HOW DO TECHNOLOGICAL INNOVATIONS AFFECT CORPORATE INVESTMENT AND HIRING?

by

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DISSERTATION ABSTRACT

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Using various measures for technological innovation, I show that corporate investment and hiring go up following technological advancements. The effect is stronger for firms with more industry- or firm-level innovations, among firms with lower capital intensity or greater marginal benefits from innovative outputs. In addition, firm-level production efficiency increases following innovations, with this effect concentrated among firms with greater industry- or firm-level innovative activity. Further, although cross-sectional heterogeneity exists, the firm-level capital-to-labor ratio does not increase significantly. Supporting the view of endogenous growth theory that firms with successful innovations tend to expand, these findings highlight the possible channels for innovations to propagate in the economy. These results also suggest, although making firms more efficient, technology does not reduce employment, suggesting technological innovations are, to some extent, Hicks-neutral.

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CHAPTER I

INTRODUCTION

Starting with Schumpeter (1911), endogenous growth theory has viewed technology not only as an important driver of economic expansion, but also closely related to the growth of employee income over the past century (Cyert and Mowery, 1987). With the recovery of the US economy from the financial crisis in 2007, increasingly more attention has been devoted to the importance of technology in economic and social development, in both academia and industry. Paul Romer's Nobel memorial prize in Economics in 2018 for his contributions to our understanding of long-term economic growth and its relation to technological innovation also confirms the importance of these issues.

Despite the rich theory concerning the real impacts of technology innovations at the aggregate level, the manner in which innovation affects the way that firms make decisions about investment and hiring is still unclear. Endogenous growth theory (Kogan et al. 2017) suggests that firms with successful innovations tend to grow in size, which naturally leads to more investment at the firm level. However, other researchers find that corporate production efficiency is usually enhanced following technological innovations (Francis, et al. 2014), suggesting that fewer capital inputs are required for the same level of output. Therefore, more evidence is needed about how firms make investment decisions in response to innovations. While these investment decisions are poorly understood, the disagreement about the impact of innovation on corporate hiring decisions is even greater. Researchers have long discussed that new technologies make employees redundant as new technologies eliminate positions that are related to earlier versions of products and services (Autor, 2015). However, a recent model by Acemoglu and Restrepo (2018) considers the dynamics of assets and finds that employment could increase with the introduction of new technologies, due to the job-creation effects of new products and related services. Overall, how firms make investment and hiring decisions in response to technological innovations, and the factors that determin the rate at which new technologies diffuse across the whole economy, need to be better explored. This research is important to fill this research gap.

Motivated by an investment model based on a Cobb-Douglas profit function that considers investment in partially irreversible goods and technological innovation shocks, the empirical analysis begins by examining the following questions: (1) how technology shocks affect the ways that firms make investment decisions, and (2) what are the factors that influence how general technology innovations propagate across the whole economy. I find that corporate investment goes up following technological advancements, especially in sectors that have greater industry- or firm-level innovative activities, lower capital intensity, or greater benefits from innovative outputs. Then, I examine how corporate hiring and the capital-to-labor ratio change in response to technological innovations. Although the labor market implications of technology are not directly generated by the model, as an essential input in the production process, the labor input itself is an important and interesting topic to examine. In addition to the analyses of corporate investment, cross-sectional heterogeneity in corporate hiring responses to technology are also examined. The results are consistent with the idea that corporate hiring goes up when new technologies emerge, and no evidence is detected for the systematic replacement of employees by capital assets.

To investigate the real impact of technological innovation, an empirical proxy for innovation is required. However, the task of finding a good proxy for technological advancement is still challenging. Despite extensive efforts in this direction, there is hardly a consensus in the technology-shock literature. In this paper, two main measures are used in a complementary fashion to the BP measure to measure the aggregate level technological innovations: The first measure is the technological-shock series developed in Beaudry and Portier (2006, and "BP series" henceforth), which is constructed based on market valuations in combination with movements in total factor productivity. The second measure is an investment-specific technology shock (IST) series (Ben Zeev and Khan, 2015; Kogan and Papanikolaou, 2014), which is constructed based on capital equipment prices, assuming that capital equipment price changes reflect their degree of obsolescence when new technologies emerge.

These measures are suitable for this study for several reasons. First, unlike variables such as firm-level R&D expenditures, the BP and IST measures, as aggregate measures of technology shocks, are less subject to the concern that they are endogenously determined by an individual firm's innovative behavior.[1] Second, by construction, the BP measure captures economic participants' expectations about increased future profitability associated with recognized technological advancements. This feature makes the BP measure highly relevant to the importance of innovations. Similarly, the IST measure which captures the information about innovations in the market, to the extent that those innovations cause price changes for capital equipment. From this perspective, the IST measure is also a good indicator for the significance of new technologies. However, as both the BP measure and the IST measure suffer from concerns of capturing noisy information, the two measures are used as complements. The consistent results based on these measures, both statistically and economically, largely alleviate any endogeneity concerns.

Next, to capture heterogeneity in innovative activity across firms, industries and firms are sorted into three broad groups, based on their patenting behavior as measured by citation-weighted patents (Hall et al. 2005). Earlier research has shown that patenting activity is closely linked to stock market valuations. This feature is consistent with the BP measure and allows me to identify broadly those groups of firms that are most innovative. Further, as the citation-weighted patent measure is constructed based on the number of patent citations, it is closely related to the demonstrated importance of these patents in later research and real production. In this sense, the citation-weighted patent measure also complements the aggregate technology shock measure—by providing more information about the prospective importance of innovations that is not available to the market at the moment.

[1] The appendix contains a more detailed discussion of the construction of the BP series.

In the empirical section, I find that a one standard deviation increase in the magnitude of the innovation shock is associated with an approximately 3.6% increase in the firm-level investment rate, a 19.2% increase in M&A expenditures, and a 2.2% increase in R&D investment compared to their average levels in the sample.[2] This impact is stronger for firms with greater firm- or industry-level innovations. For firms in industries that are more innovative, a one standard deviation increase in the magnitude of the innovation shock is associated with a 5.5% increase in capital investment rate, a 21.5% in M&A expenditure, and a 3.3% increase in R&D investment compared to their sample means. These levels are approximately 50%, 12%, and 50% higher than the average response. Similarly, the magnitude of investment and hiring activity also increases with firm-level innovative activities. For firms with in the top tercile of the firm-level innovations, a one standard deviation increase in the magnitude of the innovation shock is associated with a 3.6% increase in capital investment rate and a 10.6% in M&A expenditure compared to their sample means, while the least innovative firms nearly disinvest and engage in only about half the number of M&As as the most innovative firms. Combined with the results on industry-level innovations, these results indicate that the most innovative firms are more responsive to general technological innovations. The most innovative firms drive the increase in investments, while the least innovative firms nearly disinvest. These findings are consistent with the predictions in the model section, and support the perspective of endogenous growth theory regarding corporate growth and creative destruction. More importantly, this evidence highlights the insight that the innovativeness of individual firms and industry-level innovativeness are important factors that influence the spillover of technological innovations.

To explore potential factors that affect how new technology propagates across the economy, additional cross-sectional analysis is performed. First, the adjustment costs associated with investment decisions are not the same across firms, which reflects the degree of irreversibility of capital investment. The investigation about capital intensity is moti-

[2]The results are based on the BP measure here. As in the empirical section shows, results are robust to using the IST measure.

vated by the predictions of research in the real options literature, which emphasizes that theS irrversibility of investment plays an important role in influencing firms' to delay investment decisions in an uncertain environment (Rodrik, 1991; Dixit and Pindyck, 1994). I expect that firms with higher adjustment costs (higher degrees of irreversibility of investment) might be less motivated in reacting to new technologies. As a result, firms with higher adjustment costs are expected to exhibit lower levels of investment and hiring as a consequence of new technologies. Second, assuming that firms are value-maximizing, firms that benefit more from innovations should respond more strongly to technology shocks. Consistent with these conjectures, regression results show that firms when they have lower adjustment costs, when they have higher marginal benefits from innovative output as proxied by higher market-to-book ratio and when they belong to the high-tech industry, respond more strongly to technological shocks.

Although not directly motivated by the theoretical model in this paper, the labor market implications of technology itself are of great importance to the literature. In the extended analysis section, I examine Show new technology affects the way that firms make hiring decisions and their corresponding capital-to-labor ratio changes. The results show that following a one standard deviation increase in the technology shock measure, corporate hiring rates increase by 11% compared to the average hiring level in the sample. Similar to the pattern exhibited by corporate investment, this effect is stronger for firms that have greater industry-level innovative activities, greater firm-level innovative activities, have lower capital intensity, and have greater benefits benefits from innovative outputs, with a 15%, 12%, 19%, and 18% increase compared to the average hiring level in the sample, respectively.

Further, changes in the firm-level production efficiency and the capital-to-labor ratio are examined. Result shows that, on average, firm-level production efficiency (as proxied by firm-level TFP) increases following technological advancements, especially for highly innovative firms or firms in highly innovative industries. Specifically, the magnitude of the efficiency gains for high innovation firms is nearly double that for firms with low levels of innovation. Given more efficient production, there is no significant increase in the firm-level capital-to-labor ratio, though cross-sectional heterogeneity in this effect exists: firms with greater technology innovations experience increased capital-to-labor ratios compared to those with lesser innovations. These results are consistent with the view that technology benefits firms by increasing their efficiency, while employees are not being systematically replaced by capital assets, at least on average. Moreover, the decreased capital-to-labor ratio of less innovative firms, compared to more innovative ones is also consistent with the view that innovations could spur job creation in less-innovative industries/firms, such as those related to support services.[3]

This study extends the research on corporate innovation in many ways. First, due to the important role played by innovation, numerous studies have been focused on this area. Among those, the most effort has been devoted to finding the determinants of corporate innovative activities.[4] A wide spectrum of firm-, market- and macro-level determinants of corporate innovations have been explored over the last decade.[5] However, the evidence is limited concerning the impacts of technological innovations on corporate real decisions.[6] A few papers that examine the real consequences of innovations focus mainly on

[3]This is also consistent with the prediction by Acemoglu and Restrepo (2018).

[4]Researchers have long argued that technological innovation is one for the most import drivers to long-run economic expansion At the macro level, innovations account for approximately 50% of total GDP growth in a country, while the strength of this influence depends on the country, the level of economic development, and the phase of the economic cycle according to OECD (2015). Here, innovations include technological progress embodied in physical capital assets, investment in knowledge-based capital assets, increased productivity growth, and creative destruction. Researchers also find that technological shocks can explain the bulk of output fluctuations at the aggregate level, ranging from approximately 30% to 75% (Prescott, 1986; Basu et al, 2006; Beaudry and Portier, 2006; Ben Zeev and Khan, 2015). These papers rely on various proxies for technological innovation shocks, such as estimation based on DSGE models (Prescott, 1986), shocks to TFP based on Solow residuals (Basu et al, 2006), a news-based measure for technological shocks (Beaudry and Portier, 2006), and measures of investment-related technological shocks that are based on the relative prices of equipment (Ben Zeev and Khan, 2015).

[5]The literature has explored a series of firm-level factors that affect corporate innovative activities, including VC backing and ownership structures (Kortum and Lerner, 2000; Tian and Wang, 2011), corporate governance (Manso, 2011; Baranchuk et al., 2014), analyst coverage (He and Tian, 2013), stock liquidity (Fang et al.,2014), etc. Market-level factors are also found important in determining innovative activities, such as market competition (Aghion et al.,2005; Desmet and Rossi-Hansberg, 2012), lending market development (Benfratello et al., 2008; Mao, 2017), market-wide litigation risk (Cohen et al. 2016), etc. Some macroeconomic factors, such as laws and policies, have also been found to be important in shaping firm-level innovative activities (Lerner, 2009; Williams, 2013).

[6]To the best of my knowledge, evidence on the impacts of technological innovations on corporate de-

stock market reactions. Perhaps the most closely related research to this paper is Kogan et al. (2017) who develop a novel measure for patent innovativeness, based upon which they find that firms tend to grow in size in comparison to their competitors. This study complements and extends the work of Kogan et al. (2017) by not only examining the way that firms make decisions about investment and hiring, but also by exploring possible explanations for why innovations propagate across the whole economy, including innovativeness of firms, asset irreversibility and marginal benefits from innovative outputs. Moreover, this paper further examines the labor market implications of technology changes.[7]

Second, this study contributes to the extensive literature on technology and its labor market consequences. Theory suggests that technological progress is associated with both job creation and job destruction (Mortensen and Pissarides, 1994; Acemoglu and Restrepo, 2018), while its real impact on hiring decisions hinges on various macroeconomic- and firm-level factors. This study adds to this literature by showing that although heterogeneity exists, technological advancement can bring about greater higher hiring rates, and firms do not replace employees with machines, on average.

This research also finds evidence for the complementarity of labor and capital assets. One line of the literature, starting with Oi (1962), argues that technological advancement leads to substitution of labor by capital so that, innovations could lead to a loss of jobs. However, some other studies find a complementary relationship between capital and labor, such as Xu (2018) and Shen (2018), who both find that depressed corporate investment is associated with high-talent labor losses. In line with their findings, I show a contemporaneous increase in capital investment and hiring in response to technological innovations, consistent with the view that labor and capital assets are complemen-

cisions is limited. Probably the most relevant paper is Qiu and Wan (2015) who show evidence for the association between cash holding and technological spillover.

[7]There are also some papers investigate the real implication of technological innovation on asset pricing. For example, Hall et al. (2005) document the market value of firms is positively correlated with the scientific value of patents. Kogan and Papanikolaou (2014) explore the impact of technology shocks on the pattern of risk premia and show that technological advancement is an important source of systematic risk.

tary and technological innovations are largely Hicks-neutral.[8]

The rest of this paper proceeds as follows: Section 2 introduces the intuition behind the empirical tests in the paper based on an underlying Cobb–Douglas production function. Section 3 describes my data sources and sample construction. Section 4 presents the empirical results, and Section 5 concludes.

[8] Although some later evidence shows that assets per capita are not necessarily constant across all sectors.

CHAPTER II

SIMULATING INVESTMENT DYNAMICS WITH TECHNOLOGY SHOCKS

2.1 Basic Structure and Optimal Investment Policy

Using a model based on a Cobb-Douglas function, I formalize the intuition behind my subsequent empirical tests and show how innovation shocks affect corporate investment behavior. I first present the model, then proceed with its estimation using simulation methods. Following Bloom et al. (2007), a representative firm is assumed to operate a collection of the individual production units, and the production technology is assumed to evolve over time.[9] Considering the continuous accumulation of knowledge and the random nature of major technological breakthroughs, the process of technology diffusion is assumed to be a combination of a geometric random walk and a Poisson process. Technological shocks and optimization are assumed to occur at monthly intervals.

In the model, a production unit is assumed to optimize two types of inputs to maximize its value to current shareholders' wealth in a market without any financial frictions. At each point in time, each production unit has a revenue function $R(P_t, K_{1t}, K_{2t})$ based on an underlying Cobb-Douglas production function, given by:

$$R(P_t, K_{1t}, K_{2t}) = P_t K_{1t}^{\alpha} K_{2t}^{\beta},$$

where P_t summarizes the production technology and demand conditions, K_{1t} and K_{2t} are two types of inputs to the production process, and $0 < \alpha < 1$ and $0 < \beta < 1$ capture the curvature of the profit function. The revenue function is continuous and concave in the inputs. Factor P is a composite of a demand component (D), a firm-level production technology component (P^F), and a unit-level component (P^U), such that $P_t = D \times P_t^F \times P_t^U$. Given that this study focuses on the role played by innovation, for computational simplicity, the demand condition is assumed to be constant. The technology condition

[9] This multiple-unit nature of the firm is designed to prevent extreme values of investments. In this paper, this number is set at 100 in the simulation section. Simulations using alternative numbers of units are also performed and the results are qualitatively the same.

evolves over time:

$$P_t^F = P_{t-1}^F(1 + \mu_1 + \sigma(\epsilon_t^F + u_t^F)), \qquad \epsilon_t^F \sim N(0,1), \quad u_t^F \sim Poisson(\lambda),$$
$$P_t^U = P_{t-1}^U(1 + \mu_2 + \sigma(\epsilon_t^U)), \qquad \epsilon_t^U \sim N(0,1),$$

Here, μ_1 is the mean drift in the technology accumulation process. The parameter μ_1 is the drift of the technological innovation processes that is common to all firms. It captures the natural growth of productivity. In the baseline simulation, μ_1 is set at 0.2. A higher magnitude of μ_1 is intended to reflect a higher level of technological innovation that is common to all firms. In later simulations, μ_1 is used to capture the difference between higher and lower innovative industries. The ϵ_t^F are i.i.d. shocks to technology at the firm level, representing the disturbance in the continuation of improvement of technology. The u_t^U follow a Poisson distribution, capturing sporadic breakthroughs of firm-level technological innovations. The baseline level of λ is set at 0.1, and a higher level of λ is used to reflect greater technological advancement at the firm-level. In addition, I assume firms are also subject to technological shocks at the unit-level, which are captured by ϵ_t^U (the μ_2 is set at 0). The idea is that there exists an idiosyncratic innovation component to each unit of a firm, although the magnitude of the shock is determined mainly by the firm- and industry-level technology shocks.

Both types of capital inputs are costly to adjust. In this paper, I assume that the cost function, $C(K_{1t}, K_{2t}, I_{1t}, I_{2t})$, is homogeneous of degree one. The difference in adjustment costs is reflected by setting the resale price of capital lower than its original purchase price. In the simulation, the resale losses (c) for both inputs are set to a fixed value.[10]

The optimization problem for each unit can be summarized as:

$$V(P_t, K_{1t}, K_{2t}) = \max_{I_{1t}, I_{2t}} R(P_t, K_{1t} + I_t, K_{2t} + I_{2t}) - C(K_{1t}, K_{2t}, I_{1t}, I_{2t}) +$$
$$\frac{1}{1+r} E(P_{t+1}, (K_{1t} + I_{1t})(1-\delta), (K_{2t} + I_{2t})(1-\delta)),$$

[10] The resale discount reflects the value loss from reducing the input to production. For example, if resale loss for K_{1t} is 10%, by adjusting upward the input down by k_1, the adjustment revenue is k_1(1-0.1). On the other hand, if the input is been adjusted up by k_1, the adjustment cost is k_1. In the simulation, these resale losses are assumed to range from 10% to 90%.

where r is the discount rate, and δ is the depreciation rate. $E(.)$ is the expectation operator, I_{1t} and I_{2t} are the investments made at time t, and K_{1t} and K_{2t} are the capital stocks at time t.

2.2 Model Estimation

I solve the model numerically using simulated data, by feeding in technology shocks at monthly intervals. I simulate technology shocks for a panel of 10,000 firms over 25 years. Similar to Bloom et al. (2007), the first 120 months of the simulation are run to generate an initial distribution. Using the parameter values given in Table 1, the optimal investment policy is then calculated, based on this ergodic distribution and the final 15 years of simulated data. Annual firm-level investment/input is obtained through aggregation over two types of inputs, across all of the firm's units (100 in simulation), and over the 12 months of each year. Each input is calculated as the sum of its levels at the year-end over all units of operation. Given that the idiosyncratic shocks at the unit level are averaged across all the units of a firm, and the drift is common to all firms, a simple correspondence between the technology shock and firm-level investment outcomes can be obtained.

Figure 1 presents a plot of investment rates against technological innovations. The investment rate is measured by the total investment during the year divided by the beginning stock of capital. Annual technology growth is measured as the percentage change throughout the year, which is also the aggregation of firm-level and unit-level technology shocks. The simulation results provide several insights. First, the investment rate is positively related to innovations. As the magnitude of a technological advance becomes larger, the investment rate is increased. Quantitatively, as the average annual technology growth increases from 0 to 0.2%, the investment rate responds by increasing by approximately 0.1%.

Second, investments are more active as the industry- or firm-level technology shocks are larger. As discussed in the expositor of the model, μ_1 is the drift of the innovation process that is common to all firms, and a higher value for μ_1 reflects a higher level of technological innovation to the entire group of firms. Therefore, to capture different levels of industry-level innovation, I simulate data using different levels of μ_1. As Figure 2 shows, as μ_1 increases, the annual investment rate gets larger. Moreover, the parameter λ is used to capture technology shocks for individual firms, and a higher level of λ implies that a firm is exposed to a higher level of technological innovation. Figure 3 demonstrates this relationship between firm-level technological innovation and investment rates, where the investment rate increases as λ becomes greater.

Another prediction from the model is that firms' responses to technological innovations are negatively related to their adjustment costs. As shown in Figure 4, as the adjustment costs increase, the investment curve gets slightly flatter. This indicates that firms are less inclined to react to technological innovations when the costs associated with adjustments are higher.

CHAPTER III

DATA AND SAMPLE CONSTRUCTION

In this section, I summarize the variables that are used to measure technological innovations and the sample construction criterion.

3.1 Measuring Technology Shocks

3.1.1 Aggregate Technology Shocks

Various measures are used in this paper as proxies for technological advancements. In most of the main regressions, two proxies are used: the tome-series of technological shocks developed in Beaudry and Portier (2006, and "BP series" henceforth), which is constructed from market valuations in combination with movements in total factor productivity; and the investment-specific technology shock (IST) measure (Ben Zeev and Khan, 2015; Kogan and Papanikolaou, 2014), which is constructed from the capital asset price changes, assuming that price drops reflect the degree of obsolesce of assets due to technological advancements.

The BP series is constructed based on a moving-average representation derived from the estimation of a vector error correction model (VECM) for changes in total factor productivity (TFP) and stock prices (SP_t).[11] The BP measure fits this study in the sense that, by construction, it captures economic agents' expectations for increased future profitability associated with recognized innovations in general. It can thus be viewed as the magnitude of the technology shock to which an average firm is exposed. Using the BP series as the explanatory variable, then, one can generate insights into how firms react to technological advancement on average. There is also no significant Granger-causality relation between the BP series and other macroeconomic variables. This feature, to some extent, ensures that the results are not driven simply by macroeconomic factors such as

[11] More details on the BP series is provided in the Appendix.

GDP growth or employment.[12]

Figure 5 depicts the fluctuations in the BP series. As shown in panel A, technology shock fluctuations lead GDP growth by approximately 2-3 quarters, which is consistent with the findings in the earlier literature. Panel B shows that the trend in the technology shock series is similar to the trend in the patent citation data. Besides, the correlation between the technology shock series and the total number of citations for patents granted in the same period is 18%, indicating the technology shock series captures at least some information that coincides with the scientific value of patents. Figure 6 further shows that, at the aggregate level, technology innovation is associated with increases in both aggregate investment and TFP level growth, which is in line with both the prior literature and the model in CHAPTER II.

Considering that the BP measure and the market returns are closely related, the IST variable is used as a complementary measure, to alleviate concern that the market return is driving both the fluctuation of the technology shock measure and the changes in the dependent variables. A large body of literature has considered investment-specific technology as relevant for growth, business cycles, and asset prices. Usually, IST measure is assumed to measure the magnitude of investment-specific technical progress that can be inferred from the decline in the price of investment goods. As in Ben Zeev and Khan (2015), the IST measure is identified as the linear combination of reduced-form innovations, orthogonal to both current TFP and current IST, that maximizes the sum of contributions to the IST forecast-error variance over a finite horizon.[13] This paper fol-

[12]This feature is tested in the robustness section by adding more macroeconomic variables such as financing costs.

[13]There are different ways to proxy for IST shocks. Kogan and Papanikolaou (2014) recovered a high-frequency measure for IST shocks based on the returns for a mimicking portfolio that captures the difference between the stock return of investment good producers and those of consumption good producers. Fisher (2006) identifies unanticipated IST shocks using data on the real price of investment, and finds that technology shocks have accounted for over two-thirds of business cycle fluctuations in output over the 1982–2000 period; The DSGE literature also introduced IST shocks by imposing restrictions on identified shocks. Based on a VAR model and using the inverse of the real price of investment as the benchmark measure of IST, Ben Zeev and Khan (2015) identify IST shocks using U.S. data after WWII by restricting the IST news shock as the linear combination of reduced-form innovations orthogonal to both current TFP and current IST that maximizes the sum of contributions to IST forecast error variance over a finite period.

lows the definition in Ben Zeev and Khan (2015) as its construction is less dependent on variables that are related to the financial market, thus, less subject to the concerns of the "market timing hypothesis".

3.1.2 Industry and Firm-Level Technology Shocks

To more fully capture the magnitude of industry and firm-level technological innovations, I sort industries and firms into three broad groups based on their patenting behavior as measured by citation-weighted patents (Hall et al. 2005).[14] I use citation-weighted patents to measure innovation shocks for several reasons. First, the literature has shown that patenting activity is closely linked to stock market valuations. In Schankerman and Pakes (1985), based on a sample of 120 firms from 1968 to 1975, one additional unexpected patent is found to be associated, on average, with an approximately $810,000 increase in firm market value. Similarly, Kogan et al. (2017) measure patent values based on market reactions to patenting news and show that these values are closely related to the number of citations that patents receive, which are also supposed to capture the scientific value of these patents. This close link between patenting activity and market valuation is consistent with the idea of constructing the BP series, as discussed in the last section.

Second, citation-weighted patents could, to some extent, reflect the importance of innovations that are not fully appreciated ex-ante. Given that the citation-weighted patent measure is constructed based on the number of citations a patent receives, it reflects the patent's scientific value and is closely related to its proven importance in later production. However, this future success is hard to predict at the time a patent is filed. In this sense, citation-weighted patents could be understood as a proxy for the magnitude of corresponding technology shock.

For each firm, citation-weighted patents are measured as:

[14] Due to patent data availability, my analysis concerning industry and firm-level technology innovations is based on patent filings and citation data between 1971 and 2010.

$$V\Theta_{ijt} = \sum_{l \in P_{ijt}} \Big(1 + \frac{C_l}{\bar{C}_l}\Big),$$

where i denotes firms, j represents industries, and t indexes years. P_{ijt} is the set of patents by firm i in industry j in year t. C_l is the total number of citations received by patent $l \in P_{ijt}$, where citation number is scaled by $\bar{C}_l$ which is the average number of future citations received by all patents in the same year-class as patent l. This scaler is used by adjusting for citation truncation lags following Hall et al. (2005).

Firms are then sorted into three categories based on their citation-weighted patents. A firm for which citation-weighted patents fall into the highest tercile during year t within the firm's industry j using the Fama-French 48-industry classification, is defined as being exposed to a high incidence firm-level technology shocks. That is, $HighShock_{ij} = 1$. Otherwise, $HighShock_{ij} = 0$, indicating that this firm's citation-weighted patents fall into the middle or lowest terciles during year t within the firm's industry j.

In this manner, industries are sorted into three broad categories to reflect the magnitude of their industry-level shocks. Industry-level citation-weighted patents are calculated by aggregating the citation-weighted patents of firms within the same industry in the same year.

$$\Phi_{jt} = \sum_{i \in I_{jt}} \Big(\Theta_{ijt}\Big),$$

where j denotes industry and t indexes year. I_{jt} represents the set of firms within industry j, and Θ_{ijt} is firm i 's citation-weighted patents at time t, within industry j.

The measure Φ_{jt} is then normalized using its sample mean and standard deviation. This normalized index (Φ_{jt}^{norm}) can be understood as an industry's current relative technological innovativeness compared to its historical level. For example, if the index value for the wholesale industry is 1 at the year 2000, it can be understood that the wholesale industry in 2000 is one standard deviation more innovative, compared to its historical level. This normalization also makes the index comparable across industries, to the extent that industry-level characteristics related to patenting activities are invariant over time. To capture the different degrees of innovativeness across industries, the magnitudes of industry-year technology shocks are categorized as high, medium, and low according to whether the relevant index value falls into the highest, middle, or lowest tercile of all industry-year index values.[15]

3.2 Firm-Level Variables

Firm-level variables used in our empirical analysis come from the annual Compustat database that extends from 1971 to 2015. I exclude utility firms (SIC codes between 4000 and 4999) and financial firms (SIC codes between 6000 and 6999). Observations are discarded if they have negative values for total assets, shareholders' equity, cash flows, or property, plant, and equipment. The result is a sample of 181,701 firm-year observations corresponding to 19,337 firms.[16] To reduce the potential impact of extreme outliers, all variables are winsorized at the 1% and 99% level. Capital expenditure rates and hiring rates are constructed and winsorized following Stein and Stone (2013). Table 2 presents summary statistics for the main accounting variables for the sample used in our analysis.

[15] This sorting method assumes that technology breakthroughs come in waves. An alternative approach is to sort industries into high, medium and low levels of technology shocks based on their relative innovativeness within each year. The alternative sorting method gives qualitatively similar empirical results.

[16] For the analysis based on the IST shock measure and the cross-sectional analysis based on the patent data, the sample is restricted to 1971 to 2010 due to data availability.

CHAPTER IV

TECHNOLOGICAL INNOVATION AND CORPORATE INVESTMENT POLICIES

In this section, I test the predictions of the model described in CHAPTER II. I first test how firms change the way they make investment decisions in terms of capital investment (CAPX), M&As, and R&D expenditure, as well as hiring policies in response to technology shocks.[17] Then, based on the innovative activity of industries and firms, and other firm- and industry-level features, I explore the possible channels for technologies to propagate across the whole economy.

4.1 Empirical Specification

The baseline regression is as follow:

$$Y_{i,t+j} = \alpha_i + \beta_1 TechShock_t + \beta_2 Q_{i,t-1} + \beta_3 CF_{i,t} + \beta_4 X_{t-1} + \epsilon_{i,t+j},$$

Here, i denotes firms, t indexes the year, and $j = 0, 1, 2$ stands for the number of lead years for the dependent variable. $Y_{i,t+j}$ stands for the alternative dependent variables, including the investment rate ($I_{i,t+j}/K_{i,t+j-1}$), M&A activities ($acq_{i,t}/at_{i,t-1}$), $R\&D$ investment rates defined following Stein and Stone (2013), and the hiring rate $Hiring_{i,t+j} = emp_{i,t+j}/emp_{i,t+j-1} - 1$. $TechShock_t$ is the measure for technology shocks, including the BP series developed by Beaudry and Portier (2006) and the IST shock measure developed by Ben Zeev and Khan (2015). For each firm i, $TechShock_t$ is measured as the arithmetic average of the technological innovation series during the year t. This measure is considered to be a proxy for the average magnitude of technological innovation. The Tobin's Q is calculated as the book value of the asset minus the book value of equity, plus the market value of equity normalized by the book value of the total assets at the beginning of the period. The operating cash flows $CF_{i,t}$ are taken from a firm's statement of cash flow and are normalized on total assets at the beginning of the period. I control for cash

[17] As in Harford(2005), technological innovations are envisioned as circumstances where capital reallocation is required, making technology stimulus an important driver for corporate M&A activities.

flow, to capture measurement error in Tobin's Q as a proxy for marginal q. To alleviate the concern that investment opportunities are usually procyclical and the investment and hiring patterns that are common to certain innovating firms, series of macroeconomic, industry-level and firm-level control variables are included in the regression too. X_{t+1} is a set of macroeconomic variables to capture potential investment opportunity and macroeconomic conditions (such as GDP growth and consumer sentiment). Series of industry- and firm-level innovative activity dummies are also included to capture the potential difference in investments behavior across high and low innovative industries and firms. In all regressions, firm-level fixed effects and the error term are clustered by the firm and year level.[18] [19]

4.2 Results

I begin my analysis by estimating several benchmark investment regressions using the baseline regression for $j = 0, 1, 2$ to accommodate the possibility that the impact of technological innovations on investment may persist over multiple periods. Columns (1) to (3) in Panel A of Table 3 show the results of regressions on capital expenditure using the BP measure. The coefficients on $TechShock$ are statistically significantly starting one period after the technology shock, suggesting that technological advancement is associated with increased capital investment. Specifically, a one standard deviation increase in $TechShock$ is associated with an approximately 3.6% increase in the capital investment, and this effect lasts for about two years. As a way to expand production, firm-level mergers and acquisitions exhibit a similar pattern. The results in columns (4) to (6) show that with a one-standard-deviation increase in technological innovation, M&As increase by approximately 19.2%, compared to the sample average. Besides, columns (7) to (9) report the results on R&D investment, the results show that with a one-standard-deviation increase

[18] These dummies are constructed following the method described in the last section.

[19] As in the literature, regressions in this paper use leads $(t + j)$ of the dependent variables on the left-hand side, and the current explanatory variable (t) on the right-hand side. In unreported results, an alternative regression with the current dependent variable (t) and the lagged explanatory variable $(t - j)$ on the right-hand side is used, and the results are qualitatively the same.

in technological innovation, firm-level R&D investment rate increases by approximately 2.2% compared to its sample average. Panel B of Table 3 reports the results using the IST measure. A one standard deviation increase in the magnitude of the innovation shock is associated with a 2.7% increase in the capital investment rate, a 9.2% in M&A expenditure, and a 1.8% increase in R&D investment compared to their sample mean.

These results are consistent with the predictors of the theoretical model prediction that firms react to technological innovations by increasing their production inputs. This evidence supports the view that firms tend to grow in response to advances in technology at the firm level. The increase in capital investment and M&A also indicates that firms tend to expand with innovations. Furthermore, higher R&D investment in response to technology shocks suggests technological innovations foster even more innovative activities.[20] These consistent results based on BP measure and the IST shock measure largely alleviate endogeneity concerns with regard to these measures individually.

[20]This increased input to innovative activities possibly take the form of the catching up the behavior of firms with less advanced technologies, or in the form of exploring complementary technologies to better utilize the new technique.

CHAPTER V

SUBSAMPLE ANALYSIS

In this part of the empirical analysis, I explore possible factors that affect how general innovations spill over into the whole economy. Empirically, I examine how specific firm- or industry-level characteristics affect the impacts of technological advancements. I consider several reasons why this should be the case. First, the model in CHAPTER II predicts that firms with a greater level of the firm- or industry-level innovative activities are more likely to increase their use of inputs when new technologies emerge. This possibly due to the fact that firms, when they are more active in innovations, are more sensitive and ready to take advantage of new technologies. Second, if adjustments to investment or hiring are not equally costly for all firms, it would be natural to expect that firms with higher adjustment costs are more reluctant to adopt new technologies. For these firms, we would expect to see a smaller response of investments. Third, assuming that firms are value-maximizing when they decide their levels of investment and hiring, higher expected marginal benefits from innovative outputs should lead firms to invest and hire more. Empirically, firms that benefit more from technological innovation should respond more strongly to such innovations.

5.1 Firm- and Industry-level Innovation Intensity

Cross-sectionally, based on the model in CHAPTER II, firms that experience firm- or industry-level technology shocks will employ more inputs in their production processes compared to firms with smaller shocks. Therefore, I test two conjectures: (1) that firms in industries with greater technological advancements exhibit a greater increase in investments; (2) that firms with greater firm-level technology advancements exhibit a greater increase in their investments, all else equal. If these theoretical conjectures are correct, I expect to observe that corporate investment, in response to technological advancements, goes up more in firms with a greater firm- or industry-level innovations.

In Table 4, I first repeat the regression as in equation 3 using subsamples with high, medium, and low industry-level technology shocks, which are supposed to capture different magnitudes of industry-level technology shocks.[21] Panel A1 presents the effect of technology shocks for firms with higher industry-level technology shocks using the BP measure. The results suggest that firms' investment policies respond more strongly if the industry as a whole conducts more innovative activities. Specifically, a one standard deviation increase in the magnitude of the innovation shock is associated with a 5.5% increase in the capital investment rate, a 21.5% in M&A expenditure, and a 3.3% increase in R&D investment compared to their sample mean. These levels are approximately 50%, 12% and 50% higher than the average response as shown in panel A in Table 3. Panel A2 and A3 of Table 4 report results based on the sample of industries with the medium and lowest industry-level technology shocks, respectively. These results show that inputs of the capital assets, through M&A activities and R&D expenditures, are monotonically decreasing as the industry-level innovativeness gets weaker. It is worth noting that firms in the least-innovative industries may actually disinvest, that is, they experience a decline in corporate investment for equal to about 2.3% of the level of sample mean. This pattern matches the predictions of the model in CHAPTER II.

Panel B presents the results based on the IST measure fo the technology shocks. Similarly, a one standard deviation increase in the magnitude of the IST measure is associated with a 4% increase in the capital investment rate, a 18% in M&A expenditure and a 3% increase in R&D investment compared to their sample mean. These levels are approximately 33%, 92% and 67% higher than the average response as panel B in Table 3. In Panel B2 and B3, a similar pattern of decreased responses to technology is observed.

To further investigate the effects of firm-level innovativeness on the propagation of technology, the baseline regression is modified to include interactions between firm-level innovativeness dummies, $HighInnovate$, $MediumInnovate$, and $LowInnovate$, and

[21] Consider the different sensitiveness of corporate investment to controls across industries, subsamples are used here. A single regression with interaction terms of technological innovation and industry-level innovativenss dummies also gives qualitatively the same results.

technology shock measure. Table 5 presents the results: The most-innovative firms tend to drive the observed increases in investment and hiring, while the least-innovative firms barely increase their hiring and may actually disinvest.

Overall, the above results are consistent with the model prediction that firms do more investment and hiring following technology shocks, and this effect is stronger as the technology shock gets larger. Specifically, both firm- and industry-level technology shocks are important in determinants of firm-level investment policies, in the form of capital investment, via M&A activities and R&D expenditures. This pattern of crossectionally decreased responses, with both firm-level innovativeness and industry-level innovations, to technologies, suggests that the innovative environment to which firms are exposed plays an important role in determining their response to new technologies.

5.2 Adjustment Costs of Investments

As models of irreversible investment suggest, when contemplating the introduction of new technologies, a firm takes into consideration that other firms may introduce similar products, which will eliminate their advantage. Moreover, as the technology in question continue to advance, it also possible that more-sophisticated or cheaper versions of the same technology might be introduced by other firms, further rendering the original firm's investment unprofitable (McDonald and Siegel, 1986). Therefore, the incentive to invest in response to technological advancement should be moderated by the costs that must be incurred to adjust inputs, i.e. firms with higher adjustment costs should be less inclined to react to innovations. In contrast, firms with lower adjustment costs have less to lose if a negative outcome happens, thus should be more active in making investments when new technologies emerge.

The cross-sectional simulation results confirm these predictions. In CHAPTER II, I use the parameter *sell loss* to proxy for the degree of irreversibility of inputs, where a larger value for *sell loss* suggests that it is more difficult for the firm to adjust its existing inputs. Figure 4 illustrates the relationship between investment rates and magnitudes of innovations.[22] As in Figure 4, the curve for the investment rate becomes flatter as adjustment costs increases, suggesting that firms are less willing to make investments as adjustment costs get larger.

To test this prediction empirically, I use a firm's capital intensity as a rough measure for its adjustment costs. As in Gulen and Ion (2015), I assume that firms with higher degrees of capital intensity are more likely to invest in projects that require large upfront costs. Given that it does not differentiate among the various determinants of adjustment costs, such as asset specificity or mobility (Kessides, 1990), this proxy can be viewed as merely a rough measure of adjustment costs. A firm's capital intensity ratio is defined as the value of property, plant, and equipment normalized by the begin-of-period value of total assets. In this paper, firms with capital intensities falling into the lowest tercile in the sample are defined as low-capital-intensity firms. This proxy's validity stems from the assumption that firms with high capital intensities tend to incur higher costs to replace their capital assets and adapt to the new technology. On the other hand, low-capital-intensity firms are more flexible in making investments.

Table 6 reports the results for regressions that include an interaction between the capital-intensity dummy and the technology shock measure. The coefficients on this interaction term are positive and significant for all dependent variables. For capital investment, M&As, and R&D expenditure rates, the magnitude of the increase in investment nearly doubles for low-capital-intensity firms during years $t + 1$ and $t + 2$. These findings suggest that firms with lower capital intensities respond more strongly when innovations emerge, consist with the view that adjustment costs are a factor that influences firms' reactions to new technologies.

[22]Here, the investment rate is the aggregated increase inputs in capital asset and labor scaled by the inputs at the beginning of the period.

5.3 Marginal Benefits from Innovative Outputs

Another potential determinant of a firm's response to new technologies is its benefits from innovative outputs. Given that firms make investment decisions to maximize firm value, imagine a simple case where a firm has an opportunity to undertake a positive-NPV project, all else equal. The incentive to make this investment is stronger when the potential profitability of this project is greater. As a result, it is natural to expect that firms with greater marginal benefits from innovative outputs are more motivated to increase inputs to the production when technology shocks emerge.

Empirically, I use two measures to proxy for a firm's marginal benefit from innovative outputs: the market-to-book ratio and whether it belongs to the high-tech sector. Following Qiu and Wan (2015), consider the market-to-book ratio as reflecting the present value of future cash flows that could be generated a firm's innovative outputs. The market-to-book ratio is employed to proxy for its marginal profit per unit of output and a higher market-to-book ratio reflect the greater earning potential of a firm's output. Empirically, I sort firms into terciles, based on their market-to-book ratio at $t-1$, and a firm is defined as having higher marginal benefit from innovative outputs if its market-to-book ratio falls within the highest tercile for its industry ($Growth = 1$).

Table 7 presents the results for regressions that include the *Growth* dummy and its interaction with the technology shock measure in the baseline regression. Panel A reports the results based on the BP measure using the whole sample. The coefficients on the interaction term are positive and statistically significant. Economically, for high-growth firms, the magnitudes of capital investment and R&D associated with innovations increase by approximately 100% compared to firms average response in my sample. As shown in Panel B, results based on the IST shock measure demonstrate a consistent pattern. The effects of a technology shock on capital investment, M&As and R&D are higher by approximately 75%, 36% and 100%, relative to non-growth firms. These results show that growth firms react more strongly to innovations. Overall, to the extent that the marginal profit from innovative outputs is relatively higher among firms with higher market-to-book ratios, these results provide support for the conjecture that technology shocks are more important for firms with better growth potential.

Another measure that I use to proxy for the marginal benefits that a firm obtains from innovative outputs is by its industry classification. Given that a high technology industry usually requires firms to maintain their competitiveness by keeping up with new technologies, a high-tech firm's ability to extract profit from its product usually hinges on how advanced and unique its products are. Therefore, whether a firm belongs to the high-tech industry could be used as a rough proxy for greater marginal benefits from innovative outputs. Based on the high-technology industry classification employed by Fama and French, I find that high-tech firms exhibit increases in all three proxies for corporate investment compared to the response of average firms. As shown in Table 8, the additional increases in capital investment, M&As and R&D rates specifically for high-tech firms, are approximately 50%, 47.8% and 200% of the response of the average response of firms in my sample. Overall, the evidence in this section suggests firms that are able to benefit more from innovative outputs tend to investment more when new technologies emerge.

CHAPTER VI

LABOR MARKET IMPLICATION OF TECHNOLOGICAL INNOVATIONS

The previous section has explored how firms make investment decisions when new technologies emerge. Moreover, both the model and the empirical analyses in previous sections emphasize the possible determinants that affect how innovations spill over in the economy. Overall, the results suggest firms increase their inputs to production when technology advances, and whether a firm or an industry is more innovative, the adjustment costs of making investments, and the marginal benefits from innovative outputs, are found play an important role in determining how firms react to new technologies.

Although not directly motivated by the model in the CHAPTER II, labor, as an essential input in the production process, is an interesting issue to be explored in the context of technological shocks. This study investigates the labor market implication of technological innovations from two perspectives: (1) whether firms change their hiring behavior when new technologies emerge. (2) do firms systematically replace employees with capital assets when new technologies emerge.

6.1 Technological Innovations and Corporate Hiring

As an essential input in the production process, labor is also a factor that can be affected by technological advancements. It has been long discussed that technological advancements cause labor to be replaced by machinery or make old skill sets obsolete. Both of these changes tend to reduce employment (Autor, 2015). However, by taking the dynamics of capital asset accumulation into consideration, Acemoglu and Restrepo (2018) suggest that employment could be higher under certain circumstances after the introduction of new technology, due to the possibility of job creation associated with new products and increases in the need to fill supporting job positions in related service industries. Therefore, the direction of the overall effect of technological innovations is still unclear.

Given the variety of predictions in the literature, this study tries to disentangle these conflicting hypotheses by providing more evidence at the firm level. To be specific, by exploring what factors affect how firms change their hiring behaviors, this study provide a possible explanation for the existence of contrary predictions among prior theories.

Empirically, I estimate the baseline specification used in earlier section, but now use the hiring rate as the dependent variable. The results in Table 9 concern corporate hiring decisions. Based on the results in Panel A, columns (1) through (3) show that firms increase their hiring in the presence of technological innovations, with an 11.9% increase in hiring rates associated with a one standard deviation increase in the BP measure of technology shocks. Besides, cross-sectional results in columns (4) through (9) suggest that this effect is stronger for firms with lower capital intensity and higher market-to-book ratios (where hiring ratio are greater by 55.6% and 22.2%). These estimates suggest that firms with lower adjustment costs or greater marginal benefits from innovative outputs are more likely to increase their hiring more when new technologies emerge. Panel B repeats the same analysis using the IST measure and yields similar results.

Panel C reports heterogeneity in these corporate hiring changes according to different industry-/firm-level innovativeness. Consistent with the pattern observed for corporate investment, more-innovative firms and industries higher. This pattern of greater responsiveness of corporate hiring to technology shocks is robust to the IST measure.

6.2 Technological Innovations and Capital-Labor Ratios

Knowing that firms increase their inputs to production in response to technological shocks, a follow-up question concerns: whether firms systematically replace labor by capital assets due to the enhanced production efficiency that made possible by new technologies. To examine the labor market implications of technological advancement, I analyze the effects of technology shocks on firm-level productivity and capital-labor ratios. Empirically, I use firm-level total factor productivity (TFP) as a proxy for firm-level productivity and examine the change in TFP following technological innovations.[23] Table 10 shows that

[23]Firm-level productivity is measured by firm-level total factor productivity, where the TFP is constructed following the method employed in Imrohoroglu and Tuzel (2014).

firm-level productivity tends to increase after innovations as the coefficients of interest are positive in these regressions for $t + 1$ and $t + 2$. I also find that the increase in TFP is driven mainly by firms with greater innovative activities and those belong to industries with greater innovative activities, consistent with the idea that larger innovation shocks lead to greater TFP enhancement (Panel A2, A3 and A4). The results based on IST measure also provide consistent results.

Given that firms tend to operate more efficiently with innovations, it is natural to wonder whether firms systematically replace their employees by capital assets. The relationship between capital assets and labor has been extensively investigated in the literature: some researchers argue that capital would substitute for labor in the sense that greater capital inputs will decrease employment and diminish the welfare of employees, while other researchers find that capital investment and labor are not necessarily substitutes for each other. I approach this issue by examining the change in the firm-level capital-to-labor ratios as a result of technology innovations.

Table 11 examines changes in the capital-to-labor ratio following innovations. Several insights can be drawn from the results. First, the firm-level capital-labor-ratio does not increase significantly in general. Given that firms are expanding through capital investment and M&As, technological advancement is creating new jobs. Second, when looking at heterogeneity in the effects of innovation on capital-to-labor ratios, the results show that the capital-to-labor ratio is slightly higher for top innovating industries, while firms with the lowest level of industry- and firm-level innovations experience decreases in their capital-to-labor ratios. These results suggest that, although firms become more efficient in production, their inputs in the form of investment and hiring are increasing, and employees are not systematically replaced by new investment, on average.

CHAPTER VII

ROBUSTNESS

In this section, I describe a battery of robustness checks designed to eliminate alternative hypotheses.

First, a major concern for empirical results in this paper is that the main proxies for technological advancements contain first-moment shocks stemming from other macroeconomic forces. In the review paper by Ramey (2016), both the BP measure and the IST measure are found not to be Granger-caused by other economic factors, such as GDP, consumption, and stock prices. This alleviates concerns about the endogeneity issue of these variables. In this paper, considering that market reactions are possibly related to financing conditions, which may confound the conclusions in this paper, I did additional tests of the relationship between macroeconomic factors and the BP and IST measures. As Table 12 shows, the coefficients on variables that proxy for financing costs (the three-month T-bill rate and the investment-grade bond rate) are not statistically significant. Overall, the comments in Ramey (2016) and the additional evidence in my own analysis provide support for the view that the main results in this research are driven by technological advancements, rather than by other macroeconomic factors.

Second, given that the technology shock series is based on stock market pricing, a natural concern for the empirical analysis is whether the results could be related to the influence of market reactions on corporate behavior. For example, as in Stein (1988), myopic managers tend to forgo profitable investments to boost current performance under the pressure of a possible takeover. On the other hand, when a corporate stock's market price is higher, managers may worry less about being replaced after takeovers, and may thus choose to make more investments. To rule out this potential alternative explanation for the main results, I augment the baseline regression to include industry-level stock-price changes (Panel A), and firm-level stock-price changes (Panel B).

In the regressions presented in panel A of Table 13, I include the interaction between technological innovation and the indicator for a high-valuation-change industry, which is defined to take a value 1 if the industry-level valuation change falls into the highest tercile, and is 0 otherwise. In the regressions presented in panel B, I include the interaction between technological innovations and a firm-level valuation dummy, which equals to 1 if the firm-level valuation change falls to the highest tercile, and is 0 otherwise. By including these interaction terms in the regression, I intend to distinguish that portion of the change in investment and hiring that is driven by valuation changes. The results in both panel A and panel B of Table 13 show that firms' investment and hiring decisions are positively associated with market valuation increases. However, after controlling for market valuation changes, the coefficients on the technology shock variable are still statistically significant, with similar magnitudes as in the baseline regressions. This evidence supports the view that changes in investment and hiring policy is associated with technology shocks, and not simply with changes in firm- or industry-level market valuations.

Another concern stem from the measurement error in Q. As the Tobin's Q measure is used as a proxy for the marginal q, measurement error could arise and the explanatory power assigned to technology shocks in the basic model is possibly just a result of correlation between the technology shock measure and q. To alleviate this concern, a reverse regression is performed following Erickson and Whited (2005). The proxy for the marginal Q is regressed on investment policies, technology innovations, and all other controls (including cash flow and GDP growth). The coefficients on the technology shock measure in this reverse regression are around 0.13 to 0.14, which is very close to 0, suggesting the explanatory power is not originate from measurement error in q.

More robustness checks are described in the table appendix, including alternative cutoffs for innovative firm and industry categories, alternative definition for investments, and including aggregate TFP as a control variable.

CHAPTER VIII

CONCLUSION

In this paper, I examine how technological shock affect the way that firms make investment and hiring decisions. I start with a firm-level investment function based on a Cobb-Douglas production function to model the optimal investment decision when new technologies emerge. Based on simulations, the model predicts that profit-maximizing firms respond to innovations with higher-level investments and increased hiring.

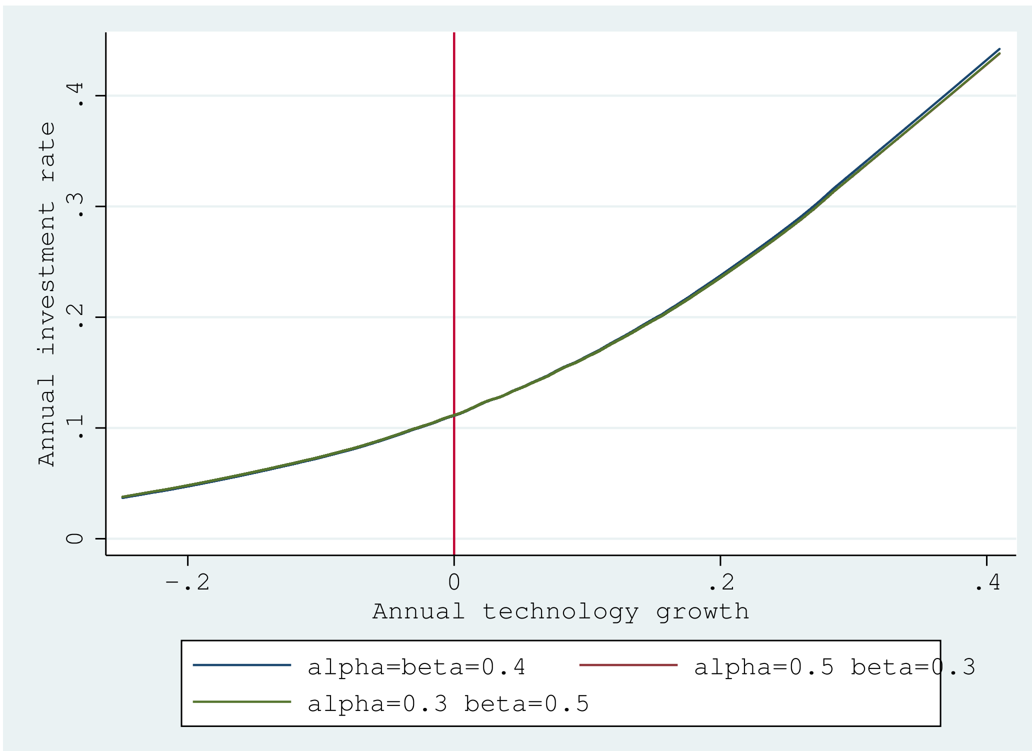
Empirically, using various measures used in the literature to proxy for technology shocks, I find that firms tend to increase both investment and hiring. Consistent with the predictions of the simulation, I also find that firms respond more strongly to technology shocks in the presence of higher industry- or firm-level innovations, lower capital intensity, and higher benefit from innovative outputs. Additional analysis also provides evidence that technology shocks increase firm-level production efficiency, especially for firms with greater firm- or industry-level technology shocks. Furthermore, on average, technology advancement does not hurt employees by taking away job positions, and capital assets and labor are complementary.

Studies about technology advancement are important to both researchers and policymakers. This study complements studies about the growth of firms in response to innovations by providing evidence that firms invest more in capital after technological advancements. In addition, this research highlights the possible channels for innovations to spread in the economy. The results also suggest that employment and capital investment tend to grow simultaneously when new technologies emerge, providing evidence that more-advanced technology does not necessarily hurt employees.

APPENDIX A

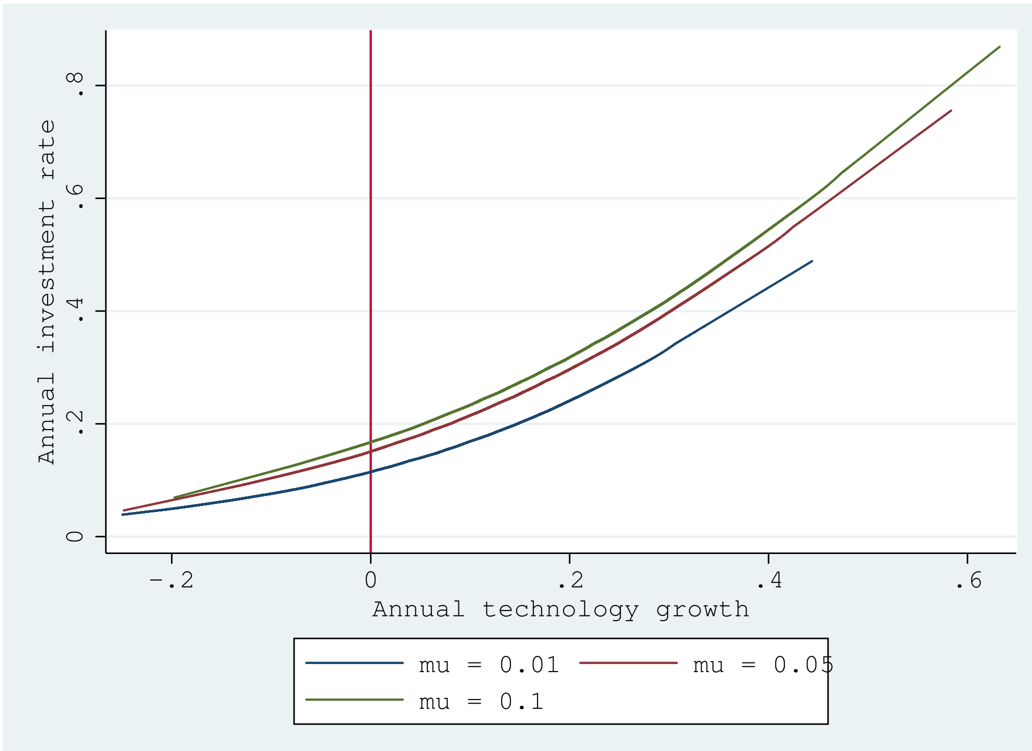
FIGURES

Figure 1: Firm-level Investment Policies in Response of Technological Innovation



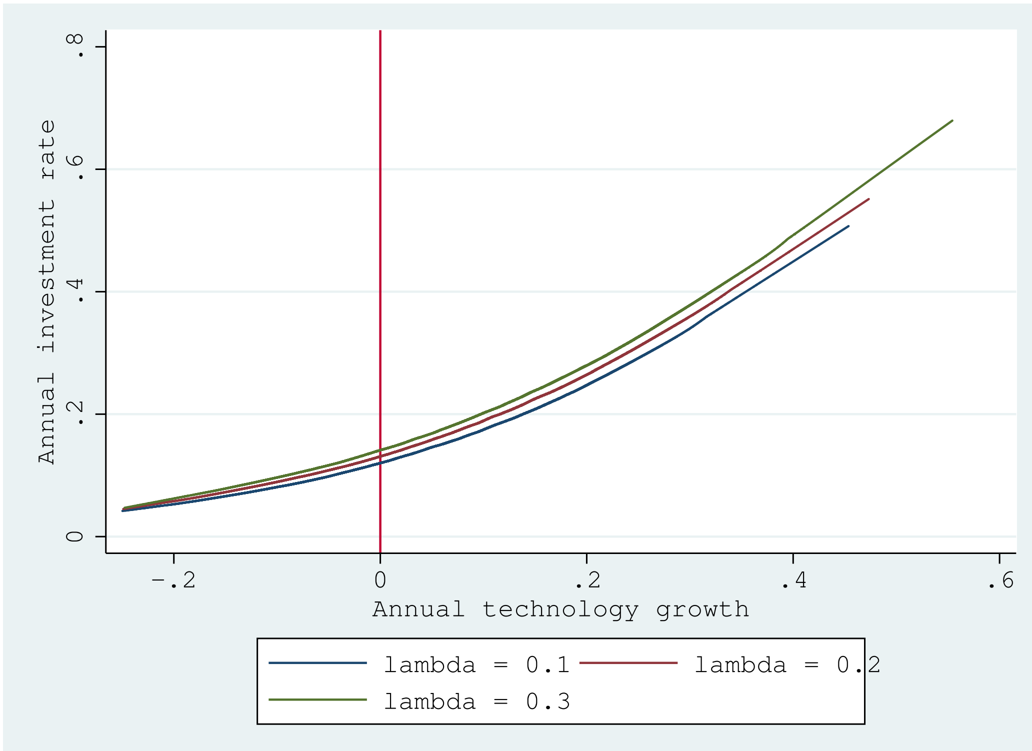
This figure presents firm investment and hiring policies against technological innovations based on simulated data. The investment rate is measured by the total investment during the year divided by year beginning capital stock. Annual technology growth is measured as the percentage change comparing the beginning and the end of the year, which is also the aggregation of firm-level and unit-level technological innovations. Parameter α and β in the revenue function $R(P_t, K_{1t}, K_{2t}) = P_t K_{1t}^{\alpha} K_{2t}^{\beta}$ ranges from 0.3 to 0.5, reflecting the importance of the two inputs in production.

Figure 2: Firm-level Investment in Response of Technological Innovation: Variation with Industry-level Innovative Activity



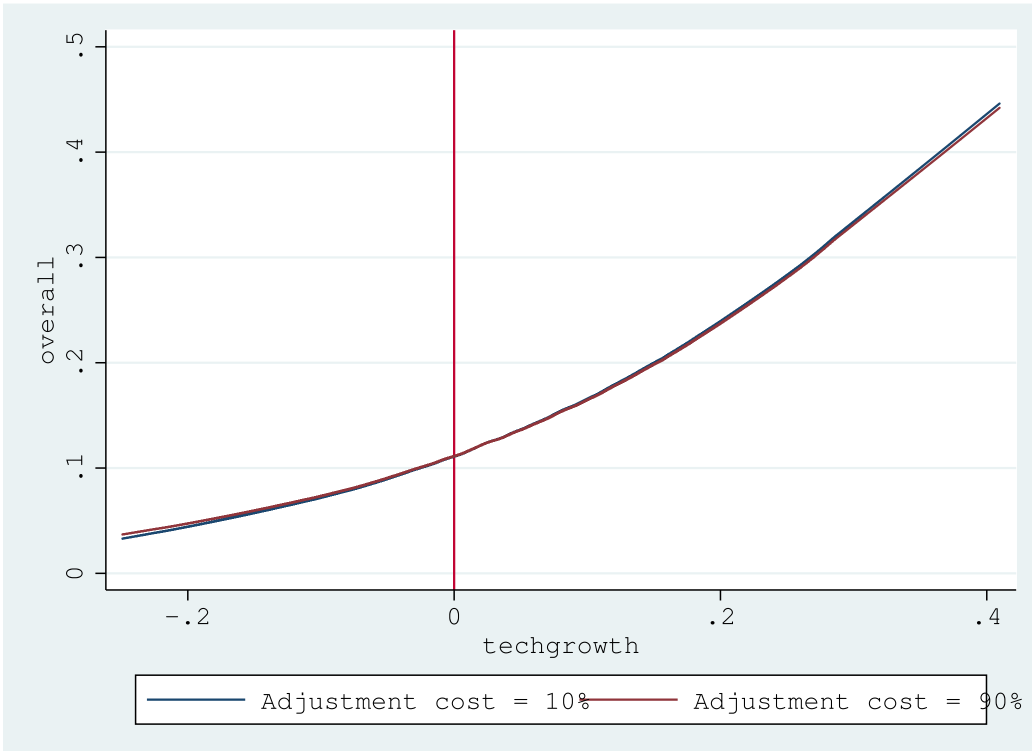
This figure presents firm investment rates against technological innovations based on simulated data, with various levels of industry-level innovations. The industry-level innovative activeness is captured by a higher level of μ_1. The investment rate is measured by the total investment during the year divided by year beginning capital stock. Parameter α and β in the revenue function $R(P_t, K_{1t}, K_{2t}) = P_t K_{1t}^{\alpha} K_{2t}^{\beta}$ are both set at 0.4.

Figure 3: Firm-level Investment in Response of Technological Innovation: Variation with Firm-level Innovative Activity



This figure presents firm investment rates against technological innovations based on simulated data, with various levels of industry-level innovations. The industry-level innovative activeness is captured by a higher level of λ. The investment rate is measured by the total investment during the year divided by year beginning stock of inputs. Parameter α and β in the revenue function $R(P_t, K_{1t}, K_{2t}) = P_t K_{1t}^{\alpha} K_{2t}^{\beta}$ are both set at 0.4.

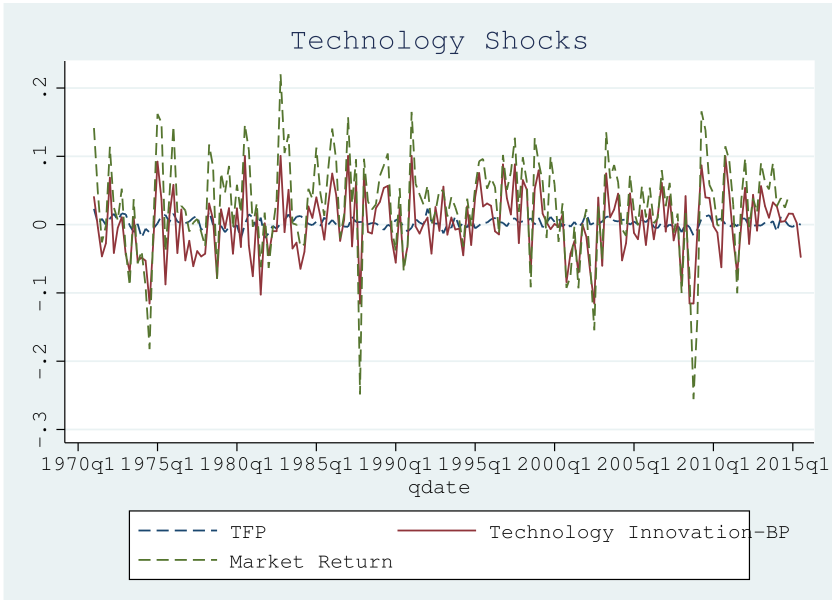
Figure 4: Firm-level Investment in Response of Technological Innovations: Variation with Adjustment Costs



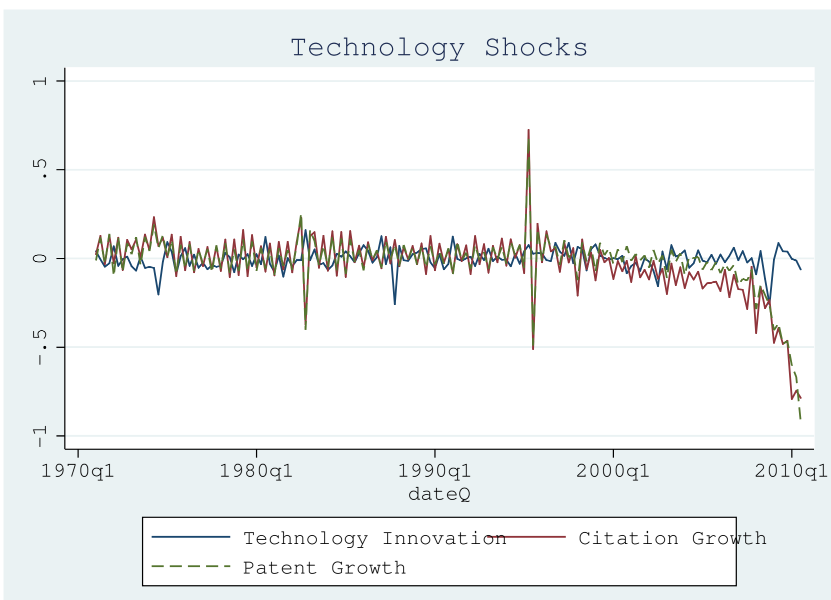
This figure presents firm investment rates against technological innovations based on simulated data, with various degrees of adjustment costs. The investment rate is measured by the total investment during the year divided by year beginning stock of inputs. The parameter α and β in the revenue function $R(P_t, K_{1t}, K_{2t}) = P_t K_{1t}^{\alpha} K_{2t}^{\beta}$ are both set at 0.4. Parameter *selllose* is the loss in reversing investment, which ranges from 10% to 90% to reflect the difficulty of adjusting existing inputs in production.

Figure 5: Technological Innovation Measures

Panel A: Technology Shocks

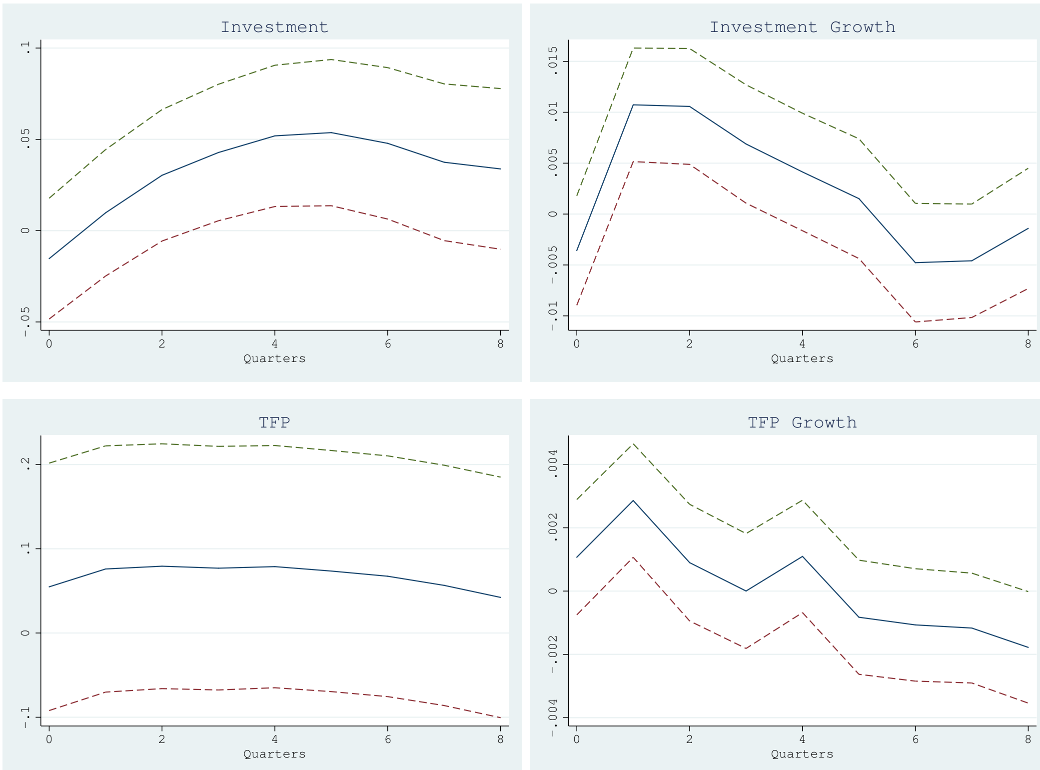


Panel B: Technology shocks and Patents



This figure depicts the technological innovation series used in this paper. The innovation series used in this study is the measure for technology shock developed by Beaudry and Portier (2006) winsorized at the 1% and 99% level. The TFP series is constructed as in Ramey(2016), and market return is defined as the return on S&P500. The sample period for technological innovation is from 1970:Q1 to 2015:Q4, and the data for patents span from 1971:Q1 to 2010:Q4.

Figure 6: Technological Innovation, Aggregate Investment, and TFP



This figure depicts the change in aggregate investment and TFP following technological innovations. The technological innovation series used in this study is the measure for technology shock developed by Beaudry and Portier (2006). The TFP series is constructed as in Ramey(2016), and GDP growth is defined as the percentage growth of quarterly real GDP. The sample period for the technological innovation is from 1970:Q1 to 2015:Q4, and the data for patents span from 1971:Q1 to 2010:Q4.

APPENDIX B

TABLES

Table 1: Parameter Values Used in Simulation

This table summarizes the parameter values used in the simulation.

Notation	Variable	Value
α	Power for capital input in the return function	0.3-0.5
β	Power for labor input in the return function	0.3-0.5
r	Interest rate	10%
δ	Depreciation	10%
λ	Parameter for the Poisson distributed technology shock	0.1
μ_1	Drift for unit level technology shocks	0.02
μ_2	Drift for firm level technology shocks	0
σ	Variance of shocks	0.1
$sellloss$	Adjustment costs	10% - 90%

Table 2: Summary Statistics

Panel A: Aggregate variables

This table presents summary statistics for the main macroeconomic variables in this paper. Data for macroeconomic variables are obtained from the FRED website. The TFP and technology shock data are obtained from Dr. Ramey' website. GDP growth, TFP growth, investment growth are defined as the percentage change of quarterly real GDP, TFP, and aggregate investment, respectively. The sample period is from 1970:Q1 to 2015:Q3.

VARIABLES	N	Mean	SD	P25	P50	P75
Real GDP	179	10147.6700	3620.8800	6578.1470	9480.1570	13830.7100
GDP Growth	179	0.0070	0.0082	0.0032	0.0075	0.0112
TFP	179	0.6768	0.1217	0.5685	0.6503	0.8073
TFP Growth	178	0.0035	0.0123	-0.0037	0.0031	0.0108
Aggregate Investment	179	1620.2170	747.2689	950.1660	1305.0030	2273.0950
Investment Growth	178	0.0099	0.0394	-0.0090	0.0078	0.0337
Technology Shock (BP)	179	-0.0021	0.0575	-0.0308	0.0006	0.0310
Technology Shock (IST)	165	0.0025	0.8852	-0.5797	-0.0389	0.5931

Panel B: Firm level variables

This table presents summary statistics for the main firm-level variables in this paper. Firm-level data are obtained from CRSP annual database for the period from 1971 to 2015, excluding utility firms (SIC code between 4900 and 4999) and financial firms (SIC code between 6000 to 6999). Firms with a negative book value of asset(at), shareholder's equity (ceq), and property, plant, and equipment (ppent) are discarded. Capital stock, knowledge stock, and investment rate based on the perpetual inventory method are constructed and winsorized following Stein and Stone (2013). The sample is restricted to the observations with capital investment rate, Tobin's Q, and cash flow nonmissing. The final sample consists of 181,701 observations, covering 19,337 firms. All variables are winsorized at 1% and 99% level.

VARIABLES	N	Mean	SD	P25	P50	P75
Book value of asset	181701	1651.94	6869.24	25.01	105.30	556.39
Capital stock	181701	679.01	2812.91	7.13	34.67	201.45
Knowledge stocks	91327	382.40	1870.64	4.12	20.65	105.20
Property, Plant, and Equipment	181590	568.53	2371.55	4.34	24.39	158.04
Sales	181684	1452.91	5664.38	23.07	111.74	569.45
Leverage ((dltt+dlc)/Lagged Asset)	181261	0.24	0.23	0.04	0.21	0.37
Cash holdings (che /Lagged Asset)	181690	0.19	0.28	0.03	0.08	0.23
Cashflow (ibc + dpc) / Lagged Asset	181701	0.04	0.21	0.02	0.09	0.14
PPE/Lagged Assets	181590	0.35	0.29	0.13	0.28	0.51
CAPX/Lagged Asset	181701	0.08	0.09	0.02	0.05	0.10
Investment Rate (I_t/K_{t-1})	181701	0.22	0.20	0.08	0.16	0.29
R&D Investment ($R\&D_t/M_{t-1}$)	91327	0.18	0.15	0.09	0.16	0.25
Tobin's Q	181701	1.76	1.54	0.97	1.27	1.91
Sales Grow	175609	0.16	0.48	-0.02	0.09	0.23
Hiring Rate	181701	0.16	0.38	-0.04	0.04	0.22
Asset Sale ($assetsale_t/K_{t-1}$)	156404	0.01	0.04	0.00	0.00	0.01
M&A rate (M&A/Lagged Asset)	150424	0.13	0.56	0.00	0.00	0.01
Net Investment (Investment Rate - Asset Sale)	156404	0.18	0.17	0.07	0.14	0.24

Table 3: Baseline Regressions

This table presents estimates from the regression:

$$I_{it+j}/K_{it+j-1} = \alpha_i + \beta_1 TechShock_t + \beta_2 Q_{it-1} + \beta_3 CF_{it} + \beta_4 X_t + \epsilon it,$$

where i indexes firm, t donates the year, and j represents the year lead between the dependent and independent variables, $j = 0, 1, 2$. I_{it}/K_{it-1} is the investment rate defined using the perpetual inventory method following Stein and Stone (2013). $TechShock_t$ is the arithmetic average to the measure for technology shocks during the year t, and then normalized by its sample mean and standard deviation. X_t is a series of macroeconomic variables to capture potential investment opportunity and macroeconomic conditions (includes GDP growth and consumer sentiment), and a series of the industry- and firm-level dummies to capture its innovative activity. Panel A presents the results based on the BP measure for technological innovations, and Panel B is based on IST measure. In each panel, column (1) to (3) report the results on capital investment. In column (4) to (6) and (7) to (9), the dependent variable is replaced by merger and acquisition $M\&A_{it+j}/K_{it+j-1}$, and $R\&D$ investment rate (defined following Stein and Stone (2013)), respectively. All regressions in this table control for firm-level fixed effects, and the standard errors are clustered at the firm and year level. Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Based on the BP measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$
Technology Shock	-0.003	0.008**	0.006**	0.010	0.025***	0.011**	0.000	0.004***	0.003**
	(0.003)	(0.004)	(0.003)	(0.008)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Tobin's Q	0.033***	0.021***	0.011***	0.025***	0.016***	0.007**	0.012***	0.012***	0.009***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Cash Flow	0.190***	0.243***	0.174***	0.113***	0.238***	0.178***	0.008	0.108***	0.125***
	(0.017)	(0.020)	(0.015)	(0.024)	(0.022)	(0.022)	(0.007)	(0.011)	(0.012)
GDP Growth	0.899***	0.886***	0.600***	-0.026	-0.036	-0.353	0.211***	0.203**	0.131**
	(0.237)	(0.200)	(0.162)	(0.274)	(0.215)	(0.322)	(0.073)	(0.079)	(0.058)
Sentiment	-0.001	-0.001***	-0.001***	0.002***	0.001***	0.001	-0.000	-0.000**	-0.001***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Observations	139,205	124,413	113,597	133,694	119,419	107,331	72,992	64,819	58,499
R-squared	0.379	0.379	0.348	0.312	0.308	0.302	0.504	0.526	0.531
Firm/Industry Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

(Table 3, Continued)

Panel B: Based on the IST measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$
Technology Shock	-0.002	0.006*	0.007**	0.012**	0.019***	0.016***	0.001	0.003***	0.003**
	(0.004)	(0.003)	(0.003)	(0.006)	(0.005)	(0.006)	(0.001)	(0.001)	(0.001)
Tobin's Q	0.033***	0.020***	0.011***	0.024***	0.014***	0.006**	0.012***	0.012***	0.009***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Cash Flow	0.190***	0.244***	0.175***	0.113***	0.242***	0.179***	0.008	0.108***	0.126***
	(0.017)	(0.020)	(0.015)	(0.024)	(0.023)	(0.023)	(0.007)	(0.011)	(0.012)
GDP Growth	0.915***	0.851***	0.548***	-0.119	-0.157	-0.470	0.201***	0.182**	0.128**
	(0.234)	(0.216)	(0.183)	(0.286)	(0.268)	(0.308)	(0.073)	(0.076)	(0.058)
Sentiment	-0.001	-0.001***	-0.001***	0.002***	0.001*	0.001	-0.000	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Constant	0.165***	0.207***	0.237***	-0.142***	-0.024	0.036	0.175***	0.187***	0.202***
	(0.038)	(0.026)	(0.029)	(0.048)	(0.047)	(0.051)	(0.015)	(0.012)	(0.013)
Observations	139,205	124,413	113,597	133,694	119,419	107,331	72,992	64,819	58,499
R-squared	0.379	0.377	0.348	0.312	0.307	0.302	0.504	0.526	0.531
Firm/Industry Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

Table 4: Response to Technological Innovations: Role of the Industry-level Innovative Activity

This table analyze the variation in investment policies with industry-level innovative activities. The results are based on regression:

$$I_{it+j}/K_{it+j-1} = \alpha_i + \beta_1 TechShock_t + \beta_2 Q_{it-1} + \beta_3 CF_{it} + \beta_4 X_t + \epsilon it,$$

where i indexes firm, t donates the year, and j represents the year lead between the dependent and independent variables, $j = 0, 1, 2$. I_{it}/K_{it-1} is the investment rate defined using the perpetual inventory method following Stein and Stone (2013). $TechShock_t$ is the arithmetic average to the measure for technology shocks during the year t, and then normalized by its sample mean and standard deviation. X_t is a series of macroeconomic variables to capture potential investment opportunity and macroeconomic conditions (includes GDP growth and consumer sentiment), and a series of the industry- and firm-level dummies to capture its innovative activity. This regression is performed for the top, medium, and bottom innovating industries separately, where industries are categorized into the top, medium, and bottom innovating industries based on their citation-weighted number of patents over the year. Panel A presents the results based on the BP measure for technological innovations, and Panel B is based on IST measure. In each panel, column (1) to (3) report the results on capital investment. In column (4) to (6) and (7) to (9), the dependent variable is replaced by merger and acquisition $M\&A_{it+j}/K_{it+j-1}$, and $R\&D$ investment rate (defined following Stein and Stone (2013)), respectively. All regressions in this table control for firm-level fixed effects, and the standard errors are clustered at the industry and year level. Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

(Table 4, Continued)

Panel A: Based on the BP measure

Panel A1: Top 33% innovating industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$
Technology Shock	0.001	0.012***	0.008***	0.006	0.028***	0.009	0.001	0.006***	0.005***
	(0.004)	(0.003)	(0.003)	(0.009)	(0.008)	(0.005)	(0.001)	(0.001)	(0.001)
Observations	51,059	45,526	41,549	49,069	43,716	39,337	29,740	25,773	22,729
R-squared	0.455	0.449	0.419	0.362	0.364	0.362	0.595	0.612	0.627

Panel A2: Medium 33% innovating industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$
Technology Shock	-0.005	0.004	0.005*	0.012**	0.021***	0.012**	0.000	0.003**	0.004*
	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.002)
Observations	45,041	40,496	37,030	42,973	38,654	34,825	24,325	21,857	19,895
R-squared	0.475	0.475	0.444	0.403	0.386	0.374	0.595	0.617	0.611

Panel A3: Bottom 34% innovating industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$
Technology Shock	-0.005**	0.007*	0.006*	0.008**	0.020***	0.007**	-0.001	0.002	-0.001
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
Observations	38,566	34,401	31,392	37,091	33,064	29,656	17,119	15,598	14,273
R-squared	0.463	0.464	0.435	0.387	0.380	0.374	0.607	0.622	0.619
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

(Table 4, Continued)

Panel B: Based on the IST measure

Panel B1: Top 33% innovating industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$
Technology Shock	-0.001	0.008**	0.010**	0.013	0.023***	0.019**	0.001	0.004***	0.006***
	(0.004)	(0.003)	(0.004)	(0.008)	(0.008)	(0.009)	(0.001)	(0.001)	(0.002)
Observations	51,059	45,526	41,549	49,069	43,716	39,337	29,740	25,773	22,729
R-squared	0.455	0.445	0.420	0.362	0.363	0.363	0.595	0.611	0.628

Panel B2: Medium 33% innovating industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$
Technology Shock	-0.005*	0.002	0.006*	0.010**	0.015***	0.015***	0.000	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.005)	(0.002)	(0.002)	(0.001)
Observations	45,041	40,496	37,030	42,973	38,654	34,825	24,325	21,857	19,895
R-squared	0.475	0.474	0.445	0.403	0.385	0.375	0.595	0.616	0.611

Panel B3: Bottom 34% innovating industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$
Technology Shock	-0.001	0.007**	0.006**	0.010***	0.013***	0.010**	0.001	0.003*	0.002
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.001)	(0.002)	(0.002)
Observations	38,566	34,401	31,392	37,091	33,064	29,656	17,119	15,598	14,273
R-squared	0.462	0.464	0.435	0.387	0.378	0.374	0.607	0.622	0.619
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

Table 5: Response to Technological Innovation: Role of the Firm-level Innovative Activities

This table analyze the variation in investment policies with firm-level innovative activities. The estimates below are based on the regression:

$$I_{it+j}/K_{it+j-1} = \alpha_i + \beta_1 TechShock_t * HighInnoation_{it} + \beta_2 TechShock_t * MediumInnovation_{it} + \beta_3 TechShock_t * LowInnovation_{it} + \beta_4 Q_{it-1} + \beta_5 CF_{it} + \beta_6 X_t + \epsilon it,$$

where i indexes firm, t donates the year, and j represents the year lead between the dependent and independent variables, $j = 0, 1, 2$. I_{it}/K_{it-1} is the investment rate defined using the perpetual inventory method following Stein and Stone (2013). $TechShock_t$ is the arithmetic average to the measure for technology shocks during the year t, and then normalized by its sample mean and standard deviation. $HighInnovation$, $MediumInnovation$, and $LowInnovation$ are defined based on firms' citation-weighted patents at year t. If a firm's number of citation-weighted patents are among the highest tercile within its industry at year t, $HighInnovation$ takes value 1. Otherwise, it equals to 0. $MediumInnovation$ and $LowInnovation$ takes value 1 if a firm's number of citation-weighted patents are among the medium and lowest tercile within its industry at year t, respectively, and 0 otherwise. X_t is a series of macroeconomic variables to capture potential investment opportunity and macroeconomic conditions (includes GDP growth and consumer sentiment), and a series of the industry- and firm-level dummies to capture its innovative activity. This regression is performed for the top, medium, and bottom innovating industries separately, where industries are categorized into the top, medium, and bottom innovating industries based on their citation-weighted number of patents over the year. Panel A presents the results based on the BP measure for technological innovations, and Panel B is based on IST measure. In each panel, column (1) to (3) report the results on capital investment. In column (4) to (6) and (7) to (9), the dependent variable is replaced by merger and acquisition $M\&A_{it+j}/K_{it+j-1}$, and $R\&D$ investment rate (defined following Stein and Stone (2013)), respectively. All regressions in this table control for firm-level fixed effects, and the standard errors are clustered at the firm and year level. Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

(Table 5, Continued)

Panel A: Based on the BP measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$
TechShock*HighInnovation	-0.003	0.009**	0.007**	0.012	0.026***	0.010**	-0.001	0.003	0.002
	(0.003)	(0.004)	(0.003)	(0.008)	(0.004)	(0.004)	(0.001)	(0.002)	(0.002)
TechShock*MediumInnovation	-0.001	0.008**	0.006**	0.004	0.022***	0.013**	0.001	0.005***	0.004**
	(0.003)	(0.003)	(0.003)	(0.009)	(0.004)	(0.005)	(0.002)	(0.001)	(0.002)
TechShock*LowInnovation	-0.028***	-0.008	0.004	0.005	0.017*	0.006	-0.002	0.005	-0.002
	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.012)	(0.011)	(0.010)	(0.006)
Observations	139,205	124,413	113,597	133,694	119,419	107,331	72,992	64,819	58,499
R-squared	0.379	0.379	0.348	0.312	0.308	0.302	0.504	0.526	0.532
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm/Industry Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

(Table 5, Continued)

Panel B: Based on the IST measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$
TechShock*HighInnovation	-0.002	0.006*	0.007**	0.013**	0.019***	0.017***	0.000	0.002	0.002
	(0.004)	(0.003)	(0.003)	(0.006)	(0.005)	(0.006)	(0.001)	(0.001)	(0.002)
TechShock*MediumInnovation	-0.002	0.005	0.008**	0.010	0.016***	0.013*	0.002	0.005***	0.005**
	(0.004)	(0.003)	(0.003)	(0.006)	(0.006)	(0.007)	(0.002)	(0.002)	(0.002)
TechShock*LowInnovation	-0.031***	-0.011	0.003	0.009	0.013	0.001	-0.015***	-0.005	0.000
	(0.006)	(0.007)	(0.008)	(0.010)	(0.009)	(0.011)	(0.005)	(0.005)	(0.005)
Observations	139,205	124,413	113,597	133,694	119,419	107,331	72,992	64,819	58,499
R-squared	0.379	0.377	0.348	0.312	0.307	0.302	0.504	0.526	0.532
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm/Industry Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

Table 6: Response to Technological Innovation: Variation with the Capital Intensity

This table analyzes the role of capital intensity in influencing the effect of technological innovations. This table presents estimates from the regression:
$I_{it+j}/K_{it-1} = \alpha_i + \beta_1 TechShock_t * LowCapIntensity_i + \beta_2 TechShock_t + \beta_3 Q_{it-1} + \beta_4 CF_{it} + \beta_5 X_t + \epsilon it$, where i indexes firm, t donates the year, and j represents the year lead between the dependent and independent variables, $j = 0, 1, 2$. I_{ijt}/K_{ijt-1} is the investment rate defined using the perpetual inventory method following Stein and Stone (2013). $TechShock_t$ is the arithmetic average to the measure for technology shocks during the year t, and then normalized by its sample mean and standard deviation. $LowCapIntensity_i$ is a dummy variable that takes value 1 if a firm's capital intensity falls in the lowest tercile of all firms, and 0 otherwise. Capital intensity is measured as $ppent_t/bookvalueoftotalasset_{t-1}$. X_t is a series of macroeconomic variables to capture potential investment opportunity and macroeconomic conditions (includes GDP growth and consumer sentiment), and a series of the industry- and firm-level dummies to capture its innovative activity. This regression is performed for the top, medium, and bottom innovating industries separately, where industries are categorized into the top, medium, and bottom innovating industries based on their citation-weighted number of patents over the year. Panel A presents the results based on the BP measure for technological innovations, and Panel B is based on IST measure. In each panel, column (1) to (3) report the results on capital investment. In column (4) to (6) and (7) to (9), the dependent variable is replaced by merger and acquisition $M\&A_{it+j}/K_{it+j-1}$, and $R\&D$ investment rate (defined following Stein and Stone (2013)), respectively. All specifications in this table include firm-level fixed effects, and the standard errors are clustered at the industry and year level. Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

(Table 6, Continued)

Panel A: Based on the BP measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$
TechShock*Low CapIntensity	0.005	0.007**	0.002	0.002	0.032***	0.005	-0.001	0.001	0.005***
	(0.003)	(0.003)	(0.003)	(0.016)	(0.010)	(0.007)	(0.001)	(0.002)	(0.002)
Technology Shock	-0.003	0.007*	0.006*	0.010	0.020***	0.010**	0.000	0.003***	0.002*
	(0.003)	(0.004)	(0.003)	(0.006)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)
Observations	139,197	124,406	113,591	133,686	119,412	107,325	72,992	64,819	58,499
R-squared	0.379	0.379	0.348	0.312	0.308	0.302	0.504	0.526	0.532
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm/Industry Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

(Table 6, Continued)

Panel B: Based on the IST measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$
TechShock*Low CapIntensity	0.006	0.009**	0.011**	0.044**	0.043***	0.041***	0.003	0.005*	0.006
	(0.004)	(0.004)	(0.005)	(0.019)	(0.013)	(0.015)	(0.002)	(0.003)	(0.004)
Technology Shock	-0.003	0.008**	0.006*	0.008	0.023***	0.009**	-0.000	0.003**	0.002*
	(0.003)	(0.004)	(0.003)	(0.008)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Observations	139,197	124,406	113,591	133,686	119,412	107,325	72,992	64,819	58,499
R-squared	0.379	0.379	0.348	0.313	0.309	0.303	0.504	0.526	0.532
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm/Industry Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

Table 7: Response to Technological Innovation: Variation with the Marginal Benefit from Innovations

This table analyzes the role of the marginal benefit from innovative outputs in influencing the effect of technological innovations. This table presents estimates from the regression:

$$I_{it+j}/K_{it-1} = \alpha_i + \beta_1 TechShock_t * Growth_{it-1} + \beta_2 Growth_{it-1} + \beta_3 TechShock_t + \beta_4 Q_{it-1} + \beta_5 CF_{it} + \beta_6 X_t + \epsilon it,$$

where i indexes firm, t donates the year, $j = 0, 1, 2$ denotes the year lead between the dependent and independent variables. I_{it}/K_{it-1} is the investment rate defined using the perpetual inventory method following Stein and Stone (2013). $Growth_{it-1}$ is a dummy variable that take value 1 if a firm's market to book ratio falls in the highest tercile within its industry at year $t-1$, and 0 otherwise. $TechShock_t$ is the arithmetic average to the measure for technology shocks during the year t, and then normalized by its sample mean and standard deviation. X_t is a series of macroeconomic variables to capture potential investment opportunity and macroeconomic conditions (includes GDP growth and consumer sentiment), and a series of the industry- and firm-level dummies to capture its innovative activity. This regression is performed for the top, medium, and bottom innovating industries separately, where industries are categorized into the top, medium, and bottom innovating industries based on their citation-weighted number of patents over the year. Panel A presents the results based on the BP measure for technological innovations, and Panel B is based on IST measure. In each panel, column (1) to (3) report the results on capital investment. In column (4) to (6) and (7) to (9), the dependent variable is replaced by merger and acquisition $M\&A_{it+j}/K_{it+j-1}$, and $R\&D$ investment rate (defined following Stein and Stone (2013)), respectively. All specifications in this table include firm-level fixed effects, and the standard errors are clustered at the firm and year. Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

(Table 7, Continued)

Panel A: Based on the BP measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$
Techshock*Growth Firm	0.002	0.007***	0.003**	-0.005	0.007	-0.007	0.001	0.003**	0.004***
	(0.002)	(0.002)	(0.002)	(0.008)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)
Technology Shock	-0.003	0.007*	0.006*	0.011	0.024***	0.013***	-0.000	0.003**	0.002
	(0.003)	(0.003)	(0.003)	(0.007)	(0.005)	(0.004)	(0.001)	(0.001)	(0.001)
Growth Firm	0.025***	0.017***	0.013***	0.009	-0.007	0.006	0.008***	0.007***	0.009***
	(0.003)	(0.002)	(0.002)	(0.006)	(0.007)	(0.006)	(0.002)	(0.002)	(0.002)
Observations	139,024	124,251	113,449	133,516	119,261	107,184	72,869	64,722	58,415
R-squared	0.381	0.380	0.348	0.312	0.308	0.302	0.505	0.527	0.532
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm/Industry Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

(Table 7, Continued)

Panel B: Based on the IST measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$
Techshock*Growth Firm	-0.001	0.006*	0.007*	0.002	0.009*	0.014**	0.003	0.004**	0.004
	(0.004)	(0.004)	(0.004)	(0.007)	(0.005)	(0.007)	(0.002)	(0.002)	(0.002)
Technology Shock	-0.002	0.008**	0.006*	0.010	0.025***	0.010**	-0.000	0.003**	0.003*
	(0.003)	(0.004)	(0.003)	(0.008)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Growth Firm	0.025***	0.017***	0.013***	0.008	-0.006	0.007	0.008***	0.007***	0.009***
	(0.003)	(0.002)	(0.003)	(0.006)	(0.007)	(0.006)	(0.002)	(0.002)	(0.002)
Observations	139,024	124,251	113,449	133,516	119,261	107,184	72,869	64,722	58,415
R-squared	0.381	0.380	0.349	0.312	0.308	0.302	0.505	0.527	0.532
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm/Industry Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

Table 8: Response to Technological Innovation: Role of High-tech firms

This table analyzes the how high-tech firms response differently when technology innovations come. This table presents estimates from the regression:

$I_{it+j}/K_{it-1} = \alpha_i + \beta_1 TechShock_t * Hightech_i + \beta_2 TechShock_t + \beta_3 Q_{it-1} + \beta_4 CF_{it} + \beta_6 X_t + \epsilon it$,
where i indexes firm, t donates the year, $j = 0, 1, 2$ denotes the year lead between the dependent and independent variables. I_{ijt}/K_{ijt-1} is the investment rate defined using the perpetual inventory method following Stein and Stone (2013). $TechShock_t$ is the arithmetic average to the measure for technology shocks during the year t, and then normalized by its sample mean and standard deviation. $Hightech_i$ is a dummy variable that takes value 1 if a firm is classified as high-tech firm according to Fama-French 5 industry definition, and 0 otherwise. X_t is a series of macroeconomic variables to capture potential investment opportunity and macroeconomic conditions (includes GDP growth and consumer sentiment), and a series of the industry- and firm-level dummies to capture its innovative activity. This regression is performed for the top, medium, and bottom innovating industries separately, where industries are categorized into the top, medium, and bottom innovating industries based on their citation-weighted number of patents over the year. Panel A presents the results based on the BP measure for technological innovations, and Panel B is based on IST measure. In each panel, column (1) to (3) report the results on capital investment. In column (4) to (6) and (7) to (9), the dependent variable is replaced by merger and acquisition $M\&A_{it+j}/K_{it+j-1}$, and $R\&D$ investment rate (defined following Stein and Stone (2013)), respectively. All specifications in this table include firm-level fixed effects, and the standard errors are clustered at the industry and year level. Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

(Table 8, Continued)

Panel A: Based on the BP measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$
TechShock*High-tech	0.004*	0.004*	0.002	-0.005	0.011***	-0.003	0.002	0.004***	0.005**
	(0.002)	(0.003)	(0.003)	(0.007)	(0.003)	(0.004)	(0.002)	(0.001)	(0.002)
Technology Shock	-0.003	0.008*	0.006*	0.011	0.023***	0.012***	-0.001	0.002*	0.001
	(0.003)	(0.004)	(0.003)	(0.007)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Observations	139,205	124,413	113,597	133,694	119,419	107,331	72,992	64,819	58,499
R-squared	0.379	0.379	0.348	0.312	0.308	0.302	0.504	0.526	0.532
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm/Industry Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

(Table 8, Continued)

Panel B: Based on the IST measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$
TechShock*High-tech	0.002	0.006*	0.009**	0.007	0.013*	0.016*	0.005*	0.006**	0.006*
	(0.004)	(0.003)	(0.004)	(0.009)	(0.007)	(0.009)	(0.002)	(0.002)	(0.003)
Technology Shock	-0.003	0.008**	0.006*	0.010	0.025***	0.010**	-0.000	0.003**	0.002
	(0.003)	(0.004)	(0.003)	(0.008)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Observations	139,205	124,413	113,597	133,694	119,419	107,331	72,992	64,819	58,499
R-squared	0.379	0.379	0.348	0.312	0.308	0.302	0.504	0.526	0.532
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm/Industry Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

Table 9: Technological Innovation and Corporate Hiring

This table presents estimates from the regression:

$$Hiring_{it+j} = \alpha_i + \beta_1 TechShock_t + \beta_2 Q_{it-1} + \beta_3 CF_{it} + \beta_4 X_t + \epsilon it,$$

where i indexes firm, t donates the year, and j represents the year lead between the dependent and independent variables, $j = 0, 1, 2$. $Hiring_{it+j}$ is the hiring rate defined following Stein and Stone (2013) ($Hiring_{it}$ ($Employee_{it}/Employee_{ij-1} - 1$). $TechShock_t$ is the arithmetic average to the measure for technology shocks during the year t, and then normalized by its sample mean and standard deviation. X_t is a series of macroeconomic variables to capture potential investment opportunity and macroeconomic conditions (includes GDP growth and consumer sentiment), and a series of the industry- and firm-level dummies to capture its innovative activity. Panel A presents the results based on the BP measure for technological innovations, and Panel B is based on IST measure. In each panel, column (1) to (3) report the baseline results. In column (4) to (6) and (7) to (9), the interaction of technological innovation with capital intensity and high growth firms are added to the regression, respectively. All regressions in this table control for firm-level fixed effects, and the standard errors are clustered at the firm and year level. Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

(Table 9, Continued)

Panel A: Based the BP measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$
Technology Shock	0.005	0.019***	-0.001	0.003	0.018***	-0.001	0.004	0.018***	-0.001
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)
Techshock*Lowcapintensity				0.010*	0.005	-0.001			
				(0.005)	(0.004)	(0.004)			
Techshock*Growth							0.004	0.004**	-0.000
							(0.003)	(0.002)	(0.002)
Growth firm							0.017***	0.011***	0.012***
							(0.003)	(0.004)	(0.004)
Observations	139,205	124,413	113,597	139,197	124,406	113,591	139,024	124,251	113,449
R-squared	0.445	0.431	0.419	0.445	0.431	0.419	0.445	0.432	0.419
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

(Table 9, continued)

Panel B: Based on IST measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$
Technology Shock	0.010**	0.015***	0.005	0.004	0.018***	-0.002	0.004	0.018***	-0.002
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
Techshock*Lowcapintensity				0.011**	0.011*	0.007			
				(0.005)	(0.007)	(0.007)			
Techshock*Growth							0.008	0.006	0.007
							(0.005)	(0.005)	(0.006)
Growth firm							0.017***	0.012***	0.013***
							(0.003)	(0.004)	(0.004)
Observations	139,205	124,413	113,597	139,197	124,406	113,591	139,024	124,251	113,449
R-squared	0.445	0.430	0.419	0.445	0.432	0.419	0.445	0.432	0.419
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

(Table 9, continued)

Panel C: Variation by industry-level innovative activity (Based on the BP measure)

Panel C1: Top 33% innovating industries

	(1)	(2)	(3)
VARIABLES	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$
Technology Shock	0.009**	0.024***	-0.005
	(0.004)	(0.005)	(0.005)
Observations	51,059	45,526	41,549
R-squared	0.493	0.480	0.463

Panel C2: Bottom 34% innovating industries

	(1)	(2)	(3)
VARIABLES	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$
Technology Shock	0.003	0.018***	0.000
	(0.006)	(0.006)	(0.006)
Observations	38,566	34,401	31,392
R-squared	0.536	0.520	0.509

Panel C3: Based on firm-level innovative shocks

	(1)	(2)	(3)
VARIABLES	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$
TechShock*HighInnovation	0.004	0.019***	-0.000
	(0.006)	(0.006)	(0.005)
TechShock*MediumInnovation	0.007	0.018***	-0.005
	(0.005)	(0.005)	(0.006)
TechShock*LowInnovation	0.007	0.013	-0.012
	(0.013)	(0.010)	(0.011)
Observations	139,205	124,413	113,597
R-squared	0.445	0.431	0.419
Firm-level Control	Y	Y	Y
Macro Control	Y	Y	Y
Firm Fixed Effect	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year

(Table 9, continued)

Panel D: Variation by industry-level innovative activity (Based on the IST measure)

Panel D1: Top 33% innovating industries

	(1)	(2)	(3)
VARIABLES	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$
Technology Shock	0.013***	0.020***	0.004
	(0.004)	(0.006)	(0.007)
Observations	51,059	45,526	41,549
R-squared	0.494	0.477	0.463

Panel D2: Bottom 34% innovating industries

	(1)	(2)	(3)
VARIABLES	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$
Technology Shock	0.013**	0.015***	0.006
	(0.005)	(0.005)	(0.006)
Observations	38,566	34,401	31,392
R-squared	0.537	0.519	0.510

Panel D3: Based on firm-level innovative shocks

	(1)	(2)	(3)
VARIABLES	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$
TechShock*HighInnovation	0.010**	0.014***	0.006
	(0.005)	(0.005)	(0.006)
TechShock*MediumInnovation	0.010**	0.016***	0.001
	(0.005)	(0.005)	(0.007)
TechShock*LowInnovation	0.017*	0.007	-0.005
	(0.009)	(0.012)	(0.013)
Observations	139,205	124,413	113,597
R-squared	0.445	0.430	0.419
Firm-level Control	Y	Y	Y
Macro Control	Y	Y	Y
Firm Fixed Effect	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year

Table 10: Technological Innovation and the Firm Level TFP

This table analyzes the change of TFP after technology innovations. The results are based on regression:

$$TFP_{it+j} = \alpha_i + \beta_1 TechShock_t + \beta_2 X_t + \epsilon it,$$

where i indexes firm, t donates the year, and j represents the year lead between the dependent and independent variables, $j = 0, 1, 2$. I_{it}/K_{it-1} is the investment rate defined using the perpetual inventory method following Stein and Stone (2013). $TechShock_t$ is the arithmetic average to the measure for technology shocks during the year t, and then normalized by its sample mean and standard deviation. X_t is a series of macroeconomic variables to capture potential firm-level heterogeneity and macroeconomic conditions, which consists of GDP growth and firm size in this table. Industries are classified into the top, medium, and bottom innovating industries based on their citation-weighted number of patents over the year, and this regression is performed for the whole sample, and the top and bottom innovating industries separately. Panel A presents the results based on the BP measure for technological innovations, and Panel B is based on IST measure. In panel A1(B1) to panel A3(B3). In panel A4(B4), the regressions is augmented to include the interaction with the activeness of firm-level innovations: $HighInnovation$, $MediumInnovation$ and $LowInnovation$. If a firm's number of citation-weighted patents are among the highest tercile within its industry at year t, $HighInnovation$ takes value 1. Otherwise, it equals to 0. $MediumInnovation$ and $LowInnovation$ takes value 1 if a firm's number of citation-weighted patents are among the medium and lowest tercile within its industry at year t, respectively, and 0 otherwise. All regressions in this table control for firm-level fixed effects, and the standard errors are clustered at the firm and year level. Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Based on the BP measure

Panel A1: All firms

	(1)	(2)	(3)
VARIABLES	TFP_{it}	TFP_{it+1}	TFP_{it+2}
Technology Shock	-0.010	0.023**	0.021**
	(0.009)	(0.010)	(0.010)
Observations	91,593	83,433	75,394
R-squared	0.565	0.578	0.586
Firm-level Control	Y	Y	Y
Macro Control	Y	Y	Y
Firm Fixed Effect	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year

(Table 10, Continued)

Panel A2: Top 33% innovating industries

VARIABLES	(1) TFP_{it}	(2) TFP_{it+1}	(3) TFP_{it+2}
Technology Shock	-0.002	0.036***	0.023**
	(0.010)	(0.011)	(0.011)
Observations	33,299	29,572	26,507
R-squared	0.636	0.659	0.668

Panel A3: Bottom 34% innovating industries

VARIABLES	(1) TFP_{it}	(2) TFP_{it+1}	(3) TFP_{it+2}
Technology Shock	-0.008	0.021***	0.017
	(0.007)	(0.007)	(0.010)
Observations	24,955	23,059	20,876
R-squared	0.624	0.640	0.643

Panel A4: Based on firm-level innovative shocks

VARIABLES	(1) TFP_{it}	(2) TFP_{it+1}	(3) TFP_{it+2}
TechShock*HighInnovation	-0.006	0.029**	0.026**
	(0.009)	(0.011)	(0.010)
TechShock*MediumInnovation	-0.023*	0.004	0.008
	(0.013)	(0.013)	(0.012)
TechShock*LowInnovation	-0.092***	-0.035*	-0.035*
	(0.026)	(0.018)	(0.017)
Observations	91,593	83,433	75,394
R-squared	0.565	0.578	0.586
Firm-level Control	Y	Y	Y
Macro Control	Y	Y	Y
Firm Fixed Effect	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year

(Table 10, Continued)

Panel B: Based on the IST measure

Panel B1: All firms

	(1)	(2)	(3)
VARIABLES	TFP_{it}	TFP_{it+1}	TFP_{it+2}
Technology Shock	0.003	0.026***	0.031***
	(0.008)	(0.006)	(0.009)
Observations	91,593	83,433	75,394
R-squared	0.565	0.578	0.586

Panel B2: Top 33% innovating industries

Technology Shock	0.012	0.039***	0.043***
	(0.010)	(0.008)	(0.012)
Observations	33,299	29,572	26,507
R-squared	0.636	0.659	0.669

Panel B3: Bottom 34% innovating industries

Technology Shock	0.003	0.023***	0.030***
	(0.006)	(0.007)	(0.007)
Observations	24,955	23,059	20,876
R-squared	0.624	0.640	0.644

Panel B4: Based on firm-level innovative shocks

TechShock*HighInnovation	0.012	0.023***	0.031**
	(0.009)	(0.007)	(0.013)
TechShock*MediumInnovation	-0.008	0.007	0.017
	(0.013)	(0.013)	(0.014)
TechShock*LowInnovation	-0.069***	-0.042***	-0.029**
	(0.013)	(0.014)	(0.014)
Observations	91,593	83,433	75,394
R-squared	0.565	0.578	0.586

Table 11: Technological Innovation and the Capital to Labor Ratio

This table analyzes the change in capital to labor ratios after technological innovation. The results are based on regression:

$$Capital_{it+j}/Emp_{it+j} = \alpha_i + \beta_1 TechShock_t + \beta_2 X_t + \epsilon it,$$

where i indexes firm, t donates the year, and j represents the year lead between the dependent and independent variables, $j = 0, 1, 2$. $Capital_{it+j}/Empit + j$ is the capital/labor ratio at $t + j$. $TechShock_t$ is the arithmetic average to the measure for technology shocks during the year t, and then normalized by its sample mean and standard deviation. X_t is a series of firm-level controls and macroeconomic variables to capture potential investment opportunity and macroeconomic conditions including firms size and GDP growth. Industries are classified into the top, medium, and bottom innovating industries based on their citation-weighted number of patents over the year, and this regression is performed for the whole sample, and the top and bottom innovating industries separately. Panel A presents the results based on the BP measure for technological innovations, and Panel B is based on IST measure. In panel A1(B1) to panel A3(B3). In panel A4(B4), the regressions is augmented to include the interaction with the activeness of firm-level innovations: $HighInnovation$, $MediumInnovation$ and $LowInnovation$. If a firm's number of citation-weighted patents are among the highest tercile within its industry at year t, $HighInnovation$ takes value 1. Otherwise, it equals to 0. $MediumInnovation$ and $LowInnovation$ takes value 1 if a firm's number of citation-weighted patents are among the medium and lowest tercile within its industry at year t, respectively, and 0 otherwise. All regressions in this table control for firm-level fixed effects, and the standard errors are clustered at the firm and year level. Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Based on the BP measure

Panel A1: All firms

	(1)	(2)	(3)
VARIABLES	$Capital_{it}/Emp_{it}$	$Capital_{it+1}/Emp_{it+1}$	$Capital_{it+2}/Emp_{it+2}$
Technology Shock	3.008	-1.661	-3.518
	(4.159)	(5.080)	(4.376)
Observations	129,430	113,097	100,733
R-squared	0.971	0.978	0.980
Firm-level Control	Y	Y	Y
Macro Control	Y	Y	Y
Firm Fixed Effect	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year

(Table 11, Continued)

Panel A2: Top 33% innovating industries

	(1)	(2)	(3)
VARIABLES	$Capital_{it}/Emp_{it}$	$Capital_{it+1}/Emp_{it+1}$	$Capital_{it+2}/Emp_{it+2}$
Technology Shock	13.870*	0.659	0.990
	(7.554)	(4.044)	(2.341)
Observations	47,658	40,923	36,012
R-squared	0.983	0.974	0.977

Panel A3: Bottom 34% innovating industries

	(1)	(2)	(3)
VARIABLES	$Capital_{it}/Emp_{it}$	$Capital_{it+1}/Emp_{it+1}$	$Capital_{it+2}/Emp_{it+2}$
Technology Shock	-11.118	-9.983	-19.811**
	(14.015)	(10.987)	(9.598)
Observations	35,409	31,414	27,966
R-squared	0.904	0.971	0.902

Panel A4: Based on firm-level innovative activities

	(1)	(2)	(3)
VARIABLES	$Capital_{it}/Emp_{it}$	$Capital_{it+1}/Emp_{it+1}$	$Capital_{it+2}/Emp_{it+2}$
TechShock*HighInnovation	4.824	-1.516	-4.660
	(5.396)	(7.387)	(6.140)
TechShock*MediumInnovation	-2.484	-1.964	0.129
	(4.408)	(3.879)	(2.532)
TechShock*LowInnovation	-17.399***	-12.968***	-8.210***
	(5.725)	(4.724)	(3.012)
Observations	129,430	113,097	100,733
R-squared	0.971	0.978	0.980
Firm-level Control	Y	Y	Y
Macro Control	Y	Y	Y
Firm Fixed Effect	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year

(Table 11, Continued)

Panel B: Based on the IST measure

Panel B1: All firms

VARIABLES	(1) $Capital_{it}/Emp_{it}$	(2) $Capital_{it+1}/Emp_{it+1}$	(3) $Capital_{it+2}/Emp_{it+2}$
Technology Shock	-8.222**	-6.822	-1.169
	(3.867)	(4.798)	(3.087)
Observations	129,430	113,097	100,733
R-squared	0.971	0.978	0.980

Panel B2: Top 33% innovating industries

Technology Shock	2.534	-3.016	2.157
	(3.765)	(7.713)	(3.862)
Observations	47,658	40,923	36,012
R-squared	0.983	0.974	0.977

Panel B3: Bottom 34% innovating industries

Technology Shock	-23.298**	-17.790**	-6.159
	(9.086)	(8.588)	(7.936)
Observations	35,409	31,414	27,966
R-squared	0.904	0.971	0.902

Panel B4: Based on firm-level innovative activities

TechShock*HighInnovation	-13.998**	-8.901	1.885
	(5.455)	(7.061)	(5.292)
TechShock*MediumInnovation	-1.517	0.729	1.142
	(5.376)	(4.080)	(4.037)
TechShock*LowInnovation	-16.635***	-8.149	-1.673
	(5.331)	(5.050)	(4.383)
Observations	129,430	113,097	100,733
R-squared	0.971	0.978	0.980
Firm-level Control	Y	Y	Y
Macro Control	Y	Y	Y
Firm Fixed Effect	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year

Table 12: Aggregate Technological Advancement and Macroeconomic Forces

This table examines the relationship between macroeconomic factors and the technology innovation measure developed by Beaudry and Portier (2006). Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Based on the BP measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	$techshock_{t+1}$	$techshock_{t+2}$	$techshock_{t+3}$	$techshock_{t+4}$	$techshock_{t+5}$	$techshock_{t+6}$	$techshock_{t+7}$	$techshock_{t+8}$
GDP deflator	-0.000	-0.000	-0.000	-0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP Growth	-0.223	-0.122	-0.242	0.038	-0.221	-0.043	0.382	-0.074
	(0.359)	(0.356)	(0.355)	(0.355)	(0.355)	(0.355)	(0.355)	(0.354)
3 month t-Bill rate	-0.003	-0.001	-0.002	-0.003	-0.001	-0.001	-0.001	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
BAA bond rate	0.002	0.000	0.001	0.002	-0.000	0.000	0.000	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.230	0.127	0.247	-0.037	0.227	0.047	-0.384	0.078
	(0.364)	(0.361)	(0.360)	(0.359)	(0.360)	(0.360)	(0.360)	(0.359)
Observations	265	265	265	265	265	265	265	265
R-squared	0.012	0.003	0.006	0.007	0.004	0.003	0.007	0.005

(Table 12, Continued)

Panel B: Based on the IST measure

VARIABLES	(1) $techshock_{t+1}$	(2) $techshock_{t+2}$	(3) $techshock_{t+3}$	(4) $techshock_{t+4}$	(5) $techshock_{t+5}$	(6) $techshock_{t+6}$	(7) $techshock_{t+7}$	(8) $techshock_{t+8}$
GDP deflator	-0.001	-0.001	-0.001	-0.001	0.000	0.001	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
GDP Growth	2.654	1.744	-1.542	-0.667	8.200	12.172*	1.708	3.158
	(6.526)	(6.505)	(6.507)	(6.513)	(6.502)	(6.357)	(6.352)	(6.237)
3 month t-Bill rate	-0.042	-0.053	-0.043	-0.034	-0.019	-0.006	-0.001	-0.004
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.044)	(0.044)
BAA bond rate	0.048	0.060	0.050	0.040	0.027	0.015	0.009	0.013
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Constant	-2.813	-1.921	1.416	0.553	-8.393	-12.403*	-1.807	-3.287
	(6.605)	(6.585)	(6.588)	(6.595)	(6.585)	(6.442)	(6.440)	(6.327)
Observations	241	241	241	241	241	241	241	241
R-squared	0.006	0.009	0.006	0.004	0.008	0.016	0.001	0.002

Table 13: Robustness: Market Valuation Change and Investment

This table presents estimates from the regression:

$$I_{it+j}/K_{it-1} =$$
$$\alpha_i + \beta_1 TechShock_t * \Delta Valuationit + \beta_2 \Delta Valuationit + \beta_3 TechShock_t + \beta_4 Q_{it-1} + \beta_5 CF_{it} + \beta_6 X_t + \epsilon it,$$

where i indexes firm, t donates the year, and $j = 0, 1, 2$ represents the year lead between the dependent and independent variables. I_{ijt}/K_{ijt-1} is the investment rate defined using the perpetual inventory method following Stein and Stone (2013). $TechShock_t$ is the arithmetic average to the measure for technology shocks during the year t, and then normalized by its sample mean and standard deviation. $\Delta Valuationjt$ is to capture market valuation changes. Two variables are used as proxy for valuation change: $HighValuationChangeIndustry$ is a dummy variable that takes value 1 if an industry average valuation change falls in the highest tercile during year t, otherwise, it equals to 0; $FirmValuationChange$ is the valuation change for each firm defined as MTB_t/MTB_{t-1}. X_t is a series of macroeconomic variables to capture potential investment opportunity and macroeconomic conditions (includes GDP growth and consumer sentiment), and a series of the industry- and firm-level dummies to capture its innovative activity. Column (1) to (3) report the results on capital investment. In column (4) to (6), (7) to (9), and (10) to (12), the dependent variable is replaced by merger and acquisition $M\&A_{it+j}/K_{it+j-1}$, $R\&D$ investment rate (defined following Stein and Stone (2013)) and hiring rate $Hiring_{it}$ ($Employee_{it}/Employee_{ij-1} - 1$), respectively. Panel A presents the results based on $HighValuationChangeIndustry$ as a proxy for market valuation change, where $HighValuationChangeIndustry$ is a dummy variable that takes value 1 if an industry's MTB change falls into the highest tercile, and 0 otherwise. Panel B reports the results based on $FirmValuationChange$, where $FirmValuationChange$ is the MTB change of each firm. All specifications in this table include firm-level fixed effects. Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

(Table 13, Continued)

Panel A: Industry market valuation change and corporate investment policy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$
TechShock*High Valuation Change Industry	0.005	0.002	0.000	-0.010	0.014**	0.003	-0.001	-0.002	-0.000	0.001	0.002	0.003
	(0.003)	(0.002)	(0.002)	(0.007)	(0.006)	(0.005)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.002)
Technology Shock	-0.005	0.007**	0.007***	0.011	0.021***	0.011**	0.000	0.004***	0.003**	0.002	0.017***	-0.001
	(0.003)	(0.003)	(0.002)	(0.007)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.004)
High Valuation Change Industry	-0.002	0.004*	0.002	-0.005**	0.001	-0.002	-0.002*	-0.001	-0.000	0.003	0.007**	-0.003***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)
Observations	154,213	134,622	119,922	148,210	129,272	113,360	80,437	71,815	65,137	154,213	134,622	119,922
R-squared	0.370	0.369	0.338	0.307	0.303	0.296	0.497	0.517	0.522	0.437	0.425	0.414
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year

(Table 13, Continued)

Panel B: Firm market valuation change and firm investment policy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$
TechShock*Firm Valuation	-0.000	0.000	-0.000	-0.000**	0.000	-0.000	0.000***	-0.000	-0.000	0.000	0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Technology Shock	-0.003	0.008**	0.007**	0.009	0.025***	0.011***	-0.000	0.003***	0.003**	0.003	0.017***	-0.001
	(0.003)	(0.003)	(0.003)	(0.007)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.005)
Firm Valuation Change	-0.000	0.000*	0.000***	-0.000*	0.000	0.000	-0.000**	0.000	0.000***	0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	153,892	134,349	119,683	147,898	129,006	113,126	80,223	71,629	64,975	153,892	134,349	119,683
R-squared	0.370	0.369	0.338	0.306	0.302	0.296	0.497	0.518	0.523	0.437	0.425	0.414
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

Table 14: Robustness: Growth Firms VS. Low Capital Intensity Firms

This table presents the results regarding the difference between growth firms and firms with low capital intensity. The baseline regression is augmented to include the dummy for firms with higher benefit from innovative outputs($Growth$) and the dummy for low capital intensity ($LowCapitalIntensity$) and their interaction with technology innovations. Besides, an additional dummy that takes value 1 if a firm is both a low capital intensity growth firm, and its interaction with technology innovation is included in the regression. The dependent variable in columns (1) to (3) are capital investment rate, I_{it}/K_{it-1} is the investment rate defined using the perpetual inventory method following Stein and Stone (2013). Here i indexes firm, t donates the year, and j represents the year lead between the dependent and independent variables, $j = 0, 1, 2$. $TechShock_t$ is the arithmetic average to the measure for technology shocks during the year t, and then normalized by its sample mean and standard deviation. X_t is a series of macroeconomic variables to capture potential investment opportunity and macroeconomic conditions, which includes GDP growth and consumer sentiment. In column (4) to (6), the dependent variable is replaced by $M\&A_{it+j}/K_{it+j-1}$, which is the M&A expenditure scaled by the year beginning capital stock. In column (7) to (9), the dependent variable is R&D investment ratio. In column (9) to (12), the dependent variable is replaced by hiring rate $Hiring_{it}$, which is defined following Stein and Stone (2013) and equals to $Employee_{it}/Employee_{ij-1} - 1$. All regressions in this table control for firm-level fixed effects, and the standard errors are clustered at industry and year level. Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

(Table 14, Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}$	$M\&A_{it+1}$	$M\&A_{it+2}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$
Growth*lowcapintense*Techshock	0.004	0.003	0.003	-0.019**	-0.006	-0.016	0.002	0.002	0.001	-0.006	-0.004	-0.001
	(0.003)	(0.002)	(0.002)	(0.009)	(0.004)	(0.015)	(0.002)	(0.002)	(0.002)	(0.005)	(0.004)	(0.005)
Growth* Techshock	0.001	0.006***	0.006***	0.001	0.009**	-0.004	0.001	0.003**	0.003**	0.005	0.005*	-0.000
	(0.002)	(0.002)	(0.002)	(0.006)	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)
Lowcapitalintensity* Techshock	0.003	0.005*	0.005*	0.001	0.029**	0.011	-0.003*	-0.000	0.002	0.012**	0.007	-0.000
	(0.003)	(0.003)	(0.003)	(0.011)	(0.012)	(0.008)	(0.001)	(0.002)	(0.002)	(0.005)	(0.004)	(0.004)
Growth	0.025***	0.018***	0.018***	0.006	-0.004	0.008	0.007***	0.007**	0.009***	0.018***	0.013***	0.014***
	(0.004)	(0.003)	(0.003)	(0.008)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Lowcapitalintensity	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Technology Shock	-0.004	0.005	0.005	0.009*	0.018***	0.011***	0.000	0.003**	0.001	-0.001	0.015***	-0.000
	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.006)	(0.005)	(0.005)
Observations	153,987	134,425	134,425	147,988	129,080	113,189	80,290	71,687	65,022	153,987	134,425	119,748
R-squared	0.372	0.371	0.371	0.306	0.303	0.297	0.497	0.518	0.523	0.438	0.425	0.414
Firm-level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Macro Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Innovation Dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year

Table 15: Robustness: Measurement Error in Q

This table presents the results regarding the alternative hypothesis that technological innovations play a role in investment decisions due to measurement error in Q. A reverse regression following Erickson and Whited (2005) is performed, where the regression of the proxy for the marginal Q is regressed on investment policies, technology innovations, and all other controls (including cash flow and GDP growth). The regressions reported in column (1) to (3) examines the results regarding capital investment rate: I_{it}/K_{it-1} is the investment rate defined using the perpetual inventory method following Stein and Stone (2013). Here i indexes firm, t donates the year, and j represents the year lead between the dependent and independent variables, $j = 0, 1, 2$. In column (4) to (6), I_{it}/K_{it-1} is replaced by $M\&A_{it+j}/K_{it+j-1}$, which is the M&A expenditure scaled by the year beginning capital stock. In column (7) to (9), the I_{it}/K_{it-1} is replaced by R&D expense rate. In column (9) to (12), the I_{it}/K_{it-1} is replaced by hiring rate $Hiring_{it}$, which is defined following Stein and Stone (2013) and equals to $Employee_{it}/Employee_{ij-1} - 1$. All regressions in this table control for firm-level fixed effects, and the standard errors are clustered at the industry and year level. Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(7)	(8)	(9)
VARIABLES	Q	Q	Q	Q	Q	Q	Q	Q	Q	Q	Q	Q
Technology shock	0.149***	0.136***	0.139***	0.149***	0.141***	0.139***	0.188***	0.176***	0.175***	0.148***	0.139***	0.145***
	(0.016)	(0.013)	(0.015)	(0.016)	(0.015)	(0.015)	(0.024)	(0.021)	(0.022)	(0.015)	(0.014)	(0.015)
cash flow	0.121	0.099	0.351***	0.158*	0.294***	0.505***	0.229**	0.311***	0.396***	0.102	0.288***	0.481***
	(0.082)	(0.095)	(0.089)	(0.087)	(0.096)	(0.098)	(0.089)	(0.095)	(0.098)	(0.080)	(0.092)	(0.092)
GDP Growth	-0.683	-1.317	-0.912	-0.468	-0.495	-0.547	-0.575	-0.820	-0.709	-0.732	-0.617	-0.565
	(0.928)	(0.886)	(0.906)	(0.953)	(0.927)	(0.930)	(1.213)	(1.154)	(1.162)	(0.906)	(0.895)	(0.921)
I_{it}/K_{it-1}	0.191***											
	(0.043)											
I_{it+1}/K_{it}		0.991***										
		(0.119)										
I_{it+2}/K_{it+1}			0.788***									
			(0.072)									
$M\&A_{it}/K_{it-1}$				-0.075***								
				(0.007)								
$M\&A_{it+1}/K_{it}$					0.059***							
					(0.008)							
$M\&A_{it+2}/K_{it+1}$						0.048***						
						(0.008)						
$R\&D_{it}$							0.116					
							(0.070)					
$R\&D_{it+1}$								0.683***				
								(0.150)				
$R\&D_{it+2}$									0.871***			
									(0.153)			
$hiring_{it}$										0.227***		
										(0.025)		
$hiring_{it+1}$											0.290***	
											(0.033)	
$hiring_{it+2}$												0.119***
												(0.024)
Constant	0.579***	0.453***	0.440***	0.623***	0.644***	0.616***	0.513**	0.447**	0.383*	0.605***	0.603***	0.578***
	(0.148)	(0.132)	(0.134)	(0.146)	(0.140)	(0.138)	(0.203)	(0.185)	(0.194)	(0.145)	(0.133)	(0.138)
Observations	154,213	134,622	119,922	148,210	129,272	113,360	80,437	71,815	65,137	154,213	134,622	119,922
R-squared	0.653	0.671	0.671	0.657	0.663	0.669	0.645	0.654	0.656	0.654	0.665	0.666
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

APPENDIX C

ADDITIONAL TESTS

Table 16: Aggregate Technological Innovation and the TFP Growth

This table examines the relation between aggregate TFP and the technology innovation measure developed by Beaudry and Portier (2006). Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Technological innovation and TFP growth

	(1)	(2)	(3)	(4)
VARIABLES	$dTFP_{t+1}$	$dTFP_{t+2}$	$dTFP_{t+3}$	$dTFP_{t+4}$
Technology Shock	0.036***	0.020**	0.008	0.010
	(0.009)	(0.010)	(0.009)	(0.009)
Observations	264	263	262	261
R-squared	0.055	0.016	0.003	0.004

Panel B: TFP growth and technology innovation

	(1)	(2)	(3)	(4)
VARIABLES	$techshock_{t+1}$	$techshock_{t+2}$	$techshock_{t+3}$	$techshock_{t+4}$
$dTFP_t$	0.000	-0.000	-0.000	0.000
	(0.395)	(0.391)	(0.392)	(0.390)
Observations	265	265	265	265
R-squared	0.000	0.000	0.000	0.000

Table 17: Valuation Change and Technological Innovations

This table examines the relationship between firm valuation change and the technological innovations as measured by Beaudry and Portier (2006)). Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Q_{it}	Q_{it+1}	Q_{it+2}	Q_{it}	Q_{it+1}	Q_{it+2}
Technology Shock	0.149***	0.071***	0.006	0.149***	0.071***	0.006
	(0.016)	(0.020)	(0.022)	(0.021)	(0.019)	(0.022)
Q_{t-1}	0.458***	0.237***	0.107***	0.458***	0.237***	0.107***
	(0.035)	(0.029)	(0.032)	(0.035)	(0.029)	(0.032)
Cash flow	0.157*	0.068	-0.025	0.157	0.068	-0.025
	(0.081)	(0.071)	(0.077)	(0.203)	(0.147)	(0.081)
GDP growth	-0.540	-1.507	-1.024	-0.540	-1.507	-1.024
	(0.927)	(1.363)	(1.317)	(0.895)	(1.335)	(1.317)
Sentiment	0.003*	0.003	0.003	0.003*	0.003	0.003
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
Observations	154,213	134,622	119,922	154,213	134,622	119,922
R-squared	0.652	0.588	0.564	0.652	0.588	0.564
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm Year	Firm Year	Firm Year	Industry Year	Industry Year	Industry Year

Table 18: Robustness: The Role of Industry Technological Innovations with Alternative Cutoffs

This table analyzes the variation in investment policies with industry-level technological innovations based on alternative cutoffs for industry-level technology innovations. The results are based on regression:

$$I_{it+j}/K_{it+j-1} = \alpha_i + \beta_1 TechShock_t + \beta_2 Q_{it-1} + \beta_3 CF_{it} + \beta_4 X_t + \epsilon it,$$

where i indexes firm, t donates the year, and j represents the year lead between the dependent and independent variables, $j = 0, 1, 2$. I_{it}/K_{it-1} is the investment rate defined using the perpetual inventory method following Stein and Stone (2013). $TechShock_t$ is the arithmetic average to the measure for technology shocks during the year t, and then normalized by its sample mean and standard deviation. X_t is a series of macroeconomic variables to capture potential investment opportunity and macroeconomic conditions, including GDP growth and consumer sentiment. This regression is performed for the top, 50%-75%, 25%-50%, and the bottom innovating industries separately, where industries are categorized into the top, 50%-75%, 25%-50%, and the bottom innovating industries based on their citation-weighted number of patents over the year. The results regarding capital investment are reported in columns (1) to (3). In column (4)-(6) and (7)-(9), the dependent variable is replaced by $Hiring_{it+j}$ and $M\&A_{it+j}/K_{it+j-1}$, respectively. All regressions in this table control for firm-level fixed effects, and the standard errors are clustered at the industry and year level. Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

(Table 18, Continued)

Panel A: Top 25% innovating industries

VARIABLES	(1) I_{it}/K_{it-1}	(2) I_{it+1}/K_{it}	(3) I_{it+2}/K_{it+1}	(4) $Hiring_{it}$	(5) $Hiring_{it+1}$	(6) $Hiring_{it+2}$	(7) $M\&A_{it}/K_{it-1}$	(8) $M\&A_{it+1}/K_{it}$	(9) $M\&A_{it+2}/K_{it+1}$
Technology Shock	0.002	0.013***	0.009***	0.010***	0.023***	-0.002	0.004	0.029***	0.006
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)	(0.009)	(0.007)	(0.006)
Observations	39,460	35,157	32,095	39,460	35,157	32,095	37,943	33,751	30,389
R-squared	0.472	0.467	0.440	0.497	0.482	0.466	0.363	0.361	0.371
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year

Panel B: Third Quartile of innovating industries (50% - 75%)

VARIABLES	(1) I_{it}/K_{it-1}	(2) I_{it+1}/K_{it}	(3) I_{it+2}/K_{it+1}	(4) $Hiring_{it}$	(5) $Hiring_{it+1}$	(6) $Hiring_{it+2}$	(7) $M\&A_{it}/K_{it-1}$	(8) $M\&A_{it+1}/K_{it}$	(9) $M\&A_{it+2}/K_{it+1}$
Technology Shock	-0.001	0.006**	0.005*	0.003	0.014***	-0.003	0.009	0.019***	0.011**
	(0.004)	(0.003)	(0.003)	(0.006)	(0.004)	(0.004)	(0.007)	(0.005)	(0.005)
Observations	33,396	29,825	27,250	33,396	29,825	27,250	31,886	28,466	25,623
R-squared	0.497	0.491	0.467	0.549	0.540	0.525	0.453	0.431	0.420
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year

(Table 18, Continued)

Panel C: Second Quartile of innovating industries (25% - 50%)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$	$M\&A_{it}/K_{it-1}$	$M\&A_{it+1}/K_{it}$	$M\&A_{it+2}/K_{it+1}$
Technology Shock	-0.006**	0.005	0.005	-0.003	0.015***	-0.000	0.010**	0.022***	0.010**
	(0.002)	(0.004)	(0.003)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Observations	34,423	30,895	28,283	34,423	30,895	28,283	32,883	29,516	26,534
R-squared	0.492	0.495	0.460	0.515	0.489	0.478	0.416	0.412	0.409
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year

Panel D: Bottom quartile of innovating industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$	$M\&A_{it}/K_{it-1}$	$M\&A_{it+1}/K_{it}$	$M\&A_{it+2}/K_{it+1}$
Technology Shock	-0.005**	0.005	0.003	0.004	0.014***	-0.004	0.005	0.013***	0.007**
	(0.002)	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)	(0.003)
Observations	25,893	23,057	21,084	25,893	23,057	21,084	24,932	22,180	19,946
R-squared	0.475	0.474	0.437	0.540	0.526	0.524	0.408	0.380	0.355
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year	Industry Year

Table 19: Robustness: Alternative Definition of Investment

This table presents estimates from the regression:

$$NetInv_{it+j} = \alpha_i + \beta_1 TechShock_t + \beta_2 Q_{it-1} + \beta_3 CF_{it} + \beta_4 X_t + \epsilon it,$$

where i indexes firm, t donates the year, and j denotes the year lead between the dependent and independent variables. I_{it}/K_{it-1} is the net investment defined as investment rate defined using perpetual inventory method net capital sales. $TechShock_t$ is the arithmetic average to the measure for technology shocks during the year t, and then normalized by its sample mean and standard deviation. X_t is a series of macroeconomic variables to capture potential investment opportunity and macroeconomic conditions, including GDP growth and consumer sentiment. All regressions in this table control for firm-level fixed effects, and the standard errors are clustered at the firm and year level. Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	$NetInv_{it}$	$NetInv_{it+1}$	$NetInv_{it+2}$	$NetInv_{it}$	$NetInv_{it+1}$	$NetInv_{it+2}$
Technology Shock	-0.003	0.007*	0.006**	-0.003	0.007**	0.006**
	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)
Tobin's Q	0.034***	0.023***	0.011***	0.033***	0.022***	0.011***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Cash Flow	0.191***	0.251***	0.181***	0.186***	0.245***	0.177***
	(0.016)	(0.020)	(0.015)	(0.015)	(0.019)	(0.014)
GDP Growth				0.696***	0.682***	0.367**
				(0.201)	(0.176)	(0.162)
Sentiment				-0.000	-0.001*	-0.001
				(0.000)	(0.000)	(0.000)
Observations	154,213	134,622	118,158	154,213	134,622	118,158
R-squared	0.361	0.362	0.337	0.366	0.366	0.338
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

Table 20: Robustness: Aggregate TFP and Technological Innovations

This table presents estimates from the regression:

$$I_{it+j}/K_{it+j-1} = \alpha_i + \beta_1 TechShock_t + \beta_2 TFP_t + \beta_3 Q_{it-1} + \beta_4 CF_{it} + \beta_5 X_t + \epsilon it,$$

where i indexes firm, t donates the year, and j represents the year lead between the dependent and independent variables, $j = 0, 1, 2$. I_{it}/K_{it-1} is the investment rate defined using the perpetual inventory method following Stein and Stone (2013). $TechShock_t$ is the arithmetic average to the measure for technology shocks during year t, and then normalized by its sample mean and standard deviation. X_t is a series of macroeconomic variables to capture potential investment opportunity and macroeconomic conditions, which includes GDP growth and consumer sentiment. Column (1) to (3) report the results on capital investment. In column (4) to (6), (7) to (9), and (10) to (12), the dependent variable is replaced by merger and acquisition $M\&A_{it+j}/K_{it+j-1}$, $R\&D$ investment rate (defined following Stein and Stone (2013)) and hiring rate $Hiring_{it}$ ($Employee_{it}/Employee_{ij-1} - 1$), respectively. All regressions in this table control for firm level fixed effects, and the standard errors are clustered at the firm and year level. Robust standard errors are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

(Table 20, Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	I_{it}/K_{it-1}	I_{it+1}/K_{it}	I_{it+2}/K_{it+1}	$M\&A_{it}/K_{it-1}$	$M\&A_{it+1}/K_{it}$	$M\&A_{it+2}/K_{it+1}$	$R\&D_{it}$	$R\&D_{it+1}$	$R\&D_{it+2}$	$Hiring_{it}$	$Hiring_{it+1}$	$Hiring_{it+2}$
Technology Shock	-0.002	0.006*	0.003	0.009	0.022***	0.006	0.001	0.004***	0.002*	-0.005	0.009*	-0.004
	(0.003)	(0.003)	(0.003)	(0.007)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)	(0.004)	(0.005)	(0.005)
TFP	-0.220	0.408**	0.594**	-0.335	0.335	0.734**	-0.179**	0.006	0.055	1.169***	1.202***	0.537
	(0.188)	(0.186)	(0.237)	(0.334)	(0.307)	(0.357)	(0.074)	(0.078)	(0.095)	(0.231)	(0.330)	(0.371)
Tobin's Q	0.032***	0.021***	0.011***	0.027***	0.017***	0.007**	0.013***	0.013***	0.010***	0.030***	0.010***	0.002
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Cash Flow	0.186***	0.239***	0.175***	0.121***	0.234***	0.177***	0.012*	0.102***	0.119***	0.237***	0.156***	0.041***
	(0.016)	(0.019)	(0.015)	(0.023)	(0.021)	(0.021)	(0.007)	(0.010)	(0.011)	(0.026)	(0.016)	(0.014)
GDP Growth	0.625***	0.608***	0.309**	0.698**	0.423**	-0.021	0.103	0.088	0.029	1.213***	0.520**	0.082
	(0.166)	(0.147)	(0.129)	(0.270)	(0.204)	(0.216)	(0.070)	(0.068)	(0.068)	(0.234)	(0.193)	(0.193)
Constant	0.114***	0.110***	0.130***	0.062***	0.066***	0.091***	0.154***	0.145***	0.148***	0.020**	0.063***	0.094***
	(0.006)	(0.005)	(0.006)	(0.010)	(0.009)	(0.009)	(0.003)	(0.003)	(0.004)	(0.008)	(0.009)	(0.010)
Observations	154,213	134,622	119,922	148,210	129,272	113,360	80,437	71,815	65,137	154,213	134,622	119,922
R-squared	0.370	0.370	0.341	0.306	0.303	0.296	0.497	0.517	0.522	0.439	0.427	0.414
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year	Firm Year

APPENDIX D

VARIABLE DESCRIPTION: AGGREGATE TECHNOLOGICAL INNOVATIONS

In this paper, I rely on the technology shock series developed in Beaudry and Portier (2006, and BP series henceforth) as a measure for technology shocks. The BP technological series is constructed based on a moving average (Wold) representation derived from the estimation of a vector error correction model (VECM) for total factor productivity and stock prices. The series on stock prices SP_t is constructed using the quarterly Standard & Poor 500 Composite Stock Prices Index, deflated by the seasonally adjusted implicit price deflator of GDP in the nonfarm private business sector and transformed in per capita terms by dividing it by the population with age from 15 to 64. The log of this index is denoted by SP_t. With regard to the series of TFP, the data source includes labor share (s_h), capital services (KS), output (Y), and hours (H) from the U.S. Bureau of Labor Statistics (BLS). Then the TFP_t series is constructed as $TFP_t = log(Y_t/H_t^{\bar{S_h}} KS_t^{1-\bar{S_h}})$, where $\bar{S_h}$ is the average level of the labor share over the whole period.

Based on the data on TFP and SP, the Wold moving average representation for ΔTFP and ΔSP are recovered from estimating a VECM with a matrix of cointegration relationship and five lags as follow.

$$\begin{pmatrix} \Delta TFP_t \\ \Delta SP_t \end{pmatrix} = \Gamma(L) \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{pmatrix}$$

where $\Gamma(L) = \sum_{i=0}^{\infty} \Gamma_i L^i$. The variance covariance matrix of ϵ is assumed to be identity matrix, and the disturbance ϵ_2 has no contemporaneous impact on TPF_t.

The innovation to SP series is found permanently affect TFP (Beaudry and Portier, 2006), which suggests that permanent changes in TFP are reflected in stock prices before they actually increase production capacity. That is, improvements in productivity are generally anticipated by market participants as there usually exists lags between the recognition of technological innovation and it's eventually applied in production. This innovation to SP series is found important in explaining the fluctuation of macroeconomic variables, such as consumption and working hours. Later, Ramey (2016) reconstructs this technology shock measure using extended data and find it explains about 50% of output fluctuation in business cycles.

This technology shock series fits our research in the sense that, by construction, it captures economic agents' expectations for increased future profitability associated with recognized technology innovations in general. Thus, it can be viewed as the magnitude of the technology shock that an average firm is exposed to. Therefore, using this technology shock series as an explanatory variable, one is able to get some insight into how firms react to technological innovations on average. On the other hand, the BP series is no statistically significant serial correlated, suggesting it more captures the shocks to technology innovation, rather than the accumulation of technology. In addition, there is no significant Granger causality relation between SP_t series and other macroeconomic variables. This feature, to some extent, ensures that the results are not driven by macroeconomic factors such as GDP growth or employment. The next section contains a more detailed discussion of the construction of the BP technology shock series.

APPENDIX E

VARIABLE DEFINITION

This table describe the main variables used in this paper.

Variable	Description
$TechShock$	Technology shock series developed in Beaudry and Portier (2006), and normalized by its sample mean and standard deviation.
I_{it+j}/K_{it+j-1}	The investment rate. It is defined using perpetual inventory method following Stein and Stone (2013). Here i indexes firm, t donates the year, and j represents the year lead between the dependent and independent variables, $j = 0, 1, 2$.
$Hiring_{it+j}$	Hiring rate. Following Stein and Stone (2013), hiring rate is defined as change in number of employees from year $t + j - 1$ to $t + j$, and them normalized by the employee number by the end of year $t + j - 1$. Here i indexes firm, t donates the year, and j represents the year lead between the dependent and independent variables, $j = 0, 1, 2$.
$M\&A_{it+j}/K_{it+j-1}$	Merger and acquisition activity. Defined as merger and acquisition spending (acq from Compustat) during year $t + j$ normalized by the capital stock by the end of year $t + j - 1$. Here i indexes firm, t donates the year, and j represents the year lead between the dependent and independent variables, $j = 0, 1, 2$.
Firm-level citation-weighted patents	$\Theta_{ijt} = \sum_{l \in P_{ijt}} \left(1 + \frac{C_l}{\bar{C}_l}\right)$, where i denotes firm, j represents industry, and t indexes year. P_{ijt} is the set of patents by firm i at year t, C_l is the total number of citations received by patent $l \in P_{ijt}$, this citation number is scaled by $\bar{C}_l$ which is the average number of forward citations received by the patents in the same year-class with patent l.

Industry-level citation-weighted patents	Aggregation of firm-level citation-weighted patents within an industry. $\Phi_{jt} = \sum_{i \in I_{jt}} \Big(\Theta_{ijt} \Big)$, where j denotes industry and t indexes year. I_{jt} represents the set of firms within industry j, and Θ_{ijt} is the firm i 's citation-weighted patents at time t.
Q	Tobin's Q. Defined as book value of total assets minus the book value of equity plus the market value of equity, then scaled by the book value of total asset.
CF	EBIT plus depreciation and amortization from cash flow statement and scaled by beginning of year book value of total assets.
GDP Growth	Change in real GDP, data from FRED.
Consumer Sentiment	Consumer Sentiment (UMCSENT) from FRED.
Capital Intensity	Value of plant, property, and equipment scaled by book value of total assets.
Firm-level TFP	Constructed following the method in Imrohoroglu and Tuzel (2014) and reflects the output that could not be explained by labor or capital inputs.
Capital-to-labor Ratio	The average capital value (ppent) per employee.

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