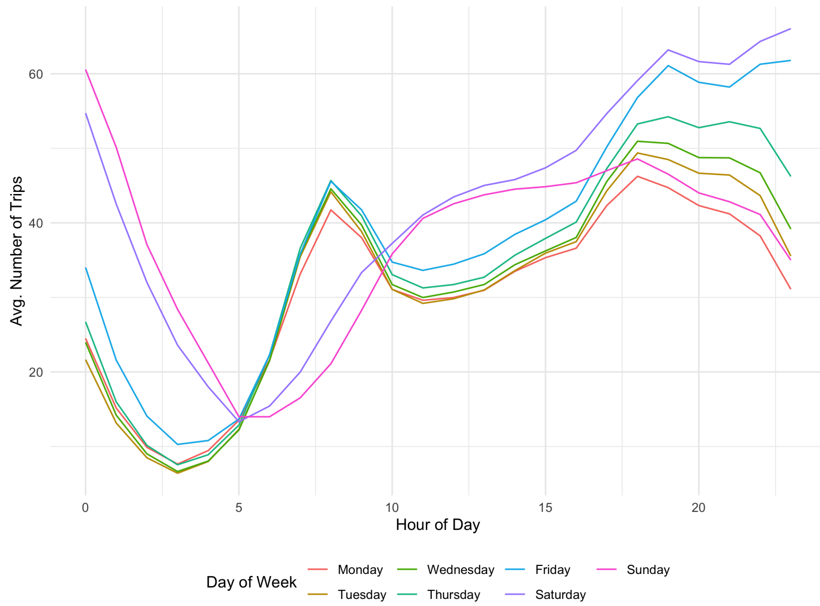
Note: This figures shows a map of taxi zones, where the colors represent the total ride share trips per square mile originating from each taxi zone. Lighter colors represent higher total ride share trips.

Figure B8: Bike-share Heatmap, New York City



Note: This figures shows where the with-bike and without-bike taxi zones are. Grey colors denotes the without-bike taxi zones. Lighter colors within the with-bike zones represent higher total bike share trips.

Figure B9: Average Number of Ride-sharing Trips - By Day and Hour



Note: This figures shows the average ride-sharing trips for each hour during each day of week.