ORGANIZATIONAL CAPITAL AND THE EFFECTS OF TECHNOLOGY SHOCKS ON THE CHARACTERISTICS OF EARNINGS

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A dissertation submitted to the faculty of the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Accounting.

Chapel Hill
2016

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ABSTRACT

VIVEK RAVAL: Organizational Capital and the Effects of Technology Shocks on the Characteristics of Earnings.
(Under the direction of Wayne Landsman and Robert Bushman)

The objective of this study is to hypothesize and test the effects that the introduction of new productive technologies into an economy have on the characteristics of earnings. To do this, I leverage theory from Eisfeldt and Papanikolaou (2013) that describes how economy-wide technology shocks affect the value of organizational capital, an important intangible asset. Because organizational capital is largely unrecognized in financial statements, I hypothesize that periods of technology shock are associated with lower earnings timeliness, particularly for firms with more organizational capital. I also hypothesize that technology shocks are associated with more subsequent goodwill impairment and restructuring, and that these associations are mediated by the quantity or efficiency of the firm's organizational capital. My findings support my hypotheses and demonstrate how investment in organizational capital creates exposure to aggregate technology shocks, the dynamics of which affect earnings quality.

ACKNOWLEDGMENTS

I thank my dissertation committee, Robert Bushman (co-chair), Wayne Landsman (co-chair), Mary Barth, Eva Labro, Mark Lang, and Sean Wang. I also appreciate comments from Travis Dyer, Atif Ellahie, John Hand, Bradley Hendricks, Preetesh Kantak, Nicholas Martin, Ed Maydew, Jim Omartian, Lorien Stice-Lawrence, Ed Sul, Donny Zhao, workshop participants at Dartmouth College, London Business School, the University of Arizona, the University of Colorado, the University of Illinois in Chicago, the University of North Carolina, Rice University, and participants at the Accounting Ph.D. Rookie Recruiting and Research Camp.

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CHAPTER 1: INTRODUCTION

In the right circumstances, the match between an employee and firm can generate value for the firm. However, employees are also free to leave their firms and ultimately control how they spend their time. These points underlie two important implications. First, because employees are not controllable by the firm, they are not accounted for as assets of the firm, creating a gap between firm value and the book value. Second, because employees may leave at will, the value that certain employees bring to a firm is at risk. This study investigates how these two implications interact during times of macro-economic shock to affect the dynamics of earnings timeliness and write-downs in earnings over time.

Organizational capital is an economically significant intangible asset that is created from the combination of a firm's technologies and key talent. Technologies are processes and systems that determine the efficiency with which a specific firm conducts its business. Key talent are the highly-skilled labor inputs that have the general education, experiences, and skills to deploy and manage technologies. Because organizational capital is based on both the firm's technologies and key talent, both the firm's shareholders and key talent have a claim to its value. In order to sustain organizational capital in a firm, the shareholders and key talent must share the value generated by organizational capital.

Aggregate, or economy-wide, technology shocks introduce more efficient processes and systems, and create large-scale potential for more efficient firms. This makes key talent more valuable in the economy, increasing their bargaining power, and changing how the value of organizational capital is shared between key talent and shareholders. Because shareholder's value in organizational capital fluctuates based on undiversifiable economy-wide technology shocks, firms with organizational capital are exposed to systematic risk. This theory, attributable to Eisfeldt and Papanikolaou (2013), provides a framework by which researchers can consider how fluctuations in the aggregate economy can affect the value of an important intangible asset.

The objective of this study is to hypothesize and test how technology shocks can affect the characteristics of earnings. I use Eisfeldt and Papanikolaou (2013) as a theoretical foundation on which I construct my hypotheses. The theory has two main implications relevant to this study. First, aggregate technology shocks reduce shareholders' value in organizational capital. Second, aggregate technology shocks increase the likelihood that firms reorganize around a new technology, particularly if they are less efficient.

Based on the theorized outcomes in Eisfeldt and Papanikolaou (2013), I form three sets of hypotheses. First, I hypothesize that earnings is less timely in reflecting of contemporaneous changes in value during times of aggregate technology shocks. Because internally-generated intangible assets are generally off-balance sheet, organizational capital is also likely to be off-balance sheet (Lev and Radhakrishnan 2005). When technology shocks reduce shareholders' value in organizational capital, the accounting system has no asset to write-down, so the accounting system will need to reflect the value through transactions over time, reducing its timeliness. Because technology shocks affect earnings by changing the value of organizational capital, I expect the effect of technology shocks on earnings to be stronger for firms with more organizational capital investment.

Second, because technology shocks reduce the value of organizational capital, I expect that firms will record more goodwill impairment subsequent to technology shocks. Acquisition accounting is a special case in which acquired internally-generated intangible assets may be recognized on the balance sheet as acquired goodwill. Therefore, after acquisition, the purchase price of organizational capital is part of the balance of acquired goodwill. Technology shocks reduce the value of acquired organizational capital, triggering goodwill impairment. Because firms with more organizational capital in goodwill are likely to record more impairment, I expect the effect of technology shocks on goodwill impairment to be stronger for firms with high levels of organizational capital investment.

Third, because technology shocks increase the likelihood of reorganizing the firm around a new technology, I hypothesize that restructuring charges increase subsequent to technology shocks.

Adopting a new technology requires that a firm reorganize its processes and systems, and allows a firm to increase its efficiency. This can result in the consolidation of facilities and the reduction or relocation of labor. These costs are recognized as restructuring charges. Because firms that have higher efficiency are less likely to restructure, I expect that the effect is lower for more efficient firms.

My empirical strategy for identifying technology shocks is also grounded in the theory in Eisfeldt and Papanikolaou (2013). A theorized outcome of technology shocks is that they reduce shareholders' value in organizational capital. Accordingly, to identify periods of technology shocks, I borrow from Eisfeldt and Papanikolaou (2013), and use a hedge portfolio that is designed to measure the economy-wide industry-balanced returns to organizational capital. Low portfolio returns indicate low organizational capital returns and periods of aggregate technology shock.

My results provide evidence consistent with my hypotheses. Using both an aggregate and more firm-specific measure of earnings timeliness, I find that technology shocks are associated with lower earnings timeliness, and that this is particularly the case for firms with higher organizational capital. I also find evidence that goodwill impairments and restructuring charges increase subsequent to technology shocks, and that this effect is stronger (weaker) firms with higher levels of organizational capital investment (efficiency).

Findings from my study shed light on how the dynamics of the aggregate economy affect the time-series and cross-sectional variation in the characteristics earnings. This study speaks to the call for research on the interaction between the fundamental drivers of firm performance and earnings quality (Dechow, Ge, and Schrand 2010). Also, because this study focuses on organizational capital, findings can contribute to the literature on intangible assets. Specifically, studies such as Srivastava (2014); Lev and Zarowin (1999) imply that investment in intangible assets expose firms to fluctuations in value that are not well measured by earnings. My study demonstrates one way in which investment in a specific intangible asset, organizational capital, can expose firms to aggregate shocks that ultimately affect the characteristics of earnings.

The remainder of this paper is organized as follows. Chapter 2 outlines the theory describing how technology shocks affect shareholders' value in organizational capital, and describes how these constructs are operationalized. Chapter 3 develops hypotheses, Chapter 4 develops the research design, Chapter 5 describes the data, and Chapter 6 presents the results. Chapter 7 concludes the study.

CHAPTER 2: CONCEPTUAL FRAMEWORK

2.1 Organizational Capital and Technology Shocks

Organizational capital is a combination of key talent with technologies that generates firm-specific efficiencies (Eisfeldt and Papanikolaou 2013; Lev and Radhakrishnan 2005). Technologies are the processes, procedures, and systems that define how a company conducts its business. Key talent are highly capable labor inputs that have the general set of skills and education required to implement and manage technologies. The premise of organizational capital is that a firm is more than just the sum of components that can be obtained in the market. Instead, a firm is a unique combination of assets worth more than those assets alone, and organizational capital is a component of the economic goodwill that is created by organizing assets into a firm (Zingales 2000; Johnson 2015; Lev and Radhakrishnan 2005).

Key talent is an essential component of organizational capital. Key talent is different from commodity labor in that key talent have a general set of skills that can make new technologies, which are of limited value on their own, useful in business. Generally, key talent are in executive, senior management, engineering, or research roles. One of many examples may be Jeff Bezos, an engineer who left Wall street to found Amazon.com. At Amazon.com, Bezos successfully initiated projects in e-commerce, cloud computing, and media streaming, demonstrating his talent for technology implementation and management.

Technologies are also inherent to organizational capital. Technologies specify how business gets done at a firm — the methods by which a firm uses its key talent to generate value. According to Evenson and Westphal (1995), technologies can contribute to three types of organizational capital efficiencies. First, they may contribute to a firm's production or operational efficiencies. This includes the ways that a firm executes engineering, design, manufacturing, marketing, or sales (Lev and Radhakrishnan 2005). An example of a firm with such capabilities is Apple Inc., which has leading product reputation and brand value (Badenhausen 2015). Second, technologies may also enhance investment efficiencies, such as project selection, training, or other corporate finance or risk management activities (Lev and Radhakrishnan 2005). For example, Kellogg's leads its industry in managing the risk of drought through the use of derivatives (Farrell and Blas 2010). Third, technologies may enhance innovation capabilities, such as the firm's R&D activities or efforts to procure or protect intellectual property from third parties (Lev and Radhakrishnan 2005). IBM is an example of a firm wiablth such capabilities. The US patent office has awarded IBM the most patents of any firm for 22 years in a row as of 2014, a feat some attribute to IBM's special teams and processes focused on patent filing (IBM 2015; Bort 2015).

Technology shocks are the introduction of new processes, procedures, and systems that dramatically increase the efficiency of firms organized around the new technology. For example, the introduction of the World Wide Web sparked the founding of Internet-based e-commerce firms. These firms designed their operations to take advantage of the Internet, and created dynamic centralized sales channels. Traditional firms, however, remained anchored to their investment in the bricks-and-mortar sales channel. Accordingly, the introduction of Internet technology created an efficiency difference between traditional firms and new or newly reorganized firms.

The intuition behind Eisfeldt and Papanikolaou (2013) is that technology shocks increase the value of key talent's option to leave their firm. When new technologies are introduced, the efficiency of newly organized firms increases, creating more valuable business start-up or reorganization opportunities. This increases the retention costs of key talent, because firms must compensate key talent at the level commensurate with their outside opportunities. From this intuition, Eisfeldt and Papanikolaou (2013) draws its main conclusions.

2.2 Theory

Eisfeldt and Papanikolaou (2013) identifies two defining characteristics of organizational capital. First, key talent embody organizational capital, which makes it distinct from physical capital and prevents shareholders from having full property rights over organizational capital. Second, the efficiencies generated by organizational capital are specific to the firm's technologies, which makes it distinct from commodity labor.[1] This makes organizational capital a special asset because both key talent and shareholders have a claim to its cash flows. Accordingly, the value of organizational capital must be split between the firm's key talent and shareholders, and a sharing rule must be in place that dictates how these cash flows are split. The theory in Eisfeldt and Papanikolaou (2013) develops this sharing rule, and describes how technology shocks affect it.

The illustrative model in Eisfeldt and Papanikolaou (2013) endows a firm with organizational capital. By definition, this organizational capital is embodied in key talent, and it has a firm-specific efficiency. Because the key talent embody the organizational capital, and because shareholders do not have property rights over key talent, the key talent have the one-time option move the organizational capital to a new firm at any time.[2] When key talent move the organizational capital from the old to the new firm, the its efficiency improves from the endowed firm-specific level, ε_i, to the most efficient, or frontier, level available at the time of the move, x_t, and it operates at that efficiency thereafter.

Eisfeldt and Papanikolaou (2013) assumes that there exists an optimal threshold of frontier efficiency, x_t, labeled $\bar{x}$, at which it is more efficient to upgrade organizational capital versus continuing to operate at the firm's current efficiency, ε. The intuition behind this requirement is that all technologies are eventually sufficiently surpassed such that it is more efficient to upgrade to the new technology versus retaining the old technology and waiting to upgrade.

The total value of organizational capital, V^{Total}, becomes:

$$V^{Total} = \text{Value of}(\text{Operating at } \varepsilon + \text{Option to Upgrade to } \bar{x}), \tag{ep1}$$

[1]These characteristics allow organizational capital to be defined as firm-specific human capital, consistent with Prescott and Visscher (1980).

[2]For simplicity, the illustrative model assumes that key talent can exercise the option to move the organizational capital to a new firm once. The more intricate model in Eisfeldt and Papanikolaou (2013) relaxes the one-time upgrade constraint and introduces a cost to adopting a new technology. This is consistent with the idea that new technologies require development of processes and training of employees to optimize new technology (Brynjolfsson and Hitt 2000). The more intricate model from Eisfeldt and Papanikolaou (2013) provides insights similar to those of the illustrative model. The model also has the same implications if shareholders control the decision to move organizational capital to a new firm.

Because of the special nature of organizational capital, V^{Total} must be shared between the shareholders and the key talent. The key talent control the option to move the organizational capital to a new firm, and therefore can obtain the value of operating at the current frontier efficiency, x_t, at any time. The value of operating at x_t dictates the participation constraint for key talent. If key talent capture less than the value of operating at x_t within the firm, the key talent will be better off moving the organizational capital outside of the firm. Accordingly, shareholders must compensate key talent at the value of operating at x_t. The residual value of organizational capital is captured by shareholders:

$$\begin{aligned} V_{i,t}^{Shareholders} = \text{Value of}(&\text{Operating at } \varepsilon \\ &+\text{Option to Upgrade to } \bar{x} \\ &-\text{Operating at } x_t). \end{aligned} \tag{ep2}$$

At any time when the frontier efficiency, x_t, is less than upgrade threshold, $\bar{x}$, upgrading to the new technology is sub-optimal. This creates a positive difference between the value of the option to upgrade to $\bar{x}$ and operating at x_t, which is the value captured by shareholders. If the frontier efficiency, x_t, is very far from the optimal level, $\bar{x}$, the benefits to waiting to upgrade far outweigh the benefits of upgrading immediately, and shareholders capture substantial value. However, as x_t increases, the difference between the option value and operating at x_t shrinks, along with the value that is captured by shareholders. Intuitively, as the firm gets closer to its optimal upgrade point, the difference between waiting and not waiting to upgrade shrinks. Eventually, when x_t reaches $\bar{x}$, the value of waiting goes to zero, and key talent will upgrade the technology from an efficiency of ε to $\bar{x}$.

Figure B.1 provides a graphical representation of the value of the components of organizational capital relative to the frontier efficiency, x. At the firm's inception, it operates at the frontier efficiency, where $x = \varepsilon$. At this point, operating at x has the same value as operating at ε. At this point, the option to upgrade to $\bar{x}$ has positive value, creating a difference between the value of the option of upgrading later versus now. This is the value captured by shareholders, as represented by the shaded area. As x approaches $\bar{x}$, the difference between upgrading at $\bar{x}$ and upgrading at x shrinks. Accordingly, the value for shareholders decreases in x.

Eisfeldt and Papanikolaou (2013) uses this illustrative model to describe how technology shocks affect the value of shareholders and the behavior of key talent. Technology shocks are interpreted in the model as an increase in the frontier efficiency of organizational capital, x. Based on the model, Eisfeldt and Papanikolaou (2013) generate five key outcomes of technology shocks:

Outcome 1: Technology shocks (increases in x) increase compensation to key talent. This is because key talent can demand the outside option value from shareholders, and the outside option value is increasing in x.

Outcome 2: Technology shocks reduce shareholder value in organizational capital. This is because compensation to key talent increases at a faster rate than the value of the option to upgrade at the optimal threshold.

Outcome 3: The effect of technology shocks on shareholder value is increasing in the quantity of organizational capital in the firm. Intuitively, firms with more organizational capital are more affected by changes to its value.

Outcome 4: When the frontier level of technology reaches a threshold ($x = \bar{x}$), key talent will upgrade the organizational capital to the frontier efficiency level. Bigger technology shocks are more likely to result in upgrades.

Outcome 5: The re-organization threshold, $\bar{x}$, is increasing in the efficiency of the firm's organizational capital, ε_i. This is consistent with more efficient firms being less likely to adopt new technologies.

2.3 Operationalization of Technology Shocks and Organizational Capital

One way to measure technology shocks is to directly measure the change in technology and the degree to which certain firms are affected. However, technology shocks, by nature, have varied causes and as a result are likely to have variation in the degree they affect particular firms. The introduction of new technologies may affect primarily firms in a certain industry, such as the introduction of just-in-time manufacturing. However, new technologies can also have a broader effect, such as the introduction of the World Wide Web, which affected how companies in general communicate.

To overcome the challenge of directly identifying and measuring technology shocks, Eisfeldt and Papanikolaou (2013) takes an indirect measurement approach grounded in the theory, and focuses on technology shocks that are large enough to be detectable economy-wide. Theoretical Outcome 2 suggests that technology shocks reduce shareholder's value in organizational capital. Therefore, to identify periods of aggregate technology shock, Eisfeldt and Papanikolaou (2013) uses the aggregate returns to organizational capital. Periods of low aggregate returns to organizational capital are consistent with periods of aggregate technology shock.

To measure the aggregate returns to organizational capital, Eisfeldt and Papanikolaou (2013) uses a hedge portfolio that is long in high organizational capital investment, and short in low organizational capital investment. The study sorts firms into quintiles based on their level of investment in organizational capital, as described below, within industry and year.[3] The firms in the top quintile comprise the long side of the portfolio, and firms in the bottom quintile comprise the short side. Because the portfolio is based on ranks within industry, it represents the industry distribution present in the economy, i.e., if an industry is a large fraction of the aggregate economy, it will also be a large fraction of the portfolio. However, because the representation of each industry is the same in the long and short sides of the portfolio, the returns do not represent differences among industries. Portfolios are re-balanced in July.

[3]Industries are based on the Fama and French (1997) 17 industry categories.

Because technology shocks have more of an affect on firms with more organizational capital (Outcome 3), the long side of the portfolio is disproportionately affected by technology shocks, while uncorrelated effects will be captured in both the long and short side of the portfolio. The annual value-weighted return to this portfolio, called OMK, measures the aggregate return to organizational capital. Based on Outcome 2, lower returns to OMK are consistent with times of technology shock.

Consistent with Lev and Radhakrishnan (2005), Eisfeldt and Papanikolaou (2013) uses selling, general, and administrative expense (SG&A) as the measure of organizational capital investment. SG&A embeds costs that cannot be directly attributed to the output of the firm and therefore are more likely to be related to investment in key talent and the technologies of the firm. SG&A reflects costs related to technology because it includes IT spending, systems consulting, development of internal knowledge, communication systems, and logistics systems. SG&A also captures costs related to key talent, including the wages and incentives of executives, engineers, researchers, and marketing and sales people, employee training, and strategy and organizational consulting. Also, because SG&A is available for a long time period and for a large cross-section of firms, it allows for a large sample.

Eisfeldt and Papanikolaou (2013) calculates organizational capital investment, OC as:

$$OC_{i,t} = (1 - \delta_{OC})OC_{i,t-1} + \frac{SGA_{i,t}}{cpi_t}, \tag{2.1}$$

where SGA is SG&A, cpi is the consumer price index, δ_{OC} is the depreciation rate of organizational capital, and i and t refer to firm and year. To implement this measure Eisfeldt and Papanikolaou (2013) calculates a starting value of organizational capital:

$$OC_0 = \frac{SGA_1}{g + \delta_{OC}}, \tag{2.2}$$

where g is the growth rate of SG&A investment. δ_{OC} is equal to 15%, the 2006 Bureau of Economic Analysis (BEA) depreciation rate for R&D (Eisfeldt and Papanikolaou 2013), and g equals

10%, the average real growth rate of SG&A that is observed in the sample of firms used in Eisfeldt and Papanikolaou (2013).[4] Missing values of SG&A are assigned a value of zero. Ranks of OC are based on prior-year amounts, scaled by total assets.

The assumptions underlying organizational capital measurement are likely to induce measurement error. To reduce the effect of error, Eisfeldt and Papanikolaou (2013) constrains the use of OC to cross-sectional ranks within industry and time period. Ranking within a time period reduces the effect of error in growth rates, depreciation rates, and the price index. Ranking within industry and time reduces the effect of including costs unrelated to organizational capital in OC. Specifically, to the extent costs unrelated to organizational capital are in SG&A, and if the fraction of such costs is consistent within an industry and time period, then ranking OC within industry mitigates their effect.

2.4 Empirical Validation

Eisfeldt and Papanikolaou (2013) performs tests to empirically validate the measure of organizational capital, OC. The theoretical model implies that key talent are at risk of departing, and that this is costlier for firms with more organizational capital. Public firms must disclose risks in their 10-K filings. In order to test whether firms with higher levels of OC are more exposed to the risk of key talent's departure, Eisfeldt and Papanikolaou (2013) tests whether the top quintile of high OC firms disclose the loss of key personnel more frequently as a risk factor in their 10-K filings. Using a random sample of 100 firm-years from 1996 to 2005, Eisfeldt and Papanikolaou (2013) finds that 48% of firms in the top quintile list the loss of key personnel as a risk, while only 20% of firms in the bottom quintile do, and statistically significant difference (t-stat = 3.06).

Eisfeldt and Papanikolaou (2013) also finds that firms with high OC demonstrate higher levels of managerial talent. To measure managerial talent, Eisfeldt and Papanikolaou (2013) uses the results from an interview-based survey tool from Bloom and Van Reenen (2007). Bloom and Van Reenen (2007) uses the tool to demonstrate that higher managerial capability is associated

[4] Eisfeldt and Papanikolaou (2013) has a sample largely overlapping the one in this study, so I do not change this value for my implementation of OMK.

with higher IT productivity, more efficient production, and better firm performance. To test if higher OC firms employ more capable managers, Eisfeldt and Papanikolaou (2013) uses a sample of firms that overlap with the sample in Bloom and Van Reenen (2007), and regresses OC on the managerial talent scores,

$$OC_{i,t} = a + bM_i + u_{i,t}, \tag{2.3}$$

where M is the managerial talent score, and standard errors are clustered by firm. The regression provides a significantly positive b, suggesting that firms with higher managerial talent also have higher levels of OC.

Technology is also a significant portion of organizational capital, and Eisfeldt and Papanikolaou (2013) also finds that high OC firms have more demand for IT. Using the IT spending budget information published in *Information Week* for the years 1995 and 1996, Eisfeldt and Papanikolaou (2013) finds that, for a sample of 500 firms, IT spending is increasing with OC, and that firms in the top quintile of OC spend almost twice as much on IT relative to firms in the bottom quintile.

Eisfeldt and Papanikolaou (2013) also finds that firms with high OC are more likely to demonstrate evidence of a missing factor of production when a measure of organizational capital is not considered. Specifically, in a regression of log sales on log capital and labor, high OC firms have higher residuals.

The descriptive statistics in Eisfeldt and Papanikolaou (2013) also provide evidence consistent with OC measuring organizational capital. Based on median statistics by quintile of OC, Eisfeldt and Papanikolaou (2013) shows that Tobin's Q, executive compensation, and labor expense per employee are all monotonically increasing in OC, consistent with higher organizational capital firms depending on more skilled employees and generating more output relative to their recorded assets. Investment in physical assets, and the amount of physical capital to labor is decreasing in OC, consistent with lower OC firms relying more on physical capital and commodity labor to generate output.

Eisfeldt and Papanikolaou (2013) also validates the measure of technology shock, OMK. The theory suggests that technology shocks increase compensation to key talent (Outcome 1). To empirically test this, Eisfeldt and Papanikolaou (2013) estimates the following regression:

$$\Delta\bar{w}_t = a_0 + b_0 OMK_t + b_1 OMK_{t-1} + c_0 MKT_t + c_1 MKT_{t-1} + \rho\Delta\bar{w}_{t-1} + e_t, \tag{2.4}$$

where $\bar{w}$ is the log of aggregate executive compensation, measured using the top three executives, or the CEO only, from Frydman and Saks (2010), MKT is the return of the market, and OMK is the measure of technology shock, as previously defined. Estimations indicate that b_1 and the sum of b_0 and b_1 are negative and statistically different from zero. This suggests that, consistent with the theory, technology shocks are associated with increases in compensation to key talent.

Outcome 4 suggests that technology shocks are associated with either a re-organization of the old firm, or re-allocation of the firm's assets to a new firm. To test this, Eisfeldt and Papanikolaou (2013) estimates the following regression:

$$X_t = a_0 + OMK_t + OMK_{t-1} + c_0 MKT_t + c_1 MKT_{t-1} + \rho X_{t-1} + e_t, \tag{2.5}$$

where X is one of the measures of re-allocation described below, and other variables are as previously defined. The measures of reallocation tested are: 1) the amount of physical capital re-allocation across firms, CEO turnover, new public offerings, and management buyouts. All tests suggest that the degree of re-allocation is increasing with the degree of technology shock indicated by OMK.

Outcome 2 suggests that aggregate technology shocks change the value that shareholders have in the firm. Because the technology shocks are economy-wide, their effect on asset prices can not be diversified. This makes technology shocks a source of systematic risk. Outcome 3 suggests that shareholders' exposure to technology shocks is increasing in the amount of organizational capital that the firm holds. Accordingly, the main prediction of Eisfeldt and Papanikolaou (2013) is that firms with more organizational capital are more risky, because these firms are exposed to the systematic risk of technology shock.

Sorting firms into quintiles of OC, Eisfeldt and Papanikolaou (2013) finds that stock returns are increasing in the level of OC, and that those returns are not explained by the Fama and French (1993); Carhart (1997) factors. The findings suggest that firms in the top quintile of organizational capital have returns over the risk-free rate that are 4.7% higher than the bottom quintile.

CHAPTER 3: HYPOTHESIS DEVELOPMENT

Internally generated organizational capital is an off-balance sheet asset. This is because costs related to organizational capital development and maintenance are not capitalized. ASC 350-20-25-3 states that, "Costs of internally developing, maintaining, or restoring intangible assets (including goodwill) that are not specifically identifiable, that have indeterminate lives, or that are inherent in a continuing business and related to an entity as a whole, shall be recognized as an expense when incurred." By nature, organizational capital is a part of the firm's economic goodwill. Also, organizational capital is embodied in the key talent of the organization, making it difficult to specifically identify. As a result, internally developed organizational capital is unlikely to be on a firm's balance sheet. However, as an input to firm productivity, organizational capital has economic value that persists over time. This creates a gap between the fair and book values of the firm.

Empirical tests in the prior literature also suggest that organizational capital is an off-balance sheet asset. Lev and Radhakrishnan (2005) develops a productivity-based measure of organizational capital, and finds that it can explain about 24% of the cross-sectional variation in the difference between firm's equity market and book values.

The theory in Section 2 describes how technology shocks can change shareholder's value of organizational capital (Outcome 2). In an efficient market, changes in the value of organizational capital will be recognized immediately in the price of the firm. However, because internally generated organizational capital is an off-balance sheet asset, the accounting system does not have a way to reflect its change in value in a timely manner. Instead, the accounting system recognizes the change in organizational capital value when the transactions of the firm reflect it. This creates a timing difference between the accounting system and market values. Accordingly, my first hypothesis is:

H1: Earnings will be less timely in reflecting changes in firm value during times of technology shock.

Outcome 3 from the theory suggests that the effect of technology shocks on shareholder value is increasing in the amount of the firm's organizational capital. Accordingly, hypothesis 1a is:

H1a: The effect of technology shocks on earnings timeliness is increasing in the firm's level of organizational capital.

In some cases, firms may choose to buy organizational capital versus develop it internally. The purchase of organizational capital is likely to occur through M&A because it is difficult to separate from the organization as a whole (Lev and Radhakrishnan 2005; Li and Zhang 2015). In cases where organizational capital is purchased via M&A, the value of organizational capital is part of the purchase price. However, because organizational capital is difficult to isolate, there are few identifiable assets that the acquiring firm can associate with organizational capital. ASC 805-30-30-1 requires that a firm recognize the portion of the purchase price greater than the fair value of identifiable assets as goodwill on the balance sheet. Accordingly, after an M&A transaction, the value of acquired organizational capital is likely to be part of recognized goodwill.

After the introduction of SFAS 142, firms need to test for impairment of acquired goodwill, and if necessary, record impairment. ASC 350-20-35-2 requires goodwill impairment if the carrying value of acquired goodwill exceeds its implied fair value. Because acquired organizational capital is likely to be part of recognized goodwill, decreases in the fair value of organizational capital are likely to be associated with goodwill impairments. Because technology shocks can reduce the value of acquired organizational capital to shareholders (Outcome 2), I hypothesize:

H2: Firms record more goodwill impairment after periods of technology shock.

Firms for which organizational capital comprises more of the balance of goodwill will be more likely to record impairment at the time of technology shocks (Outcome 3). Accordingly, hypothesis 2a is:

H2a: The effect of technology shocks on goodwill impairment is higher for firms with more organizational capital in their goodwill.

Technology shocks make the adoption of new technologies more likely (Outcome 4). However, adopting a new technology is costly. Changing the processes, programs, and systems that generate the firm's goodwill and sustainable competitive advantages requires that managers commit to costly internal changes to reorganize assets around the new technology. The need for reorganization is consistent with prior studies that show that firms need to change business processes in conjunction with computing assets to get the most return from their investment (Brynjolfsson and Hitt 2000). Additionally, these changes will make the firm more efficient, reducing reliance on physical capital and labor.

The FASB defines restructuring as a program planned and controlled by management that changes the scope of, or manner in which, a firm conducts business (ASC 420-10-20). ASC 420-10-05-2 allows for costs related to involuntary one-time termination benefits, facility consolidation, employee relocation, and termination of non-lease contracts to be classified as restructuring expense. Costs related to new technology adoption are likely to fall into these categories, because the need for labor and capital inputs will fall as the firm becomes more efficient. Consistent with this, Shea (1999) finds that, when innovation accelerates, long run use of physical and human capital falls, and production-focused labor is substituted for non-production labor. Also, changing processes requires adjusting the supporting infrastructure, and may result in the consolidation of facilities and the relocation of employees. Accordingly, I hypothesize:

H3: Firms record more restructuring expense after periods of technology shock.

Outcome 5 suggests that the likelihood of a technology shock leading to new technology adoption is decreasing in the organizational capital efficiency of the firm. That is, all other things equal, technology shocks will be less likely to induce new technology adoption for firms where the efficiency of organizational capital is high. Accordingly, hypothesis 3a is:

H3a: The effect of technology shocks on restructuring is decreasing in the efficiency of organizational capital.

CHAPTER 4: RESEARCH DESIGN

4.1 Tests of H1: Earnings Timeliness

My first test of the relation between technology shocks and earnings timeliness uses a time-series of aggregate-level observations. To test the relation, I estimate the following OLS regression:

$$TIME_q = \alpha_0 + \beta_1 SHOCK_q + \beta_2 MKT_q + \beta_3 SMB_q + \\ \beta_4 HML_q + \beta_5 UMD_q + \varepsilon_q, \quad (4.1)$$

where *TIME* is an aggregate measure of earnings timeliness, described below. *SHOCK* is an indicator for periods when annual returns to *OMK* are in the bottom quartile of the time-series from 1971 to 2013. OMK is calculated following Eisfeldt and Papanikolaou (2013) as indicated in equations 2.1 and 2.2. *MKT*, *SMB*, *HML*, and *UMD* are annual returns to the Fama and French (1993) and Carhart (1997) factor portfolios, and are included to control for other aggregate fluctuations. Calendar years are indicated by q, and significance of coefficients is tested using Newey-West standard errors with a lag of 1 year.

I measure *TIME* as the adjusted R-squared from a regression of earnings on returns, an indicator for negative returns, and their interaction:

$$E_{i,t} = \alpha_0 + \beta_1 R_{i,t} + \beta_2 DR_{i,t} + \beta_3 (R_{i,t} \times DR_{i,t}) + \varepsilon_{i,t}, \quad (4.2)$$

where *E* is net income per share divided by the beginning-of-year stock price, *R* is the annual stock return ending three months after fiscal year-end, *DR* is an indicator for negative return, i refers to firm, and t refers to fiscal year-end. I allow the coefficient on negative return to vary from that of positive return, consistent with evidence of the asymmetric timeliness of earnings (Basu 1997). I remove firms with less than $10 million in sales or total assets or with a share price less than $5 to reduce the influence of very small firms. I also remove observations in the top and bottom 1% of earnings and returns each year to reduce the influence of outliers.

I estimate *TIME* each month using firms with fiscal year-ends in the prior 12 months to create a monthly rolling estimate of timeliness. I also calculate OMK, MKT, SMB, and HML monthly using annual returns that overlap with the period used to calculate R in equation (4.2). I then average the 12 monthly measures by calendar year to create 43 annual observations from 1971 to 2013.

TIME measures the degree to which earnings captures the information impounded into a firm's price over the contemporaneous period (Bushman, Chen, Engel, and Smith 2004; Ball, Kothari, and Robin 2000). If earnings is slow to reflect information, then the change in the firm's price will be relatively poorly explained by earnings, and *TIME* will be lower. A negative coefficient on *SHOCK* is consistent with the prediction that the timeliness of earnings is lower in periods of technology shock.

My second test of the relation between technology shocks and the timeliness of earnings tests whether the effect of technology shocks is stronger for firms with higher levels of organizational capital. Because technology shocks affect the value of organizational capital, firms with more organizational capital should demonstrate more of a decline in earnings timeliness during technology shocks.

Conducting such a test requires a measure of timeliness that varies cross-sectionally and in the time-series. I construct a measure of timeliness following Barth, Konchitchki, and Landsman (2013) and Barth, Landsman, Raval, and Wang (2015). My measure of timeliness for each firm-year, *TIME_XS*, is the sum of the adjusted R-squared from the estimation of equation (4.2), performed in two steps. I perform the first estimation by industry-year.[1] This estimation approach recognizes that timeliness likely differs by industry because of variation in accounting practices

[1] Year refers to the year of the firm's fiscal year-end, unless otherwise specified.

(Barth, Beaver, Hand, and Landsman 1999).[2] The second estimation is performed by portfolio-year, where portfolio membership is determined by the residuals from the first estimation. This estimation captures cross-sectional variation in timeliness that is not captured by industry categories. The second-stage regression is industry-neutral, in that each portfolio contains an equal number of firms from each industry. I use five portfolios each year, where observations with residuals from the industry-year regression that are in the first, second, third, fourth, and fifth quintiles are in the first, second, third, fourth, and fifth portfolios.

I measure organizational capital as of the beginning of the firm's fiscal year based on Equation 2.1 and rank it into quintiles within industry-year-end group. Ranking *OC* in this manner eliminates the effect that time or industry variation in *OC* have on the relation between technology shocks and timeliness.

To test hypothesis 1a, whether the relation between timeliness and technology shocks is increasing in the level of organizational capital, I use OLS to estimate equation (4.3):

$$TIME\_XS_{i,t} = \gamma_0 + \omega_1 OMK_t + \omega_2 OC\_R_{i,t} + \omega_3 (OMK_t \times OC\_R_{i,t}) + CONTROLS + \varepsilon_{i,t}, \quad (4.3)$$

where *OC_R* is the within-industry-year-end rank of *OC* as of the beginning of the year and OMK provides a continuous measure of the degree of technology shock, with lower values indicating higher degrees of shock. All other variables are as described above. The controls are the same as those in equation (4.1). Additionally, I include firm fixed effects in the regression to control for time-invariant firm characteristics. I cluster standard errors by fiscal year-end.

To the extent that increased investment in organizational capital increases a firm's exposure to technology shock, I predict the coefficient on $(OMK \times OC\_R)$, ω_3, to be positive. This is because lower returns to OMK indicate technology shocks, and therefore are predicted to be associated with lower timeliness. I also expect the coefficient on OC_R, ω_2, to be negative, which

[2] I require at least 10 observations in each industry-year to estimate industry-year timeliness.

is consistent with investment in organizational capital creating exposure to other factors that reduce the timeliness of earnings that are unrelated to technology shocks.

As an additional test of the relation between technology shocks and earnings timeliness, I examine whether future expected earnings reflects the information in returns during technology shocks. To test whether returns during times of technology shock induce a different relation between current and future earnings, I borrow a specification from Lundholm and Myers (2002). I estimate the following OLS regression:

$$\begin{aligned} R_{i,t} = \alpha_0 + \beta_1 E_{i,t-1} + \beta_2 E_{i,t} + \beta_3 E_{i,t+1} + \beta_4 E_{i,t+2} + \beta_5 E_{i,t+3} + \\ \beta_6 OMK_t + \beta_7 (OMK_t \times E_{i,t-1}) + \beta_8 (OMK_t \times E_{i,t}) + \\ \beta_9 (OMK_t \times E_{i,t+1}) + \beta_{10} (OMK_t \times E_{i,t+2}) + \beta_{11} (OMK_t \times E_{i,t+3}) + \\ + \beta_{12} R_{i,t+1} + \beta_{13} R_{i,t+2} + \beta_{14} R_{i,t+3} + \\ \beta_{15} (OMK_t \times R_{i,t+1}) + \beta_{16} (OMK_t \times R_{i,t+2}) + \beta_{17} (OMK_t \times R_{i,t+3}) \\ + CONTROLS + \varepsilon_{i,t}, \end{aligned} \tag{4.4}$$

where ***OMK***, ***R***, and ***E*** are as previously defined and controls are the same as those in equation (4.1). The coefficient on E, β_2 reflects the relation between returns and contemporaneous unexpected earnings, with E_{t-1} controlling for expected earnings. The coefficient on E_{t+1}, β_3, reflects the relation between current returns and expected returns at time $t+1$, with R_{t+1} controlling for future unexpected earnings. Coefficients on E_{t+2} and E_{t+3} similarly reflect the relation between current returns and expected earnings in years $t+2$ and $t+3$. I use three years of future earnings because prior research suggests that additional years provide little explanatory power (Lundholm and Myers 2002; Collins, Kothari, Shanken, and Sloan 1994).[3] I cluster standard errors by fiscal year-end.

Consistent with prior literature, I expect the coefficient on E_{t-1}, β_1, to be negative, reflecting

[3] I also use three years of future goodwill and restructuring charges in later tests, consistent with this specification and the findings in prior literature.

the mean reverting nature of earnings, and the coefficient on E_t, β_2, to be positive, reflecting the positive association between contemporaneous returns and unexpected earnings, and the coefficient on E_{t+1}, β_3, to be positive, which is consistent with current returns reflecting expected future earnings (Lundholm and Myers 2002; Collins et al. 1994). I expect coefficients on E_{t+2} and E_{t+3}, β_4 and β_5, to either be positive or insignificantly different from zero, because I expect returns to reflect future earnings, but with diminishing power. Because I expect returns during times of technology shock to be less associated with current earnings, and more associated with expectations of future earnings, consistent with less timely earnings, I expect the coefficient on $OMK_t \times E_t$, β_8, to be positive, and the coefficient on $OMK_t \times E_{t+1}$, β_9, to be negative.

4.2 Test of H2: Goodwill Impairment

My tests of the second hypothesis require a measure of goodwill impairment. I measure firm-year goodwill impairment as the downward change in goodwill, scaled by the amount of goodwill on the balance sheet as of the beginning of the year.[4] My measure of future goodwill impairment, $FUTIMP$ is the sum of goodwill impairment over the three years $t+1$ to $t+3$.

To test hypothesis 2, whether firms record more goodwill impairment after periods of technology shock, I use a Tobit estimation given by equation (4.5):

$$FUTIMP_{i,t} = \alpha_0 + \beta_1 OMK_t + \beta_2 R_{i,t} + CONTROLS + \varepsilon_{i,t}, \tag{4.5}$$

where controls are the same as those in equation (4.3). I include industry fixed effects and fixed effects for the decade of the firm's first appearance on Compustat to control for the generational effects documented in Srivastava (2014), which I refer to as cohort fixed effects.[5] I include R as a control for the idiosyncratic news revealed about the firm during the year, and I expect its

[4] I add amortization to prior year goodwill for the less than 10% of firm-years in the sample with non-zero goodwill amortization. I assign a value of zero to the 5% of observations where goodwill is missing.

[5] Including fixed effects in non-linear models may induce bias. However, the bias goes towards zero in sufficiently large samples, so I include fixed effects that encompass larger groups in non-linear tests than I do in tests that use linear estimation (Greene 2004). Excluding fixed effects in the estimation of equation (4.5), (4.6), 4.7, and 4.8 provides indentical inferences.

coefficient, β_2, to be negative, which is consistent with lower returns being associated with more impairment. I expect the coefficient on OMK, β_1, to be negative, which is consistent with goodwill impairment increasing as the degree of technology shock increases. Standard errors are clustered by fiscal year-end. All observations have non-zero goodwill balances and are after 2001 to align with the implementation of SFAS 142.

As a test of hypothesis 2a, whether the effect of technology shocks on goodwill impairment is higher for firms with more organizational capital in their goodwill, I use a Tobit estimation given by equation (4.6):

$$\begin{aligned} FUTIMP_{i,t} = \alpha_0 + \beta_1 OMK_t + \beta_2 HIOC_{i,t} + \beta_3 (OMK_t \times HIOC_{i,t}) \\ + \beta_4 R_{i,t} + CONTROLS + \varepsilon_{i,t}, \end{aligned} \tag{4.6}$$

where $HIOC$ is an indicator for observations in which beginning-of-year OC is in the top quintile within the industry-year-end group, and the other variables, fixed effects, and clusters are the same as equation (4.5). I use high levels of investment in organizational capital, $HIOC$ as a proxy for the level of organizational capital in goodwill. Organizational capital consists of the key talent and technologies of the firm. While these assets can be acquired, they also require continuous investment subsequent to acquisition. For example, compensation of key talent and investment in technologies and consultants are required to integrate and sustain the acquired technologies. Accordingly, I use OC, the measure of investment in organizational capital, as a proxy for the level of organizational capital in goodwill. To the extent that firms with more organizational capital in goodwill record more goodwill impairment after technology shocks, I expect that the coefficient on the interaction of OMK and $HIOC$, β_3, to be negative.

4.3 Test of H3: Restructuring

To test the relation between the magnitude of restructuring charges and technology shock, I employ a design similar to my tests of the second hypothesis. Restructuring charges are collected from Compustat and scaled by total assets as of the beginning of year. All observations are after the year 1999, when restructuring data became largely available in Compustat. My measure of future restructuring, $FUTRESTR$, is the sum of a firm's restructuring charges from year $t+1$ to $t+3$.[6]

To test the association between periods of technology shock and the magnitude of restructuring charges, I use a Tobit estimation given by equation (4.7):

$$FUTRESTR_{i,t} = \alpha_0 + \beta_1 OMK_t + \beta_2 OC\_R_{i,t} + \beta_3 R_{i,t} + CONTROLS + \varepsilon_{i,t}, \tag{4.7}$$

where controls are the same as those in equation (4.3) and other variables are as previously defined. I include OC_R to control for the amount of organizational capital, because firms with more organizational capital may incur larger restructuring charges. I also include R as a control for the idiosyncratic news revealed about the firm during the year, and I expect lower returns to be associated with more restructuring, i.e., β_2<0. I include industry and cohort fixed effects, and I cluster standard errors by fiscal year-end. I expect the coefficient on OMK, β_1, to be negative, which is consistent with restructuring increasing as the degree of technology shock increases.

To test hypothesis 3a, whether the effect of technology shocks on restructuring is decreasing in the efficiency of organizational capital, I use a Tobit estimation given by equation (4.8):

$$\begin{aligned} FUTRESTR_{i,t} = \alpha_0 + \beta_1 OMK_t + \beta_2 HIATO_{i,t} + \beta_3 (OMK_t \times HIATO_{i,t}) \\ + \beta_4 R_{i,t} + \beta_5 OC\_R_{i,t} + CONTROLS + \varepsilon_{i,t}, \end{aligned} \tag{4.8}$$

where $HIATO$ is an indicator for an asset turnover ratio in the top quintile within an industry-year-end group, and other variables, controls, fixed effects, and clusters are as in equation (4.7). Asset turnover is measured as current sales divided by beginning-of-year total assets, and is a proxy for the efficiency of organizational capital. Because I hypothesize that firms with higher efficiency in

[6] I treat missing values as zero, assuming the Compustat data item is populated if non-zero during my sample period, which is consistent with the approach in Doyle, Ge, and McVay (2007).

organizational capital are less likely to restructure after technology shocks, I expect the coefficient on the interaction of ATC and $HIATO$, β_3, to be positive.

CHAPTER 5: DATA

I collected my accounting and returns data from Compustat and CRSP, my Fama and French (1993) and Carhart (1997) portfolio returns from Kenneth French's website, and CPI from the February 2015 CPI detailed report from the Bureau of Labor Statistics.[1] My observations are from 1971-2013, although I use earlier years to calculate beginning balances and lagged variables. Following Eisfeldt and Papanikolaou (2013), I remove financial institutions from all analyses and calculations.[2]

The sample used to calculate OMK comprises 201,091 firm-years with data available to calculate OC based on equations (2.1) and (2.2). This sample provides 516 monthly observations over the 43 years of the sample period. To calculate $TIME$ I use 120,254 observations that meet the size and data requirements to estimate equation 4.2. Because I require at least 10 observations for each industry-year, the number of firm-years I use to estimate $TIME\_XS$ is reduced to 120,207.

In order to be included in the estimation of equations (4.3) through (4.7), I require $TIME\_XS$ to be calculable, more than four years of prior data, and a non-zero beginning balance of OC. These requirements reduce the effect of very small firms, error in the estimated starting value of OC, and firms with no accumulated organizational capital. I winsorize OMK, $TIME\_XS$, $FUTIMP$, and $FUTRESTR$ at 1% and 99%. Any additional data requirements are as specified in the research design above.

Table A.1 presents the annual means of OMK, $SHOCK$, and $TIME$. The table reveals that OMK demonstrates non-monotonic variation in the time-series, consistent with fluctuations in the degree of technology shock over time. $SHOCK$ indicates the percent of months in each year that

[1] CPI data are available at: http://www.bls.gov/cpi/.

[2] Financial institutions comprise firms with SICs between 6000 and 6999.

are in the lowest quartile of OMK across the sample, and ranges from 0 to 1. Interestingly, mean $SHOCK$ is at its highest in 1981, 1993, 1999, and 2007, years around which IBM introduced the first PC, the World Wide Web was launched, Internet commerce expanded, and social media became mainstream.[3]

To further validate OMK, I also obtained the annual wage growth statistics for Santa Clara and San Mateo counties, two counties comprising the Silicon Valley, as a proxy for wage growth of key talent.[4] I use Silicon Valley wage growth as a proxy for the wage growth of key talent because the Silicon Valley has historically been known for its active technology entrepreneurship, and it has a high density of engineers, researchers, and managers. I find that the average wage growth in these two counties is negatively correlated with OMK (Pearson correlation of -0.36, p-value of 0.02), consistent with OMK reflecting the market's response to rising costs of key talent retention. I also obtain the US aggregate annual percent wage growth data from the BEA for NAICS group 54, professional, scientific, and technical services. This category of business is likely to employ professionals that would be considered key talent. Data are available from 1998-2013, and are negatively correlated with OMK over that period (Pearson correlation of -0.44, p-value of 0.09), also consistent with OMK capturing the market's response to the increased cost of retention of key talent.

I also obtain technology book publishing data from Alexopoulos (2011) to determine variation in OMK is correlated with the introduction of new technologies. Alexopoulos (2011) uses data on technology book publications as a bottom-up measure of the introduction of new technologies. However, this data is likely to lag the actual introduction of the new technology. Therefore, in order to estimate the times of new technology introduction using this data, I calculate the annual average percent growth of computer books and networking books over the period $t+1$ to $t+3$ as a proxy for the degree of new technology introduction in year t. Higher future technology

[3]These examples are descriptive. Years for the introduction of the PC (1981) and World Wide Web (1992) are from Alexopoulos (2011).

[4]Data are collected from the current dollar Wage and Salary Summary from the Bureau of Economic Analysis (BEA).

book publications are an indication of the introduction of new technologies. Data are available to calculate this measure from 1972-1994. Over this period, I find that future book publications are negatively correlated with OMK (Pearson correlation of -0.45, p-value of 0.03), consistent with lower levels of OMK aligning with the introduction of new technologies.

$TIME$ demonstrates a significant downward trend, consistent with findings regarding the diminishing earnings-returns relation (Srivastava 2014; Lev and Zarowin 1999), but it also demonstrates variation from year-to-year (Basu 1997). By year, the lowest values of $TIME$ are near zero in 1992 and 2004 and the highest are around 0.24 in 1977 and 1985.

Table A.2 presents the means, medians, and standard deviation across all years for OMK, $SHOCK$, MKT, SMB, HML, UMD, and $TIME$. The mean and median of OMK is 0.05, consistent with the main finding in Eisfeldt and Papanikolaou (2013) that firms in the top quintile of OC have returns on average about 4.7% higher than those in the lowest quintile, indicating that these firms are exposed to more systematic risk. Average OMK is also in the range of returns of the other factor portfolios.

Table A.3 presents the correlations of the annual time-series variables. The negative correlation between $TIME$ and the calendar year, $YEAR$, is significantly negative (Pearson (Spearman) correlation = -0.76 (-0.68), p-value = <0.01 (<0.01)), consistent with the downward time trend documented in prior studies. No other variable demonstrates any significant time trend. The correlation between $SHOCK$ and $TIME$ is significant and negative (Pearson (Spearman) correlation = -0.28 (-0.28), p-value = 0.07 (0.07)), consistent with periods of technology shock being associated with lower earnings timeliness. The correlation between $SHOCK$ and the other factor portfolios is insignificant, suggesting that the effect captured by $SHOCK$ is different from that captured by other factors.

The descriptive statistics for the sample used in the estimation of equations (4.3) through 4.7 are presented in Table A.4. Panel A presents the descriptive statistics for the sample used to perform the additional tests of earnings timeliness. The mean of $TIME\_XS$ is higher than the mean of the time-series variable $TIME$. This is likely because $TIME\_XS$ is the sum of the R-squareds from two estimations of equation (4.2). Also, the explanatory power of the estimation may be higher because the estimation is conducted within industry-year and portfolio-year groups, which relaxes the assumption that all firms in a year have the same coefficients. The means of the time-series variables have means similar to the aggregate averages presented in Table A.2.

Panel B presents descriptive statistics for the sample used to perform the goodwill tests. The mean of $FUTIMP$ indicates that future impairments are on average about 16% of total goodwill, but that the median is near zero. The summary statistics of OMK, $SHOCK$, and OC are generally consistent with the statistics in the larger sample in panel A. The means and medians of the factor returns appear different from those presented in Table A.2, reflecting the difference in the time period of the sample, but remain in the 0.02 to 0.09 range of factor returns presented on Table A.2.

Panel C presents descriptive statistics for the sample used to perform the restructuring tests. The mean and median of $FUTRESTR$ indicate that the average future impairment charge is about 1% of total assets, but that the median firm does not record any impairment charge. The means and medians of the time-series variables are in the same range as those presented in Panels A and B, and Table A.2, but differ because of the different time period covered by this sample.

CHAPTER 6: RESULTS

Table A.5 presents regression summary statistics for the estimation of equation (4.1) over the 43 year sample period. Column (1) uses OMK as the measure of technology shock, and indicates a positive coefficient for OMK (coefficient of 0.257, t-statistic of 2.09), consistent with technology shocks being associated with lower levels of earnings timeliness, as measured by $TIME$. Columns (2) through (4) use $SHOCK$ as the measure of technology shock, and include either no controls (column (2)), market returns as a control (column (3)), or the full set of Fama and French (1993) and Carhart (1997) factor returns as controls (column (4)). In all three columns, the coefficient for $SHOCK$ is significantly negative (coefficient between -0.060 and -0.063, t-statistic between -2.22 and -2.00). The results are in-line with the bi-variate correlations presented on table A.3, which indicate a significantly negative correlation between times of technology shock and earnings timeliness. These results provide evidence consistent with hypothesis 1, that earnings is less timely during times of technology shock. The magnitude of the coefficient suggests that periods of technology shock demonstrate levels of timeliness that are about six percentage points lower, all else equal. No other variable has a significant coefficient, consistent with correlations on Table A.3.

Table A.6 presents regression summary statistics for the $TIME\_XS$ estimating equation (4.3) including OMK as a measure of technology shock and including either no interaction with OC_R or controls (column (1)), the interaction with OC_R and no controls (column (2)), or both the interaction and controls (column (3)). The results in column (1) are consistent with the finding in table A.5, that OMK has a positive association with earnings timeliness, measured in this case by $TIME\_XS$ (coefficient of 0.243, t-statistic of 1.91). Column (2) and column (3) indicates that the positive association between OMK and $TIME\_XS$ is stronger for firms with higher levels of OC within their industry and time period, as indicated by the positive coefficient on the interaction between OMK and OC_R (coefficient of -0.015 or -0.013, t-statistic of -5.38 or -5.78). These results are consistent with hypothesis 1a, that the effect of technology shocks on earnings timeliness is increasing in the firm's level of organizational capital. I interpret this as an indication that organizational capital is a mediator by which technology shocks affect timeliness. The coefficient on OC_R is also negative and significant (coefficient of -0.015 or -0.013, t-statistic of -5.38 or -5.78), indicating that firms with higher levels of organizational capital on average have lower timeliness. The coefficients for the control variables are insignificant, with the exception of MKT and UMD. The coefficient on MKT is significantly negative, which is consistent with the notion that bad news is more effectively reflected in earnings than good news. I have no interpretation for the significant coefficient on UMD. Untabulated results indicate that using $SHOCK$ as an indicator for technology shock instead of OMK provides the same inferences, and that results are robust to the inclusion of R, a measure of the firm's idiosyncratic returns.

Table A.7 presents the regression summary statistics for the return estimating equation (4.4). The coefficients on E_t and E_{t+1} are positive, which is consistent with returns being reflected in earnings contemporaneously or with a delay on average. The interaction term $OMK \times E_t$ has a significantly positive coefficient (coefficient = 0.274, t-statistic = 1.78). Because lower returns to OMK are consistent with a higher degree of technology shock, the positive coefficient is interpreted as current earnings being less associated with current returns during times of technology shock. To the extent that current returns reflect the information revealed during the period, I interpret this as an indication that current earnings captures less value-relevant information during technology shocks. Also, the coefficient on $OMK \times E_{t+1}$ is negative and significant (coefficient = $-.081$, t-statistic = -2.20). This is consistent with current returns being more associated with future expected earnings. I interpret this as an indication that current value-relevant information is more likely to be reflected in future expected earnings during times of technology shock. I interpret these coefficients together as an indication that periods of technology shock reveal information that is reflected in earnings more slowly relative to non-shock periods.

Column (1) of table A.8 presents regression summary statistics from the goodwill estimating equation (4.5). Consistent with hypothesis 2, the coefficient on OMK is significantly negative (coefficient = -0.850, t-statistic = -2.04). Because lower levels of OMK are consistent with more technology shock, this result suggests that periods of technology shock lead to higher goodwill impairment charges, in line with the notion that technology shocks reduce the value of organizational capital. This result provides an indication of how exogenous shocks to the value of intangible assets can change the likelihood of a goodwill impairment charge appearing in earnings. The coefficient on R is significantly negative, which is also consistent with expectations. Untabulated results indicate that using $SHOCK$ as an indicator for technology shock instead of OMK provides identical inferences.

Column (2) of table A.8 presents regression summary statistics from the goodwill estimating equation (4.6). Consistent with hypothesis 2a, the coefficient on the interaction of OMK and $HIOC$ is significantly negative (coefficient = -0.053, t-statistic = -2.54). This suggests that firms with higher levels of organizational capital in goodwill are more subject to the effects of technology shocks on goodwill impairment. This effect is incremental to the main effects that technology shocks and investment in organizational capital have on goodwill impairment, as indicated by the significantly negative coefficients on OMK and $HIOC$.

Column (1) of table A.9 presents regression summary statistics from the restructuring charge estimation, equation (4.7). Consistent with hypothesis 3, the coefficient on OMK is significantly negative (coefficient of -0.027, t-statistic of -2.45). Because lower levels of OMK indicate times of technology shock, this finding is consistent with technology shocks being associated with higher and more frequent restructuring charges. This finding provides evidence that technology shocks increase the attractiveness of new technology adoption, and provides insight as to how exogenous shocks to the value of intangible investment can affect the likelihood of a firm incurring a restructuring charge. The coefficient on R is significantly negative, also consistent with expectations. Untabulated results indicate that using $SHOCK$ as an indicator for technology shock instead of OMK provides identical inferences.

Column (2) of table A.9 presents regression summary statistics from the restructuring charge estimation, equation (4.8). Consistent with hypothesis 3a, the coefficient on the interaction between OMK and $HIATO$ is significantly positive (coefficient of 0.015, t-statistic of 1.70). This result provides evidence that during times of technology shock, the increase in restructuring charges is lower for firms with more efficient organizational capital. This effect is incremental to the main effect that technology shocks have on increasing restructuring charges, as indicated by the negative coefficient on OMK, and the effect that higher efficiency of organizational capital has on reducing restructuring charges, as indicated by the negative coefficient on $HIATO$.

CHAPTER 7: CONCLUSION

This study investigates the effect that aggregate technology shocks have on the characteristics of earnings. Eisfeldt and Papanikolaou (2013) suggests that technology shocks have two main effects. First, they reduce shareholder's value in organizational capital, and second, they increase the likelihood of new technology adoption. Based on these effects, I generate my hypotheses. First, I hypothesize that earnings reflects contemporaneous changes in value in a less timely manner when technology shocks occur, particularly for firms with more organizational capital. Second, I hypothesize that goodwill impairments increase subsequent to technology shocks, and particularly for firms with more organizational capital in goodwill. Third, I hypothesize that restructuring charges increase subsequent to technology shocks, and that more efficient firms will be less likely to restructure after technology shocks. My tests provide evidence consistent with my hypotheses.

Findings from my study shed light on how the dynamics of the aggregate economy affect the time-series and cross-sectional variation in the characteristics earnings. More specifically, this study demonstrates one way in which investment in a specific intangible asset, organizational capital, can expose firms to aggregate shocks that ultimately affect earnings quality.

APPENDIX A: TABLES

Table A.1: Aggregate Means by Year

YEAR	OMK	SHOCK	TIME
1971	0.07	0.00	0.17
1972	0.05	0.00	0.13
1973	0.00	0.50	0.11
1974	0.03	0.00	0.18
1975	0.01	0.50	0.14
1976	0.02	0.50	0.17
1977	0.11	0.00	0.24
1978	0.14	0.00	0.20
1979	0.22	0.00	0.11
1980	0.16	0.17	0.10
1981	−0.05	0.92	0.12
1982	0.05	0.00	0.19
1983	0.12	0.00	0.10
1984	0.14	0.00	0.15
1985	0.08	0.00	0.24
1986	0.07	0.00	0.19
1987	0.06	0.00	0.12
1988	0.08	0.00	0.07
1989	0.05	0.08	0.02
1990	0.11	0.00	0.02
1991	0.06	0.08	0.01
1992	−0.02	0.67	0.00
1993	−0.06	1.00	0.01
1994	0.09	0.17	0.02
1995	0.05	0.00	0.01
1996	0.07	0.00	0.02
1997	0.00	0.50	0.02
1998	0.01	0.33	0.02
1999	−0.10	1.00	0.03
2000	−0.03	0.67	0.02
2001	0.20	0.00	0.03
2002	0.11	0.00	0.03
2003	0.01	0.33	0.02
2004	0.05	0.00	0.00
2005	0.09	0.00	0.01
2006	0.04	0.25	0.01
2007	−0.03	1.00	0.02

Continued on next page

Table A.1 – continued

YEAR	OMK	SHOCK	TIME
2008	0.10	0.42	0.04
2009	−0.10	0.67	0.06
2010	−0.06	0.75	0.01
2011	0.05	0.00	0.02
2012	0.03	0.25	0.03
2013	0.12	0.00	0.02

Table A.1 provides the means of the monthly aggregate time-series variables by calendar year. OMK is the annual return to a portfolio that is long in high organizational capital firms and short in low organizational capital firms. $SHOCK$ is an indicator variable for values of OMK in the bottom quartile. $TIME$ is the adjusted R-squared from the regression of earnings on returns.

Table A.2: Descriptive Statistics of Annual Aggregate Variables

	Mean	Median	Std
OMK	0.05	0.05	0.07
SHOCK	0.25	0.00	0.33
MKT	0.07	0.09	0.14
SMB	0.02	0.03	0.09
HML	0.05	0.02	0.10
UMD	0.09	0.09	0.14
TIME	0.08	0.03	0.07

Table A.2 provides the descriptive statistics of the annual averages of the time-series variables. OMK is the annual return to a portfolio that is long in high organizational capital firms and short in low organizational capital firms. $SHOCK$ is an indicator variable for values of OMK in the bottom quartile. MKT, SMB, HML, and UMD are annual returns to the Fama and French (1993) and Carhart (1997) factor portfolios. $TIME$ is the adjusted R-squared from the regression of earnings on returns. N = 43.

Table A.3: Correlations of Annual Aggregate Variables

Variable	YEAR	OMK	SHOCK	TIME	MKT	SMB	HML	UMD
YEAR		−0.23	0.22	**−0.76**	0.11	0.00	−0.16	−0.24
OMK	−0.20		**−0.79**	**0.25**	−0.19	0.17	0.14	0.22
SHOCK	0.24	**−0.78**		**−0.28**	0.03	0.01	−0.06	−0.04
TIME	**−0.68**	0.26	**−0.28**		−0.13	0.17	0.18	0.07
MKT	0.13	−0.15	0.06	−0.20		0.07	**−0.43**	−0.23
SMB	0.00	0.18	0.05	0.12	0.05		0.04	−0.22
HML	−0.18	−0.01	−0.04	0.15	**−0.36**	0.09		−0.03
UMD	−0.17	0.06	0.05	0.05	−0.23	−0.17	−0.09	

Table A.3 presents correlations of the annual aggregate variables presented on Table A.2, and $YEAR$. Pearson (Spearman) correlations are above (below) the diagonal. $YEAR$ is the calendar year of the observation. OMK is the annual return to a portfolio that is long in high organizational capital firms and short in low organizational capital firms. $SHOCK$ is an indicator variable for values of OMK in the bottom quartile. $TIME$ is the adjusted R-squared from the regression of earnings on returns. MKT, SMB, HML, and UMD are annual returns to the Fama and French (1993) and Carhart (1997) factor portfolios. Bold indicates statistical significance at a 10% 2-sided level. N = 43.

Table A.4: Descriptive Statistics - Panel Samples

Panel A - Cross-Sectional Timeliness

	Mean	Median	Std
TIME_XS	0.48	0.48	0.25
OMK	0.05	0.05	0.10
SHOCK	0.25	0.00	0.43
MKT	0.07	0.08	0.18
SMB	0.02	0.01	0.11
HML	0.05	0.04	0.15
UMD	0.09	0.09	0.15
OC	0.01	0.01	0.01

Panel B - Goodwill

	Mean	Median	Std
FUTIMP	0.16	0.00	0.31
OMK	0.03	0.03	0.10
SHOCK	0.30	0.00	0.46
MKT	0.06	0.07	0.22
SMB	0.04	0.02	0.09
HML	0.03	0.01	0.10
UMD	0.02	0.05	0.19
R	0.11	0.07	0.47
OC	0.01	0.01	0.01

Panel C - Restructuring

	Mean	Median	Std
FUTRESTR	0.01	0.00	0.02
OMK	0.05	0.03	0.11
SHOCK	0.27	0.00	0.44
MKT	0.02	0.06	0.22
SMB	0.04	0.02	0.09
HML	0.07	0.08	0.19
UMD	0.03	0.05	0.19
R	0.10	0.05	0.50
ATO	1.22	1.02	0.83

Table A.4 presents the means of variables used in the estimation of equations (4.3) through (4.7). $TIME\_XS$ is the firm-year measure of earnings timeliness calculated using the two-stage methodology from Barth et al. (2015, 2013). OMK is the annual return to a portfolio that is long in high organizational capital firms and short in low organizational capital firms. $SHOCK$ is an indicator variable for values of OMK in the bottom quartile. MKT, SMB, HML, and UMD are annual returns to the Fama and French (1993) and Carhart (1997) factor portfolios. OC is the measure of organizational capital calculated following Eisfeldt and Papanikolaou (2013). $FUTIMP$ is the magnitude of goodwill impairment over the period $t + 1$ to $t + 3$. $FUTRESTR$ is the magnitude of restructuring charges over the period $t + 1$ to $t + 3$. ATO is the asset turnover ratio. R is the annual returns to the firm ending three months after fiscal year-end. Panel A has N = 78,484, Panel B has N = 17,254, and Panel C has N = 26,403.

Table A.5: Aggregate Earnings Timeliness and Technology Shocks

Column:	(1)	(2)	(3)	(4)
Dep. Var:	TIME	TIME	TIME	TIME
OMK	0.257^{**}			
	(2.09)			
SHOCK		-0.063^{**}	-0.062^{**}	-0.060^{*}
		(-2.22)	(-2.14)	(-2.00)
MKT			-0.063	-0.029
			(-0.78)	(-0.31)
SMB				0.156
				(1.02)
HML				0.094
				(0.80)
UMD				0.051
				(0.88)
Constant	0.062^{***}	0.091^{***}	0.095^{***}	0.079^{***}
	(4.51)	(4.74)	(4.85)	(4.35)
Observations	43	43	43	43
R-squared	0.064	0.080	0.094	0.148

Table A.5 presents regression summary statistics from the estimation of equation (4.1). The dependent variable, $TIME$, is the adjusted R-squared from the regression of earnings on returns. OMK is the annual return to a portfolio that is long in high organizational capital firms and short in low organizational capital firms. $SHOCK$ is an indicator variable for values of OMK in the bottom quartile. MKT, SMB, HML, and UMD are annual returns to the Fama and French (1993) and Carhart (1997) factor portfolios. The Newey-West (1 lag) t-statistics are in parenthesis. ***, **, and * indicate 2-sided significance at 1%, 5%, and 10% respectively. The sample comprises annual averages of monthly measures from 1971 to 2013.

Table A.6: Earnings Timeliness and Technology Shocks by Level of Organizational Capital

Column:	(1)	(2)	(3)
Dep. Var:	TIME_XS	TIME_XS	TIME_XS
OMK	0.243^{*}	0.206	-0.114
	(1.91)	(1.65)	(-1.25)
OMK × OC_R		0.016^{***}	0.017^{***}
		(2.82)	(2.83)
OC_R		-0.015^{***}	-0.013^{***}
		(-5.38)	(-5.78)
MKT			-0.357^{***}
			(-5.93)
SMB			-0.152
			(-1.18)
HML			0.088
			(1.31)
UMD			0.150^{**}
			(2.12)
Observations	78,484	78,484	78,484
Adj. R-squared	0.135	0.137	0.230

Table A.6 presents regression summary statistics from the estimation of equation (4.3). The dependent variable, $TIME\_XS$, is the firm-year measure of earnings timeliness calculated using the two-stage methodology from Barth et al. (2015, 2013). OMK is the annual return to a portfolio that is long in high organizational capital firms and short in low organizational capital firms. OC_R is the industry-year-end rank of accumulated organizational capital. MKT, SMB, HML, and UMD are annual returns to the Fama and French (1993) and Carhart (1997) factor portfolios. The t-statistics based on standard errors clustered by fiscal year-end are in parenthesis. The regression includes untabulated firm fixed effects. ***, **, and * indicate 2-sided significance at 1%, 5%, and 10% respectively. The sample comprises firm-year observations from 1971 to 2013.

Table A.7: Relation Between Current Returns and Future Earnings Conditional on Technology Shock

Dep.Var:	R_t
E_{t-1}	-0.038^{***}
	(-3.86)
E_t	0.091^{***}
	(5.07)
E_{t+1}	0.018^{***}
	(2.66)
E_{t+2}	-0.000
	(-0.05)
E_{t+3}	-0.001
	(-0.51)
OMK_t	0.060
	(0.71)
$OMK_t \times E_{t-1}$	0.073
	(0.79)
$OMK_t \times E_t$	0.274^{*}
	(1.78)
$OMK_t \times E_{t+1}$	-0.081^{**}
	(-2.20)
$OMK_t \times E_{t+2}$	0.003
	(0.09)
$OMK_t \times E_{t+3}$	-0.003
	(-0.36)
Constant	0.045^{***}
	(4.39)
Observations	58,201
Adjusted R-squared	0.239

Table A.7 presents regression summary statistics from the estimation of equation (4.4). E is the firm's annual earnings per share, scaled by the beginning of the year market value of equity. R is the annual returns to the firm ending three months after fiscal year-end. OMK is the annual return to a portfolio that is long in high organizational capital firms and short in low organizational capital firms. The t-statistics based on standard errors clustered by fiscal year-end are in parenthesis. The regression includes untabulated variables R_{t+1}, R_{t+2}, R_{t+3}, and their interaction with OMK_t. The regression also includes untabulated control variables MKT, HML, SMB, and UMD, the annual returns to the Fama and French (1993) and Carhart (1997) factor portfolios. ***, **, and * indicate 2-sided significance at 1%, 5%, and 10% respectively. The sample comprises firm-year observations from 1971 to 2013.

Table A.8: Goodwill Impairment and Technology Shocks

Column:	(1)	(2)
Dep.Var:	FUTIMP	FUTIMP
OMK	-0.850^{**}	-0.803^{*}
	(-2.04)	(-1.90)
HIOC		-0.053^{***}
		(-4.88)
HIOC × OMK		-0.053^{***}
		(-2.54)
R	-0.189^{***}	-0.188^{***}
	(-4.88)	(-4.86)
MKT	-0.061	-0.058
	(-0.32)	(-0.31)
SMB	0.257	0.251
	(0.69)	(0.68)
HML	0.187	0.182
	(0.78)	(0.76)
UMD	0.279^{**}	0.278^{**}
	(2.28)	(2.27)
Observations	17,254	17,254

Table A.8 presents regression summary statistics from the Tobit estimation of equations (4.5) and (4.6). The dependent variable, $FUTIMP$, is the magnitude of goodwill impairment over the period $t+1$ to $t+3$. OMK is the annual return to a portfolio that is long in high organizational capital firms and short in low organizational capital firms. $HIOC$ is an indicator for firms with organizational capital in the top quintile of their industry-year-end group. R is the annual returns to the firm ending three months after fiscal year-end. MKT, SMB, HML, and UMD are annual returns to the Fama and French (1993) and Carhart (1997) factor portfolios. The t-statistics based on standard errors clustered by fiscal year-end are in parenthesis. The regressions include untabulated cohort and industry fixed effects. ***, **, and * indicate 2-sided significance at 1%, 5%, and 10% respectively. The sample comprises firm-year observations from 2002 to 2013.

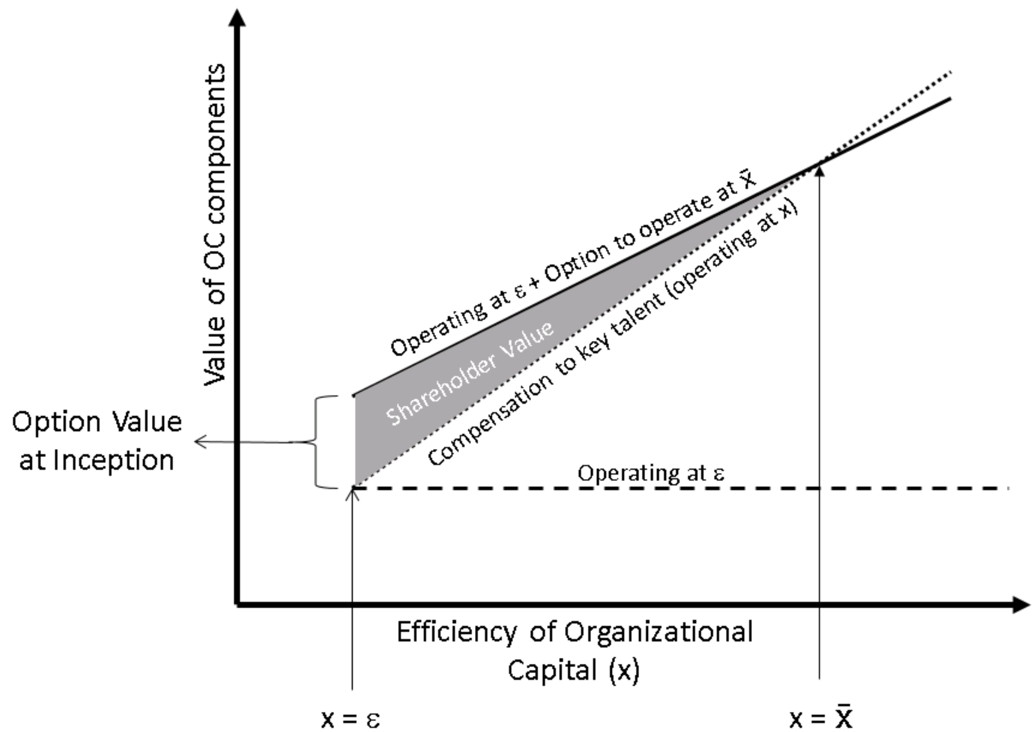
Table A.9: Restructuring and Technology Shocks

Column:	(1)	(2)
Dep.Vars:	FUTRESTR	FUTRESTR
OMK	-0.027^{**}	-0.029^{**}
	(-2.45)	(-2.50)
HIATO		-0.007^{***}
		(-9.68)
OMK $\times$ HIATO		0.015^{*}
		(1.70)
OC_R	0.335^{***}	0.437^{***}
	(6.99)	(9.29)
R	-0.012^{***}	-0.011^{***}
	(-4.78)	(-4.73)
MKT	-0.008	-0.008
	(-1.13)	(-1.17)
SMB	0.015^{**}	0.015^{**}
	(2.19)	(2.13)
HML	0.018^{***}	0.017^{***}
	(4.50)	(4.38)
UMD	0.001	0.001
	(0.35)	(0.30)
Observations	26,403	26,403

Table A.9 presents regression summary statistics from the Tobit estimation of equations (4.7) and (4.8). The dependent variable, $FUTRESTR$, is the magnitude of restructuring charges over the period $t+1$ to $t+3$. OMK is the annual return to a portfolio that is long in high organizational capital firms and short in low organizational capital firms. $HIATO$ is an indicator for observations in the top quintile of asset turnover within their industry-year-end group. Asset turnover is measured as sales divided by beginning total assets. R is the annual returns to the firm ending three months after fiscal year-end. OC_R is the industry-year-end rank of organizational capital. MKT, SMB, HML, and UMD are annual returns to the Fama and French (1993) and Carhart (1997) factor portfolios. The t-statistics based on standard errors clustered by fiscal year-end are in parenthesis. The regressions include untabulated cohort and industry fixed effects. ***, **, and * indicate 2-sided significance at 1%, 5%, and 10% respectively. The sample comprises firm-year observations from 2000 to 2013.

APPENDIX B: FIGURE

Figure B.1: A graphical representation of the value of components of organizational capital.



The organizational capital operates at the frontier level at the firms inception, so $x = \varepsilon$ at that point. The value of upgrading at the optimal threshold, $\bar{x}$, plus the value of operating at ε, is represented by the solid line. The value of upgrading immediately and operating at the frontier efficiency, x, is represented by the dotted line. At inception, the option has a positive value reflected in the different y-values of the solid and dashed lines when $x = \varepsilon$. Key talent capture the value of operating at x, so the difference between the value of the option (solid line) and operating at x (dotted line) is captured by the shareholders, as represented by the shaded area. As the technological frontier, x, increases, both the value of operating at x and the option value increase. However, because there is an optimal point of upgrade, where $x = \bar{x}$, the slope of the option is lower than the slope of operating at x. Intuitively, as x increases, the value captured by shareholders diminishes, because the value difference between upgrading at the optimal time and upgrading immediately diminishes.

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