Technology Shocks, Capital Reallocation Frictions and the Cross-Section of Stock Returns

Mengyu Zhou

Department of Finance

The University of Melbourne

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Abstract

I study the cross-sectional return implications of technology shocks through the channel of capital reallocation. I present a model in which capital reallocation frictions limit the ability of non-innovating firms to redeploy assets when facing technology shocks and force them to hold unproductive capital. As a result, the values of non-innovating firms depreciate more when reallocation frictions are higher. The frictions also amplify firms’ risk exposure to technology shocks and hence the risk premium by altering consumption dynamics. Empirically, I find that the stock prices of non-innovating firms respond more negatively to technology shocks in industries with lower asset liquidity, while innovating firms’ responses to technology shocks do not vary with the degree of asset liquidity in their industry. The results shed light on the role of capital reallocation in the creative destruction process and its asset pricing implications.
Declaration

I hereby declare that:

1. the thesis comprises only my original work towards the Doctor of Philosophy,

2. due acknowledgement has been made in the text to all other material used,

3. the thesis is fewer than the maximum word limit of 100,000 words in length, exclusive of tables, maps, bibliographies and appendices,

4. *Elite Editing* provided copyediting and proofreading services which were restricted to Standard D and E of the University-endorsed guidelines and the Australian Standards for editing research theses.
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Chapter 1

Introduction

Technological advances often come in waves, and are associated with large movements in financial markets. When a new technology is implemented, innovating firms gain at the expense of non-innovating firms. This process is also known as creative destruction and is one mechanism through which technology shocks can be a source of systematic risk.\(^1\) Previous studies mainly rely on firms’ exposures to technology shocks to explain the well-documented facts related to the equity premium and the value premium. This study explores the richer cross-sectional return implications of technology shocks by examining an important process in technology adoption - namely, capital reallocation.

In this thesis, I show that the efficiency of capital reallocation in the technology adoption process is an important determinant of cross-sectional stock returns. Technology shocks introduce dispersions in firms’ productivity and create an incentive to reallocate physical capital from less productive firms to more productive firms.\(^2\) I show that the high costs of selling used capital force non-innovating firms to hold more unproductive capital and exacerbate the diminution in their value induced by technology shocks. I then show that

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\(^1\) See Bena, Garlappi, and Grüning (2014); Gârleanu, Kogan, and Panageas (2012); Kogan, Papanikolaou, and Stoffman (2013) for new developments in asset pricing implications of technology shocks.

\(^2\) See for example Aghion, Akcigit, and Howitt (2013).
inefficient capital reallocation drives up the demand for new capital investment used to adopt new technologies. As a result, reallocation frictions amplify the risk premium of technology shocks and the risk exposure of non-innovating firms by affecting consumption dynamics. The results are consistent with the role of capital reallocation in facilitating technology adoption and support the systematic risk feature of the creative destruction effect.

To provide the main intuition of my work, I discuss the mobile phone industry as an example of the interactive effect of technology shocks and capital reallocation on stock returns. Before smartphones were introduced, Blackberry and Nokia were the former dominant mobile phone suppliers, but they lacked the core technology of an advanced computing system to produce smartphones. As Apple and Samsung’s smartphones became more popular, Blackberry and Nokia started losing market shares and their market values collapsed by 93% and 71% respectively over seven years, as plotted in Figure 1. Interestingly, the under-performance of their stocks began to diverge in September 2013 when Microsoft announced its plan to acquire Nokia’s mobile phone business (see Figure 2). Nokia’s market value more than doubled within two months, while Blackberry’s stock remained at a low price after the firm declined a series of takeover offers. This example shows that capital reallocation can provide a valuable exit option for the less innovative firms before their capital becomes obsolete.

I present a static general equilibrium model to analytically examine the role of capital reallocation in the cross-section of stock returns. I consider a production economy where an existing non-innovating firm faces the threat of competing with a new innovating entrant. My model relies on two salient features: costly capital reallocation and time-to-build investment. I show that firms’ differential return responses to technology shocks have two facets.

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3Apple and Samsung first introduced their smartphones in 2007 and 2009 respectively and have continued to release a series of upgraded phones since then. In contrast, Blackberry and Nokia were slow in adopting a more advanced operating system. In 2014, Apple and Samsung together accounted for approximately 40% of total shipments worldwide, while Blackberry and Nokia accounted for only 3%. The market values of Apple and Samsung had surged by 528% and 125% over the past 7.5 years.
First, innovating firms and non-innovating firms respond in opposite directions to technology shocks. Adopting a new technology boosts the productivity and the output of the innovating firm but hampers the competitiveness of the non-innovating firm. In particular, the technology shock pushes down the price of goods and reduces the market share of the non-innovating firm. As with the contrasting stock performances of the mobile phone firms displayed in Figure 1, the model predicts that new technologies are value-enhancing for innovating firms, but value-destroying for non-innovating firms.

Second, non-innovating firms’ return exposure to technology shocks varies with changes in the efficiency of the capital reallocation process. The model shows that capital reallocation alleviates the value destruction suffered by non-innovating firms by providing an exit option. In a frictionless economy, low-productivity non-innovating firms would immediately disinvest all their capital and exit the market with the proceeds from capital sale. The presence of reallocation frictions erodes the net proceeds of capital sale and reduces the incentive to reallocate capital. The innovating firm is forced to hold more unproductive capital and compete with the innovating firm on output. Hence, high capital reallocation costs amplify the negative return response of non-innovating firms to technology shocks.

Capital reallocation frictions also affect the innovating firm’s return negatively. Technology adoption is associated with capital accumulation. New technologies can only boost output after they are implemented on physical capital. In my model, the innovating firm can accumulate capital through both new investment and used capital. I show that reallocation frictions reduce the used capital available for redeploying and hence inhibit the growth of the innovating firm. However, the impact of frictions on the innovating firm’s return is less pronounced than that on the non-innovating firm because the innovating firm has the alternative of expanding its production scale through building new capital.

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4The technology is also referred to as the embodied technology shock or investment shock in the literature (Greenwood, Hercowitz, and Krusell, 1997; Jorgenson, 1966; Solow, 1960).
In addition, my model shows that capital reallocation frictions can raise the risk premium of technology shocks and further increase the risk dispersion among firms. Reallocation frictions will influence the intertemporal substitution between investment and consumption as the size of the frictions changes the demand for new investment. In the model, used assets are imperfect substitutes for new investment. When reallocation costs are high, innovating firms have to invest more in new capital to adopt new technologies. As new capital takes time to build, high investment leads to low consumption growth in the short term. As a result, reallocation frictions also influence equilibrium expected returns. Capital reallocation frictions amplify the price of risk associated with technology shocks as well as the non-innovating firm’s risk exposures to technology shocks. Hence, the risk dispersion between the non-innovating firm and the innovating firm increases with reallocation frictions.

I find empirical supporting evidence in the cross-section of stock returns. I analyze firms’ heterogeneous return responses to technology shocks at the industry level, as the composition of firms’ capital stock varies significantly across industries (Shleifer and Vishny, 1992, 2011). I use industry asset liquidity as a measure of the inverse of reallocation frictions since the model implies that the size of reallocation frictions and the fraction of capital reallocated are inversely related. Prior literature also uses asset liquidity as an indicator of friction size in the used asset market (Eisfeldt and Rampini, 2006; Gavazza, 2011b). I use patent data to identify real technology shocks and group firms into innovating and non-innovating firms within each industry to examine their responses to these technology shocks. The results are consistent with the predictions of the model. First, the returns of non-innovating firms are negatively correlated with technology shocks, but only in industries with low asset liquidity (i.e., high reallocation frictions). Second, the returns of innovating firms are positively associated with technology shocks, but their responses to technology shocks do not vary significantly with reallocation frictions. In addition, when there are technology shocks the return spread
between non-innovating firms and innovating firms is wider in industries with lower asset liquidity.

Frictions in the used asset market provide a natural link between firms’ underlying assets and their stock returns. Cochrane (2011) asks in his presidential address: “Where do betas come from? ... Why are betas exogenous?” These questions remain as puzzles in the asset pricing literature. This thesis studies one explanation of cross-sectional differences in betas, in particular betas to technology shocks. The cross-sectional variation in frictions in used asset markets can amplify cross-sectional return differences. Hence, heterogeneous assets can lead to heterogeneous exposures to technology shocks.

Clearly, the mechanism I propose here is not the only one that links firm characteristics to cross-sectional beta dispersion. The existing production-based asset pricing literature is rich with alternative theories: profitability, investment intensity, financial constraint, labor heterogeneity, intangible capital and other important firm characteristics could all lead to co-movement among stocks. This study focuses on one production input, namely physical capital, and investigates how heterogeneous physical capital alone might generate cross-sectional return differences. Betas are generated endogenously from firms’ co-movement with technology shocks.

The remainder of this thesis is organized as follows. Chapter 2 reviews the related literature. Chapter 3 presents the model with a numerical example. Chapter 4 describes the data and measurement of various proxies. Chapter 5 reports the empirical findings. Chapter 6 concludes. An outline of each chapter is provided in the next section.
1.1 Chapter Outline

1.1.1 Chapter 2: Literature Review

This study builds on three strands of literature: i) frictions in the capital reallocation process; ii) endogenous growth theory; and iii) asset pricing implications of technology shocks. In this chapter, I selectively review the studies in these three areas, emphasizing both theory and empirical evidence.

First, I review the papers that study capital reallocation and frictions in the reallocation process. Prior literature shows that capital reallocation accounts for a significant fraction of firm investment. Papers have documented that frictions such as information asymmetry and trading frictions in used asset markets exist so that the reallocation process is neither instantaneous nor costless. Used assets are heterogeneous in terms of their functions and quality (Shleifer and Vishny, 1992). Consequently, used asset markets are often thin and illiquid. In my study, I build on these existing studies of reallocation frictions and examine whether frictions can affect firms’ exposure to technology shocks without explicitly modeling the mechanism that generate the reallocation frictions.

This thesis is also related to the large literature on Schumpeterian endogenous growth, in which resource reallocation is an important component. Aghion and Howitt (1992) develop the fundamental theoretical framework to show that economic growth is a result of technology advancement. The core mechanism of “creative destruction” has been adopted by the recent asset pricing literature on technology shocks, where innovating firms displace non-innovating firms by supplying quality-improved products. A new generation of Schumpeterian growth models focuses on the role of resource reallocation in the restructuring process induced by technology advancement (Aghion, Akcigit, and Howitt, 2013). Lentz and Mortensen (2008) show that economic growth is accompanied by labor reallocation. Kogan, Papanikolaou, Seru, and Stoffman (2012) document that innovation-induced reallocation also occurs with
physical capital. Moreover, the efficiency of the reallocation process affects not just the speed of technology adoption, but also the ex-ante incentive to innovate (Acemoglu, Akcigit, Bloom, and Kerr, 2013; Caballero and Hammour, 1996; Eberly and Wang, 2009). My study complements this literature by exploring the interactive effect between technology shocks and resource reallocation on financial assets.

This thesis contributes to the small but growing literature that studies the asset pricing implications of technology shocks. The most closely related works are Gârleanu, Kogan, and Panageas (2012) and Kogan, Papanikolaou, and Stoffman (2013). They argue that innovation increases competition pressure on existing firms and renders old workers’ skills obsolete. They show that technology shocks create a systematic risk factor, as these shocks cannot be hedged by purchasing the financial assets of future innovating firms. These studies aim to explain the high equity premium and the value premium. My work complements the literature by focusing on the cross-sectional return implications of innovation. In particular, I examine not only the difference between innovating firms and non-innovating firms, but also how firms within the non-innovating group differ in their responses to technology shocks. One recent paper by Lin and Palazzo (2015) examines the impact of the adoption and financing costs of new technology on cross-sectional average returns. Their study relies on the conditional Capital Asset Pricing Model (CAPM) and argues that firms that do not adopt new technology due to high adoption costs suffer more in economic downturns. In my study, technology shocks create an additional systematic risk. Moreover, capital reallocation costs affect firms’ investment decisions and hence aggregate consumption dynamics in a general equilibrium environment in this thesis.

More broadly, the ease of selling capital is also related to the literature that examines the implication of investment reversibility on optimal investment and stock returns. Costly reversible investment amplifies firms’ losses in economic downturns ex-post and also delays investment decision ex-ante (Abel, Dixit, Eberly, and Pindyck, 1996; Abel and Eberly, 1994;
Kim and Kung, 2014). Zhang (2005) shows that costly reversibility of investment and fixed costs together can explain the value premium. Ortiz-Molina and Phillips (2014) is the only existing paper that examines the direct impact of asset illiquidity on cross-sectional returns. They use the implied cost of capital (Pástor and Stambaugh, 1998) as a proxy for expected returns and report that the cost of equity is positively related to asset illiquidity. My empirical work tests the effect of asset illiquidity on firms’ realized returns through its interaction with technology shocks. The intuition is that the effect of asset illiquidity is most observable when firms are hit by irreversible shocks such as technology shocks and demand asset sales the most.

1.1.2 Chapter 3: Model

I present a static general equilibrium model to show that capital reallocation frictions can amplify firms’ risk exposure to technology shocks and also affect how technology shocks are priced by the financial markets. In the model, I consider a production economy augmented with a used asset market. The technology shock is exogenous and arrives in the form of a new firm with a more advanced production method. I show that the heterogeneous return responses to technology shocks have two facets. First, innovating firms and non-innovating firms respond oppositely to technology shocks due to competition. New technologies boost the productivity and sales of innovating firms, but at the expense of non-innovating firms, which become less competitive and gradually lose their product market share. Similar to the contrasting stock performances of the mobile phone firms displayed in Figure 1, the model predicts that new technologies are value-enhancing for innovating firms, but are value-destroying for non-innovating firms.

Second, non-innovating firms have different exposures to technology shocks among themselves. The model shows that the extent of value destruction exerted by technology
Chapter Outline

1.1 Chapter Outline

shocks depends on the efficiency of the capital reallocation process. Capital reallocation alleviates the value destruction suffered by non-innovating firms by providing an exiting alternative. In the absence of reallocation frictions, low-productivity firms can immediately disinvest all their capital at a fair price and exit the market. Meanwhile, high-productivity firms can expand their production scale rapidly through redeploying used capital. The presence of reallocation frictions would erode the net proceeds of capital sale and slow down the capital flow. Hence, high capital reallocation costs can amplify the negative price response of non-innovating firms to technology shocks. For innovating firms, slow capital reallocation due to frictions reduces their growth rates. However, the impact of frictions is less pronounced on the innovating firms than that on the non-innovating firms, because innovating firms have an alternative to expand their production scale through building new capital.

In addition, the model shows that capital reallocation frictions can affect the price of risk carried by technology shocks. Reallocation frictions can influence the intertemporal rate of substitution between investment and consumption, as the intensity of frictions can change the demand for new investment. In my model, used assets is an imperfect substitute for new investment. When reallocation costs are high, entrant firms must invest more in new capital to adopt new technologies, at the expense of slowing down consumption growth in the short term. As a result, reallocation frictions can influence the pricing kernel. When reallocation frictions are high, capital reallocation frictions can amplify the price of risk carried by technology shocks as well as firms’ exposure to technology shocks. My model predicts that the two forces reinforce each other, resulting in larger co-movements between stock prices and the pricing kernel.

Lastly, I use a numerical example to examine the impact of other factors on the model’s predictions. I find that the size of innovation determines the marginal benefit of old vintage capital. The likelihood of a technology shock has a similar effect on the equilibrium as
the size of the innovation does. The transformation rate of capital, which determines the elasticity of substitution between used assets and new capital, is similar to the reallocation friction in its effect on the equilibrium.

1.1.3 Chapter 4: Empirical Test Design

The model generates several testable hypotheses. First, the returns of non-innovating firms should be negatively affected by technology shocks. In addition, non-innovating firms should show heterogeneous return responses to technology shocks. This heterogeneity can be explained by the cross-sectional variation in capital reallocation frictions. The returns of innovating firms should respond positively to technology shocks. However, the impact of reallocation frictions on innovative firms’ return responses is ambiguous in the model. Moreover, when there is a technology shock, the return spread between non-innovating firms and innovating firms should widen as the intensity of the frictions increases.

Cross-sectional variation of reallocation frictions mainly arises from the heterogeneous assets used across industries. Firms within an industry often hold similar compositions of assets and participate in similar used asset markets. Therefore, I measure both technology shocks and capital reallocation frictions at the industry level. In addition, I split firms within an industry into a non-innovating portfolio and an innovating portfolio, based on whether the firm is granted a patent in a given year. By separating the non-innovating firms and innovating firms, I can examine their opposite responses to technology shocks. I also form non-innovating-minus-innovating (NMI) portfolios by taking long positions in shares of non-innovating firms and short positions in shares of innovating firms to study the variations of return spread between non-innovating firms and innovating firms across industry. In doing so, I also control for portfolio-level characteristics.
To test the hypotheses, I construct measures of technology shocks and reallocation frictions. I derive the measure of technology shocks from patent data. I estimate the implied market value of each patent and count its forward citations to account for patent heterogeneity. The implied market value is an ex-ante measure of patent value and is computed from firms’ abnormal returns around the patent granting date. On the other hand, the citation count is an ex-post measure of patent value, and is measured as the number of citations of patents within the five years after granting. Patents’ market values and the citation counts are then aggregated up to the industry level as measures of industry technology shocks.

I measure the relative intensity of industry capital reallocation frictions based on asset liquidity and asset redeployability. Asset liquidity is a natural candidate for reallocation frictions, as my model suggests a monotonic and negative relation between reallocation frictions and capital turnover. As a robustness check, I also use a measure of asset redeployability. Following Kim and Kung (2014), I construct the measure based on how widely each asset class is used across industries. This proxy captures an additional dimension of reallocation frictions, as it emphasizes the potential inter-industry asset reallocation. Old vintage capital could become useless to innovating firms in the same industry with completely new production methods, but the capital may still retain some salvage values for firms in other industries.

I then examine the quality of the proxies of technology shocks and capital reallocation frictions. I show that the implied market values of patents can predict forward citation counts. This suggests that stock prices do contain forward-looking information, including the quality of patents. I also find that asset redeployability can predict future asset liquidity.

Lastly, I survey the measurement of technology shocks and reallocation frictions adopted in prior literature and discuss the strengths and weaknesses of each proxy relative to my measures. Common proxies of technology shocks include total factor productivity, fluctuations in the price of capital, as well as patent-related measures. In terms of capital reallocation
frictions, market turnover, liquidation value of assets, and number of potential buyers are often used.

1.1.4 Chapter 5: Empirical Results

In this chapter, I test the hypothesis with various specifications and measures of technology shocks and capital reallocation frictions. I document supporting evidence for the model on the cross-sectional stock returns.

First, I examine the factors that could explain cross-sectional differences in asset liquidity and asset redeployability. Industry research and development (R&D) intensity, industry average vintage capital age, industry average firm market capitalization, and industry concentration are negatively associated with asset liquidity, while technology shocks, investment ratio, and Tobin’s Q are positively associated with asset liquidity. Similar relations are also found for asset redeployability.

In the main tests, technology shocks alone do not necessarily have a negative effect on non-innovating firms. This is different from the predictions of standard Schumpeterian models, where no resource reallocation is allowed and the non-innovating firms bear all the loss induced by technology shocks (Aghion and Howitt, 1992; Gârleanu, Kogan, and Panageas, 2012; Kogan, Papanikolaou, Seru, and Stoffman, 2012). However, it is consistent with the findings documented by (Bloom, Schankerman, and Van Reenen, 2013). They show that the positive spillover effect of innovation significantly dominates the negative creative destruction effect on non-innovating firms. The results are robust to using different measures of technology shocks and capital reallocation frictions.

I then show that non-innovating firms respond differently to technology shocks. In industries with high reallocation frictions, the impact of technology shocks on non-innovating firms are significantly negative. The negative return responses to technology shocks decreases
in industries with less reallocation frictions. These results support the model’s prediction, and suggest that capital reallocation is one channel through which non-innovating firms could reduce their exposures to technology shocks.

In term of innovating firms, their returns are positively associated with technology shocks alone. When controlling for the effect of capital reallocation frictions, I find that the positive return responses of innovating firms to technology shocks do not vary with the frictions. This is consistent with model’s prediction as the impact of frictions on innovating firms is ambiguous.

In addition, when there is a technology shock, the return spread between non-innovating firms and innovating firms is wider in industries with higher capital reallocation frictions. This suggests that the non-innovating firms bear higher costs of capital reallocation than the innovating firms do.

In the robustness tests, I conduct a placebo test and show that the main results documented are not driven by measurement errors in the market-based proxy of technology shocks. I re-estimate each patent’s market value from its innovating firm’s abnormal returns, but randomly assign a non-patent granting date within the same year the patent is granted, as if it is the true patent granting date for that patent. I aggregate the arbitrary patent values to the industry level to construct the measure of technology shocks. This retains the same measurement errors as the true market-based measure of technology shocks does, but does not contain any information related to patent grants. I perform the same set of regressions as the main tests using the arbitrary measure of technology shocks and repeat the procedure 200 times. The results show that the significant cross-sectional return impact of technology shocks and asset liquidity all disappear when an arbitrary measure of technology shock is used in the regressions.
Chapter 2

A Literature Review of Technology

Shocks, Reallocation Frictions and Asset Prices

2.1 Introduction

The macroeconomics literature frequently associates waves of real economic activities with the arrival of major technological breakthroughs. In particular, large innovations are often accompanied by waves of resource reallocation. Old firms exit, while new firms enter; old jobs are destroyed while new jobs are created (e.g., Foster, Haltiwanger, and Krizan, 2006, 2001). However, such large-scale restructuring is costly and slow, leading to a prolonged technology adoption process and delayed economic growth (Eberly and Wang, 2009). A small but growing literature explores the implication of technology shocks on financial assets, taking into account the slow adoption feature (Gârleanu, Panageas, and Yu, 2012; Greenwood and Jovanovic, 1999). My study complements this literature by examining the cross-sectional implications on stock returns through resource reallocation induced by technology shocks. In
this review, I survey the related studies to provide a background of the technology adoption process and its asset pricing implications.

The technology shocks referred to in this thesis are often called embodied technology shocks or investment-specific shocks (Greenwood, Hercowitz, and Krusell, 1997; Jorgenson, 1966; Solow, 1960). These technological advances start to boost output only after they have been installed in capital. For example, innovations like genome mapping and 3D printing techniques are merely blueprints for hospitals, and they cannot change our way to detect diseases or design products until DNA sequencing machines and 3D printers are built and installed. In this regard, capital accumulation and reallocation are essential to technology adoption. In comparison, another type of technology shock is referred to as disembodied technology shocks; for instance, shocks to supply chains. These disembodied technology shocks can also influence output but are independent from capital accumulation.

Technology shocks create winners and losers as new technologies change firms’ relative positions in the competition. Innovators will benefit by developing and adopting their new technologies. They can supply products with improved quality or at lower cost. On the other hand, non-innovating firms will be negatively affected by technology shocks as their products become less competitive and gradually replaced by new products. This “creative destruction” process induced by technology shocks is first discussed by Schumpeter (1942) and developed into an endogenous growth framework by Aghion and Howitt (1992). These technology shocks can lead to opposite responses across firms and generate wide cross-sectional dispersions among firms. This distinctive feature could have important implications on real economic activities and cross-sectional stock returns.

In terms of real economic impact, technology shocks are often accompanied by waves of resource reallocation involving both labor and physical capital. In recent years, resource reallocation and industry dynamics have become the focus of a new generation of Schumpeterian growth theory (see Aghion, Akcigit, and Howitt (2013) for a review of Schumpeterian
2.1 Introduction

Large innovations introduce dispersions in firm productivities, generating incentives to reallocate production inputs. Firms that fail to adopt new technologies may reduce their production scale through layoffs and asset sales to cut their fixed costs, while innovating firms expand by increasing labor hires and capital accumulation (e.g., Kogan, Papanikolaou, Seru, and Stoffman, 2012; Lentz and Mortensen, 2008). According to Foster, Haltiwanger, and Krizan (2006, 2001), resource reallocation through firm entry and exit accounts for 50% of manufacturing and 90% of retail productivity growth in the United States. Thus, resource reallocation is a crucial mechanism for sustained economic growth, especially when resources are scarce.

The efficiency of resource reallocation largely affects the speed of technology adoption and economic growth. Adoption of new technologies requires capital accumulation, either through new investment or the purchase of used assets. Caballero and Hammour (1996) suggest that frictions in the capital reallocation process can significantly prolong the overall technology adoption process. They also affect the ex-ante incentives to innovate. Caballero and Hammour (1996) argue that search and contractual frictions in the labor market erode the innovation rents generated, leading to less R&D investment ex-ante. Consequently, reallocation frictions hamper the pace of innovation in the economy.

The size of the frictions in the reallocation process determines the efficiency of the resources reallocated. As my study focuses on the capital side, I survey the sources of frictions in asset markets and their influence on firms’ investment and financing decisions.1 Costly searching and information asymmetry are the two main types of frictions in used asset markets. They erode the gains from trade from both parties and reduce the incentive to disinvest and redeploy assets (Eisfeldt and Rampini, 2006; Ramey and Shapiro, 2001).

Studies of search frictions show that it is costly and time-consuming to match with a high

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1See Mortensen and Pissarides (1999); Rogerson, Shimer, and Wright (2005) for surveys of labor market frictions in depth.
value of assets under trade, since assets vary in their features and asset markets are thin (Gavazza, 2011b; Ramey and Shapiro, 2001). In addition, a large body of literature in adverse selection shows that both transaction prices and volume in asset markets will be undermined by information asymmetry, when sellers have better information about the assets they are selling than buyers do (Akerlof, 1970; Fuchs, Green, and Papanikolaou, 2015; Li and Whited, 2014).

Recently, more studies have started to incorporate technology shocks into asset pricing models. One strand of this literature builds on the Schumpeterian creative destruction framework and argues that technology shocks transfer wealth from existing firms to future innovating firms. Thus, technology shocks create a systematic risk factor since investors of existing firms cannot hedge those shocks by purchasing the financial assets of future innovating firms (Gârleanu, Kogan, and Panageas, 2012; Kogan, Papanikolaou, and Stoffman, 2013). Another strand of this literature builds on the endogenous growth theory, which argues that economic growth is self-sustained by profit-driven R&D activities. A standard demand shock can be amplified and extended due to less R&D expenditure and lower expected future growth. Both approaches that incorporate technology shocks help to improve the match of asset pricing moments in data – in particular, the equity premium and the value premium. My work follows the creative destruction approach and complements the existing literature by exploring the richer implications of technology shocks on cross-sectional returns. In particular, I examine not only the differences between innovating firms and non-innovating firms, but also how firms differ within the non-innovating group in their responses to technology shocks. In addition, I show that differences in firms’ sensitivity to technology shocks vary with the efficiency of the capital reallocation process. Given the close association between resource reallocation and the technology adoption process, my study provides additional evidence to the creative destruction approach of asset pricing models.
Overall, my study builds on three strands of literature: i) capital reallocation frictions; ii) technology shocks in macroeconomic growth theory; and iii) asset pricing implications of technology shocks. In this review, I selectively discuss some of the research in these three areas, emphasizing both theories and supporting empirical evidence. I begin by discussing the mechanisms and determinants of costly capital reallocation and summarize its impact on investment and external financing in Section 2. In Section 3, I move on to studies that link technologies with economic growth by introducing and comparing two endogenous growth models: Romer (1990) and Aghion and Howitt (1992). These two frameworks of growth theory are also the foundations of asset pricing studies of technology shocks. In section 4, I discuss the impact of technology shocks on the financial market. I first summarize the evidence to show that the stock market responds vigorously to major technology shocks. I then review several recent studies that incorporate technology shocks into asset pricing models to explain the equity premium and the cross-sectional return spreads. Section 5 concludes.

### 2.2 Reallocation Frictions in Secondary Asset Markets

Resource reallocation is driven by changes in productivity among firms induced by shocks. High-productivity firms can afford to purchase more assets and hire more labor at a higher price, while low-productivity firms are more likely to reduce their investment and hiring. In a frictionless world, competition among potential buyers ensures that resources are allocated to the most efficient producers and prices are close to the value in best use. With the presence of friction in secondary asset markets, the reallocation process is time-consuming and assets are sometimes allocated to low productivity firms.

In this section, I focus on the frictions in used asset markets, since this study examines the capital reallocation channel in transmitting technology shocks. Nevertheless, it is important
to recognize that labor reallocation plays an equally important role in the economy. I first summarize the basic features of secondary asset markets. Next, I discuss the sources of reallocation frictions in real asset markets. I categorize them into two broad groups; namely, search frictions and information asymmetry. The two forces are interrelated and amplify the overall deadweight loss in the capital reallocation process. I then survey the impact of secondary asset market frictions on investment decisions and debt financing. Lastly, I survey the studies on the asset pricing implications of asset reallocation frictions.

### 2.2.1 Facts about Secondary Asset Markets

Reallocation of resources is necessary as the supply of resources is relatively inelastic. The aggregate labor supply is constrained by the population of the workforce; new capital takes time to build, and used assets serve only as imperfect substitutes to new capital. The benefit of used assets is that they can be quickly redeployed so as to start the production process more quickly (Yang, 2008).

Transactions of used assets are economically significant. Eisfeldt and Rampini (2006) report that the sale of property, plant and equipment (SPPE) together with mergers and acquisitions (M&A) account for nearly a quarter of the total capital expenditure each year. In particular, more than two-thirds of all machine tools sold in the United States in 1960 were used tools (Waterson, 1964) and more than half of the trucks traded in 1977 were used trucks (Bond, 1983). As an example of more specific assets, the number of transactions for used commercial aircraft is almost three times the number of purchases of new aircraft in 2002 (Gavazza, 2011a).

It is important to realize that resource reallocation is neither costless nor instantaneous. Assets are often resold at a price considerably less than their purchasing price even when adjusted for age-related depreciation (e.g., Pulvino, 1998; Shleifer and Vishny, 1992). In
addition to monetary costs, it is time-consuming to find a good match of counterparties. Participants sometimes trade-off better deals for quicker turnover, resulting in resource misallocation. Furthermore, Eisfeldt and Rampini (2006) argue that reallocation costs are time-varying as asset turnover is procyclical at the aggregate level, suggesting that it is more difficult to sell assets when firms need to sell the most.

2.2.2 Sources of Capital Reallocation Frictions

Search friction in real asset markets

Real assets are traded in decentralized markets. The fundamental feature of a decentralized market is that market participants must search for their trading counterparties, and the two parties bargain to determine the price of traded assets once they meet. Some financial assets, such as corporate bonds and derivatives, are traded in the over-the-counter (OTC) markets, which are also decentralized. Assets traded in decentralized market are often not standardized.

Real asset markets inherit the typical trading frictions of decentralized markets. Participants incur non-trivial costs for advertisement, inspection and legal services during the searching and matching process. These costs are deadweight losses to both buyers and sellers. As a comparison, trading costs are significantly less in those organized exchanges where financial assets like stocks and futures are traded. The centralized exchanges provide the immediacy of trade and historical price transparency.

The magnitude of search frictions is largely determined by market thickness. Gavazza (2011b) builds a bilateral search-and-bargaining model to study the trading frictions in secondary asset markets\(^2\). In his model, firms optimally adjust their production scale according

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\(^2\) The search-and-bargaining model is developed in the seminal paper by Diamond (1982) to study the labor market. Duffie, Gärleanu, and Pedersen (2005) adopt this framework and first apply it to the OTC financial markets.
to changes in their productivity due to exogenous shocks. Heterogeneous productivity across firms generates the incentive to trade capital. By assuming an increasing return of matching technology functions in market size (i.e., the mass of active sellers and buyers), Gavazza (2011b) shows that searching costs decrease as the market gets thicker, since the contact rate between buyers and sellers increases more rapidly than the size of the market does. The model fits the characteristics of the used aircraft market data well. As the used aircraft market gets thicker, more aircraft are traded, the average price of used aircraft increases, the price is also less volatile, and the productivity of firms is less dispersed.

Market thickness is tightly linked with the notion of asset specificity. As defined in Caballero and Hammour (1996):

“An asset is specific to a relationship to the extent that its value is greater within the relationship than outside ... Specificity in a relationship reduces the flexibility of separation decisions, which induces reluctance in the investment decision...”

Despite age and quality, a piece of capital often carries a set of physical characteristics that are designed specifically for its original owner. This limits the number of potential buyers who can utilize most of its functions, as some of these characteristics are useless to many potential buyers (Gavazza, 2011b; Ramey and Shapiro, 2001). Thus, real asset markets are mostly very thin and trading frictions are significant. Machine tools are the most traded used assets, and transactions of machine tools in secondary markets accounted for two-thirds of their total trade in the U.S. in 1960 (Waterson, 1964). Meanwhile the share of used aircraft accounted for less than 10% of total aircraft traded (Gavazza, 2011a). Compared to machine tools, aircraft are a more specific class of asset and are difficult to be redeployed by firms outside the airline industry.

3The aircraft market was very illiquid in the 1950s and 1960s. However, Gavazza (2011a) also shows that trading volume has surged since the mid-1980s due to the growth of the aircraft leasing business.
In addition to those monetary costs, it is also time-consuming to find good matches of counterparties in used asset markets. Firms face a trade-off between quickly selling assets at a low price and searching for the best match for a long period of time (Ramey and Shapiro, 1998). In a thin market it may be optimal for firms not to search exclusively, but to sell assets to any buyer who appears early in the market, especially when capital depreciates fast. In this case, high trading frictions may lead to the reallocation of capital to low-value users and could result in misallocation of resources. This further amplifies the real economic costs of frictions (Ramey and Shapiro, 2001).

As a result, search friction in thin markets also depresses the transaction prices of used assets. Ramey and Shapiro (2001) conduct a case study of aerospace plants that shut down in the 1990s and report direct evidence that the thin market for assets of aerospace plants can significantly affect their liquidation values. They show that the average proceeds from the sale of equipment is only 28% of their estimated replacement cost, since the equipment for aerospace companies is very sector-specific. Among the types of physical capital, machine tools have the most active used market as they are relatively less specific. According to Ramey and Shapiro (2001), their resale price is 40% of the replacement cost, on average.

The transaction price is also affected by the relative bargaining power between counterparties. The financial status of the sellers is one of the factors that influence the relative bargaining power. Firms with low debt capacity may choose to sell assets quickly to fund their liquidity needs. This leads to fire sales, in which assets are traded at prices far below their values in best use. Pulvino (1998) reports that used aircraft are sold at 14% lower prices by financially distressed airlines than the average market price. Campbell, Giglio, and Pathak (2011) find an even larger discount of 28% in forced sales of homes. Significant search frictions, together with low transaction prices, can make fire sales extremely costly.

The punchline of search friction in secondary asset markets is that high asset specificity shapes used asset markets to be considerably thinner than other decentralized markets.
Search frictions in the matching process and the market depth are negatively correlated. Search frictions can hamper market liquidity, depress the prices of used assets, lengthen the reallocation process, and can sometimes lead to misallocation.

**Information asymmetry**

Secondary asset markets also suffer from the typical adverse selection issue. Adverse selection can arise when sellers hold superior information about the quality of their used assets than potential buyers do. Although informational friction is prevalent in most markets, including stock markets, which have small search frictions in normal times, the secondary asset market is often the starting place where academics study the adverse selection problem.

Akerlof (1970) first recognizes the issue and develops a theoretic framework for studying adverse selection. He studies the second-hand car market, where sellers can observe the true quality of their car while potential buyers cannot. In a static setting, adverse selection can lead to a breakdown in the market, because buyers who cannot distinguish good-quality cars from poor-quality cars would only offer a price according to the average expected quality of cars in the market. This then drives out the sellers of good-quality cars. As a result, the average quality and prices of cars in the market continue to decrease until the market breaks down in equilibrium.

Several studies then extend this model into dynamic settings to further examine the adverse selection problem (Hendel and Lizzeri, 1999; Hendel, Lizzeri, and Siniscalchi, 2005). Their models show that the used asset market will not shut down in dynamic settings. However, both asset prices and trading volume in these markets are low. Gilligan (2004) further shows theoretically that capital age and trading volume are negatively related, since the true depreciation rate is stochastic and quality dispersion increases with capital age.

In theory, trading volume is a negative indicator of the size of adverse selection and should be negatively related to capital age. However, empirical findings of adverse selection
2.2 Reallocation Frictions in Secondary Asset Markets

in real asset markets are inconclusive. Bond (1983) only finds weak evidence for the inverse relation between trading volume and age in the used truck market. Meanwhile, Genesove (1993), Fabel and Lehmann (2000) and Emons and Sheldon (2002) report strong evidence of the existence of adverse selection in the used car market. Gilligan (2004) documents strong supporting results in the used business aircraft market. One reason for the inconclusive empirical evidence is that assets with high depreciation rates would be traded more often, especially during their early age. This counteracts the impact of the quality dispersion associated with capital aging. Hendel and Lizzeri (1999) and Porter and Sattler (1999) document that the high trading volume of used car brands is mostly explained by the rapid depreciation of some car brands rather than the size of their quality dispersion. Gilligan (2004) reports a significant and sizable negative relation between trading volume and depreciation for those aircraft types that have above-average quality dispersion and below-average leasing frequency.

Industry condition is a crucial factor that affects the severity of adverse selection in used asset markets. Shleifer and Vishny (1992) argue that industry insiders are high-value users, as they have better knowledge to assess the quality of industry-specific capital and can deploy the assets in similar production. In normal times, used asset markets are overrepresented by industry insiders, especially for specialized industries (Ramey and Shapiro, 2001). However, when an industry underperforms, most of its firms become financially constrained and cannot purchase additional capital. Firms can only sell capital to deep-pocketed industry outsiders, who consider entering the industry by acquiring existing assets or establishments. However, industry outsiders may often demand a large discount due to the considerable information asymmetry they encounter. As a result, industry distress can also lead to asset fire sales. Acharya, Bharath, and Srinivasan (2007) report that industry performance significantly affects the liquidation value of capital served as collateral.
The efficiency with which capital can be redeployed to other firms is an important determinant of the economy’s speed of transition after a shock. Recent studies use dynamic models of adverse selection to further explain the cyclicality of the aggregate capital reallocation and final output. Eisfeldt and Rampini (2006) document that capital reallocation is procyclical, while the cross-sectional dispersion of capital productivity is counter-cyclical. They argue that the implied reallocation frictions should be counter-cyclical, as the cost of selling capital must increase significantly to prohibit firms from exploiting gains from trade in bad times. The time-varying nature of capital reallocation further suggests that informational and contractual frictions account for a considerable proportion of overall frictions in used asset markets. Two recent working papers, Li and Whited (2014) and Fuchs, Green, and Papanikolaou (2015), endogenize the adverse selection problem in used asset markets in a real business cycle (RBC) model. Their models can generate cyclical capital reallocation and aggregate output. Kurlat (2013) and Bigio (2015) also show that the information friction regarding the quality of entrepreneurs’ capital is mathematically equivalent to a tax on capital that amplify the original shocks.

Costly capital reallocation has promoted the increasing use of capital lease contracts over recent decades. Operating leasing arises when firms forego the ownership of capital to avoid future costly resale of capital. Research further shows both theoretically and empirically that capital leasing improves the efficiency of used asset markets by enhancing the average quality of used assets and boosting the trading volume (Gavazza, 2011a; Gilligan, 2004).

In summary, search frictions and adverse selection together lead to thin secondary asset markets, low and volatile transaction prices, and slow capital reallocation. These two forces often interact and magnify the overall reallocation costs.

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4Ownership of capital usually provides lower user costs per period than the operating lease does.
2.2.3 Reversibility of Investment and Collateralized Debt Financing

Frictions make investment partially irreversible and alter optimal investment behavior, as they create a wedge between the price at which the firm can purchase capital and the price at which it can sell capital. Firms delay investment under high economic uncertainty to avoid costly reverse investment. In terms of debt financing, physical capital is often served as collateral in debt contracts, which can be liquidated to pay back creditors in the case of default. Hence the resale price of capital also affects the recoverability of debt ex-post and thus firms’ debt capacity ex-ante.

Costly reversibility of investment helps to understand the lumpy pattern of investment at the micro-level documented by Doms and Dunne (1998). Abel and Eberly (1994) use asymmetric adjustment costs of investment to examine costly reversible investment. They specify the adjustment cost function such that disinvestment is more costly than investment. They show that three regions exist along the optimal investment path: positive investment, inaction, and negative investment (disinvestment). Abel and Eberly (1996) further show that the gap between the resale price and the purchase price of capital determines the width of the inaction range. Even a tiny wedge between two prices can generate a substantial range of inaction under uncertainty. Abel, Dixit, Eberly, and Pindyck (1996) reconcile the q-theory approach with the real options approach. They show that costly reversible investment resembles a call option to invest and a put option to disinvest. Under uncertainty, low reversibility reduces the values of both the call and the put, resulting in delays in investment and disinvestment.

document strong supporting evidence by studying the investment behavior around two events, the Gulf War I and the 9/11 terrorist attack. They show that industries with less redeployable capital\(^5\) reduced investment considerably more after the two uncertainty shocks.

Frictions in the capital reallocation process also influence firms’ debt capacity through the collateral channel. Collateral entitles the creditor to foreclose on the debtors’ assets to at least partially recover the loan in the case of default. Redeployable physical assets are natural candidates for collateral and are often known as credit multipliers (Kiyotaki and Moore, 1997). A large body of theoretical literature studies the mechanisms through which collateral can alleviate financial frictions stemming from adverse selection and moral hazard (e.g., Berger and Udell, 1990; Besanko and Thakor, 1987; Bester, 1985; Booth, 1992). Though the two types of information asymmetry reach different conclusions on whether high-quality or low-quality firms use collateral, both approaches predict that a firm’s debt financing capacity increases with the expected liquidation value of the collateral.

Empirical findings are supportive of these theories. Acharya, Bharath, and Srinivasan (2007) find that the ex-post recoverability of defaulted loans is significantly higher for secured loans (e.g., loans with collateral) and it increases with the liquidation value of the collateral. Some studies analyze specific asset markets, such as the aircraft market, and report that a higher repurchase price of collateral is associated with a lower credit spread, higher credit rating, longer debt maturity, greater loan size, and fewer creditors (Benmelech, 2009; Benmelech and Bergman, 2009; Benmelech, Garmaise, and Moskowitz, 2005).

Frictions in real asset markets and financial frictions are interrelated. Studies further examine the impact of financial frictions on firm investment through the collateral channel. Almeida and Campello (2007) and Campello and Hackbarth (2012) show that investment sensitivities to both cash flow and Tobin’s Q increase with firms’ average liquidation value

\(^5\)Capital redeployability captures the flexibility with which assets can be deployed by other firms. It is inversely related to asset specificity as highly specific assets are less redeployable by other firms.
of total assets.\(^6\) Both Tobin’s Q and cash flow are positively associated with investment profitability. This suggests that financial frictions through the collateral channel further amplify the distortion of costly reversibility to optimal investment by widening the inaction range of investment.

### 2.2.4 Reallocation Frictions and Stock Prices

Evidence from costly reversibility of investment and collateralized financing implies that real asset market frictions may further transmit to financial asset prices.

Assets with differential reallocation frictions provide one explanation for the cross-sectional stock return spread. Zhang (2005) relies on costly reversibility of investment, fixed costs and time-varying risk premium to explain the value premium. He shows that firms that suffer from persistent negative productivity shocks often carry unproductive capital due to costly disinvestment, while incurring considerable fixed costs. Therefore, those firms have higher book-to-market ratios and are more exposed to persistent future productivity shocks. Hence, they have a higher risk premium. Livdan, Sapriza, and Zhang (2009) augment the model with collateralized debt financing and show that collateral constraints can further amplify the cross-sectional return spread. In these studies, assets are still homogeneous but the price discount increases with the quantity of assets sold. Firm heterogeneity comes from idiosyncratic shocks and the level of their capital stock. Ortiz-Molina and Phillips (2014) report significant positive association asset liquidity and the implied cost of capital derived from analysts’ forecasts.

Prior literature that links costly asset resale and stock returns does not specify the source of shocks. Aggregate shocks can stem from various sources and influence the economy through different mechanisms. This could be one reason that there is only limited empirical evidence of a direct association between real asset market frictions and stock returns. In

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\(^6\)The average liquidation value of total assets is one measure of asset tangibility in their paper.
my thesis, I identify one specific type of shock, namely technology shocks, and analyze its interactive effect with real asset market frictions on cross-sectional stock returns. Prior literature also relies on the persistence of shocks to generate incentive to sell capital. In the subsequent chapters, I show that technology shocks can endogenously generate a permanent differential effect on firms’ productivity and induce incentives to reallocate capital.

2.3 Technological Progress in Macroeconomic Models

Technology shocks are one factor that triggers capital reallocation. In this section, I review the literature on technological progress in macroeconomics that sheds light on the mechanisms through which new technologies diffuse throughout an economy. I start with the two seminal papers of the endogenous growth theory, Romer (1990) and Aghion and Howitt (1992). They show that economic growth is a result of profit-motivated R&D activities that continuously push forward the technology frontier. I also make a comparison of the two frameworks. I then survey some new developments in the area of endogenous growth theory.

2.3.1 Two Endogenous Growth Models

The Romer model

The seminal paper by Romer (1990) initiates a new era for the endogenous growth theory. He models technological progress in the form of an expansion in product variety. Each innovation from successful R&D adds one new differentiated type of product to the economy. Romer (1990) introduces a monopolistic intermediate goods sector in the model in addition to a standard competitive final goods sector. The final sector combines labor with a range of intermediate goods to produce final goods. The production function of the final goods is

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7Early studies of endogenous growth theory in the mid-1980s treat technology growth only as a by-product of capital investment or “learning-by-doing”.
specified as an additively separable function of all different types of intermediate products 
\( Y_t = L^{1-\alpha} \sum_{j=1}^{O_t} X_j^{\alpha} \), where \( L \) and \( X_j \) denote labor and intermediate goods, respectively. \( O_t \) is the number of varieties of intermediate goods. \( \alpha < 1 \), is the share of intermediate goods in final goods production. Innovation occurs in the intermediate sector through the expansion of intermediate goods varieties. Each type of intermediate product is exclusively supplied by its innovator. Monopolistic rent motivates the development of new intermediate goods. In turn, an increase in the number of intermediate goods types enhances both labor productivity and output growth.

The additively separable production function simplifies the valuation of monopolistic profits generated by each product line. Different intermediate products are not substitutable with each other with the separable production function. The arrival of new products has no effect on the demand for existing products. Thus, the optimal price of each intermediate good and the maximum profit stay constant over time. The value of a new product is just the discount value of a perpetuity of monopolistic profits. The equilibrium R&D investment ex-ante is equal to the expected value of new products. The long-run growth rate is then the expected growth rate of intermediate goods varieties. In practice, an additively separable production function of intermediate goods can be a strong assumption, as it presumes that the old innovation is never obsolete and is equally efficient in production as the new innovation.

The Aghion and Howitt model

Aghion and Howitt (1992) develop another fundamental endogenous growth framework by incorporating the concept of Schumpeter’s creative destruction. Firms with new technologies displace firms with old production technologies, as consumers shift their demand from old products to new products for better quality or lower costs. Therefore, the authors consider a simple life cycle of innovations, adding an extra dimension of technology progress to the model.
In Aghion and Howitt (1992)’s model, output and labor productivity growth come from quality improvements in products. The model has a monopolistic intermediate goods sector similar to Romer’s product variety model. Monopolistic rents generate the incentive to innovate. In addition, the quality of each intermediate product determines its productivity.

The model introduces quality into the additively separable production function of the final sector, which determines the productivity of each intermediate product \( Y_t = L^{1-\alpha} \sum_{j=1}^{N} (q_{tj}^{kj} X_j)^{\alpha} \), where \( q_{tj}^{kj} \) is the best quality of intermediate product \( j \) at time \( t \). Different from Romer’s model, the number of types of intermediate goods \( N \) is fixed. Different intermediate products are still not substitutable, while displacement of old products takes place within each intermediate product type. An entrepreneur who can produce an intermediate good with better quality will take over the whole market share of the industry. However, the entrepreneur will then face the risk of being displaced by future innovators, as his predecessors did. Therefore, the value of an innovation is the present value of the monopolistic profit adjusted for the probability of being replaced in the next period.

**A comparison of the two frameworks and extensions to asset pricing theory**

The two innovation-based theories both rely on monopolistic rents of innovations to sustain endogenous growth. In Romer’s model, innovation does not necessarily lead to heterogeneity among firms. The arrival of new products does not affect the existing products, and the productivity of each non-substitutable intermediate good is identical. Firms are collections of differentiated products. As a comparison, Schumpeterian growth theory argues that innovating firms gain at the expense of non-innovating firms. Technology advancements hence naturally introduce heterogeneity among firms. In addition, the productivity of intermediate goods is determined by the best quality of each product type, which depends on the historical path of its R&D outcomes. Therefore, Schumpeterian growth theory provides a rich frame-
work for cross-sectional studies, with differences in productivity between innovating and non-innovating firms naturally leading to resource reallocation and industry dynamics.

Furthermore, both frameworks generate a deterministic long-run balanced growth equilibrium. The number of innovations and the growth rate each period are stationary if there are large enough numbers of R&D projects and the innovating efficiency stays stable. Introducing randomness to the aggregate number of innovations could lead to shocks to output and productivities. In the asset pricing literature, I recognize that future investment opportunities affect investors’ portfolio decisions and hence asset returns (Merton, 1973). However, the theory does not tell us what forms the investment opportunity set and how it varies with macroeconomic quantities over time. Technology shock is one identifiable variable that can influence future investment opportunities. There is a growing literature that links aggregate technology shocks with large movements in financial markets and explores its potential impact on systematic risk. The uniqueness of Schumpeterian technology shocks is that they have opposite impacts on innovating and non-innovating firms.

### 2.3.2 New Developments in Endogenous Growth Theory

A new generation of Schumpeterian growth models explores this model’s rich implications for firm and industry dynamics by relaxing some of the assumptions imposed in Aghion and Howitt (1992). The Aghion and Howitt (1992) model assumes that a new entrant with one innovation can immediately displace the incumbent as the new monopoly, but does not innovate until it is suddenly displaced by another entrepreneur. To avoid sudden growth and death of firms, Klette and Kortum (2004) and Lentz and Mortensen (2008) allow incumbent firms to invest in R&D, but to have less innovating efficiency than potential entrepreneurs do. Successful development adds one product line to the innovating firm, but destroys the product line of another firm that produces the old version. In such a way, incumbent firms
can produce multiple types of products that they have developed in the past, and they are able to gradually grow and shrink depending on their R&D outcomes. Klette and Kortum (2004) show that the size distribution of firms is highly skewed. Young firms with a small number of production lines have a high exiting rate, but those that survived tend to grow faster than larger firms due to their higher innovating efficiency. These predictions are consistent with stylized empirical evidence (Caves, 1998). Mortensen (2011) further show that technology shocks are accompanied by labor reallocation. These developments enrich our understanding of the technological implications on firm and industry dynamics.

Another strand of Schumpeterian growth models links competition with innovations (e.g., Aghion, Bloom, Blundell, Griffith, and Howitt, 2005; Aghion, Harris, Howitt, and Vickers, 2001). They argue that incumbent firms invest in R&D in order to escape the threat of being displaced. Their models can explain the positive correlation between competition and R&D investment studies found in the data (e.g., Qian (2007)).

2.4 Technology Shocks and Asset Prices

The wide impact of technology shocks on the real economy naturally leads to questions about their implications for the stock market. How does the stock market respond to technology shocks? What characteristics cause firms to react heterogeneously to technology shocks? How do these shocks impact the welfare of investors? How do investors price the technology shocks? In this section, I first survey the studies that link some of the historically large movements in the stock market with technology shocks. I then review the innovation-augmented asset pricing models.
2.4.1 Evidence on Movements in the Stock Market

Recent studies document increasing evidence suggesting the association between major technological innovations and large movements in the stock market. The prolonged depression of the stock market in the 1970s is one of these examples. The ratio of market capitalization to GDP plummeted by 60% in 1973–1974. It did not recover until the mid-1980s, then continued to rise sharply in the 1990s. Similar patterns of movements are also found in the stock markets of other leading economies. Greenwood and Jovanovic (1999) and Hobijn and Jovanovic (2001) find that the surge of market-value-to-GDP ratio in the mid-1980s was largely driven by the boom of newly listed or young companies. Firm entry and exit rates, as well as the capital destruction rate, increased in the late 1970s and 1980s. Mergers and acquisitions were also active during this period. Laitner and Stolyarov (2003) show that the average Tobin’s Q of public firms, which is a measure of investment opportunity, fell below 1 during that period, while aggregate investment remained stable. This implies that a large fraction of investment may be contributed by newly incorporated but not yet listed firms.

The empirical evidence suggests that the contraction and expansion of the stock markets in the 1970s and 1980s may be related the information technology revolution during that period (Greenwood and Jovanovic, 1999; Hobijn and Jovanovic, 2001). The rapid development of information technology induced an economy-wide restructuring. The market values of incumbent firms evaporated as they were not expected to adopt the new technology effectively, while it took time for firms to accumulate capital embedded with the new technology to grow and go public. Ghossoub and Beladi (2011) argue that the slow adoption of infrequent large technology can drive stock prices in a cyclical manner. They argue that technology advances can raise the discount rate due to an intertemporal substitution effect of consumption, and result in a decline of stock prices in the early phase of technology adoption.
Pástor and Veronesi (2009) develop a Bayesian learning model for new technology shocks that can induce a bubble-like pattern of stock prices. They argue that the prices of innovating firms initially surge in response to good news about the new technology and later fall, as the large-scale adoption of the new technology turns the idiosyncratic risk into systematic risk, pushing up the discount rate. The model relies on the assumptions that new technologies inherit high uncertainty and they can be adopted quickly to generate pronounced bubble patterns. Their theory provides a rational explanation for the bubble-like behavior of the stock market in 1830–1861 and 1992–1995, which coincided with the two major technological revolutions of the steam-powered railroad and the Internet.

This empirical evidence suggests that the impact of technology shocks on stock prices is significant and epidemic. Most studies recognize that such shocks can affect asset prices through both the cash flow channel and the discount rate channel. The relative size of the two effects is time-varying. These studies make various assumptions about technology shocks to explain the ad hoc behaviors of stock prices for specific periods. How investors price technology shocks in general is still unclear. To answer this question, more parsimonious asset pricing models incorporating innovation shocks are necessary.

2.4.2 A Source of Systematic Shocks

Technology shocks arrive in waves. The randomness of the arrival of innovations generates uncertainty and fluctuations in macroeconomic quantities. In the asset pricing literature, technology shocks are recognized as one of the state variables that affect investors’ future investment opportunity sets and generate a source of systematic risk. The differential exposure to technology shocks across firms also helps to explain cross-sectional spreads in returns.
I categorize studies of technology-embedded asset pricing models into three groups by the mechanisms through which the shocks transmit through the economy. I discuss these in the order of the investment adjustment cost approach, the creative destruction approach and the long-run risk approach.

**Technology shocks in investment cost**

The early literature on asset pricing often incorporates technology shocks into the adjustment cost function of investment. It can be interpreted as an increasing transformation rate of resources into capital goods due to quality-improving innovations.

This idea originates from Solow (1960)’s definition of capital-embodied technology shocks, which only affect the productivity of new vintage capital, to be distinguished from disembodied technology shocks, which impact all vintages of capital. Studies show that capital-embodied technology shocks are able to explain substantial fractions of long-run growth and business cycle fluctuations (Greenwood, Hercowitz, and Krusell, 1997; Justiniano, Primiceri, and Tambalotti, 2011).

In these models, exogenous technology shocks appear in the adjustment cost function, resulting in time-varying costs of investment (e.g., \( Z_t^{-1} \phi(I_t, K_t) \)), where \( Z_t \) denotes the technology progress, \( I_t \) and \( K_t \) are new investment and capital stocks respectively. \( \phi(\cdot) \) is the adjustment cost function and can be either convex or linear in investment). A positive shock in technology progress results in a reduction in the marginal cost of capital \( Z_t^{-1} \phi_t \), *ceteris paribus*. This is consistent with the empirical finding that the relative price of equipment has decreased over the past 60 years (e.g., Gordon, 1990; Greenwood, Hercowitz, and Krusell, 1997). As a comparison, the aggregate productivity shocks normally enter the production function directly and affect the productivity of all capital.

Technology shocks in the adjustment cost function only affect investment, and hence new capital, but not existing vintages of capital. In Kogan and Papanikolaou (2013)’s partial
equilibrium model, a firm is a collection of projects and technology shocks affect the relative price of projects the firm can acquire. They show that the technology shocks only affect the value of future projects (the growth opportunities) by determining the equilibrium marginal cost of future investment. As a comparison, aggregate productivity shocks normally enter the production function directly and affect the productivity and value of both existing and future projects (the assets in place). Thus, a firm’s exposure to the technology shocks depends on the share of growth opportunities in its value.

Kogan and Papanikolaou argue that technology shocks should carry a negative market price of risk so that the average return spread between assets in place and pure growth opportunities is positive. Technology shocks cause firms with high growth opportunities to positively co-move with each other, while existing projects are not affected. Hence, the lower risk premium of growth opportunities and their positive exposure to technology shocks together suggest that innovation risk is negatively priced in stock markets.

In the asset pricing literature, macroeconomic shocks are priced depending on how they affect investors’ consumption or wealth (Merton, 1973). To examine the pricing mechanism for technology shocks, Papanikolaou (2011) extends Kogan and Papanikolaou (2013)’s model to a tractable general equilibrium framework by adding two more features: i) a representative household with power or Epstein-Zin preferences; and ii) decomposition of the production sector into an investment sector and a consumption sector. The investment sector uses labor to produce investment goods. The consumption sector first transforms the investment goods into capital while incurring adjustment costs, and then uses capital with labor to produce consumption goods. In his model, a positive technology shock would push down the marginal price of capital, as it increases the productivity of investment good sector and reduces investment adjustment costs.

Papanikolaou (2011) shows that the price of innovation risk can be negative, but only when investors have power utility or Epstein-Zin utility with a preference for late resolution of
uncertainty (i.e., low elasticity of intertemporal substitution (EIS<1)). A positive technology shock lowers consumption today but boosts future consumption, because it enhances the productivity of the investment goods sector and reduces investment adjustment costs. As a result, the marginal price of investment goods falls and the demand for investment goods rises. Labor initially moves from the final sector to the investment sector to increase the supply of investment goods. This leads to low consumption today and high future consumption. For power utility investors, a positive technology shock raises the marginal utility of wealth and the discount factor today. An Epstein-Zin utility agent with a low EIS prefers smoothing his consumption path across time more than across states. The U-shaped pattern in consumption growth would also lead to high marginal utility of wealth and a high discount factor today. In these circumstances, technology shocks carry a negative risk premium.

Papanikolaou (2011) further uses the negative risk premium of technology shocks to explain cross-sectional return spreads. Similar to Kogan and Papanikolaou (2013), technology shocks only affect the value of growth opportunities positively. With a negative price of innovation risk, the model can generate a positive expected return spread between assets in place and pure growth opportunities. The simulated quantity would be the upper bound of the value premium, since firms cannot operate with pure growth opportunities. However, the return spread implied by the model is 1.9%. The magnitude is relatively small compared with the value premium of approximately 6% in the data. Furthermore, a positive technology shock can lead to value appreciation of investment goods firms relative to consumption goods firms. The negative risk premium of technology shocks hence generates a negative difference in expected returns between investment firms and consumption firms. This explains the empirical findings quantitatively (Kogan and Papanikolaou, 2010).

Technology shocks in the investment adjustment costs affect the value of new investment but not existing capital. Given the fact that existing capital accounts for a large fraction of a firm’s values, technology shocks in these models are only able to generate a limited impact
on financial wealth. In addition, the sign of the innovation risk premium depends on the specification of the utility functions.

**Creative destruction of technology shocks**

A small but growing literature has started to incorporate some key features of endogenous growth theories into asset pricing models. Technological advances take the form of expansion of product varieties or quality improvement. These studies still assume an exogenous process for technology progress, but they emphasize the creative destruction effect to widen the dispersion in cross-sectional returns.

As discussed in Section 2.3, especially in the Schumpeterian growth models (e.g., Aghion and Howitt, 1992; Lentz and Mortensen, 2008), technological advances benefit innovating firms at the expense of non-innovating firms as new technology emerges and render old capital obsolete. However, technology-induced displacement effects alone cannot generate a source of systematic risk, as investors can hedge out the effect by holding shares of both innovating and non-innovating firms. There should be some frictions that prevent risk sharing, such that the displacement effect can be systematic.

Gârleanu, Kogan, and Panageas (2012) show that the displacement effect induced by innovations could generate a systematic risk factor if a large fraction of future technologies belongs to future entrepreneurs who do not exist today. They adopt an overlapping generation framework with Romer’s product variety technology to model technology progress. They argue that future generations will develop a large fraction of new products and capture most economic rents from innovation, and innovations will raise competitive pressure on existing firms and make the labor skills of the older generation depreciate. Existing investors cannot perfectly hedge this innovation-induced business-stealing effect by purchasing shares of firms created by future generations, since these firms do not yet exist.
Romer’s product variety model does not endogenously generate displacement effects across products, as the additively separable production function of intermediate goods ensures that the creation of new products does not affect the demand for existing products. Gârleanu, Kogan, and Panageas (2012) adopt the Romer framework to obtain a tractable equilibrium. To generate the displacement effect induced by innovation, they exogenously specify that the market share of existing products and the human capital of current workers are both negatively associated with the arrival of new products.

They further show that non-hedgeable risk induced by technology shocks helps to generate quantitatively plausible equity premium and value premium. They point out that the pricing kernel is determined by the consumption growth of the current generation instead of aggregate consumption growth. The displacement effect introduces additional volatility to the consumption growth of the current generation and hence boosts the size of the equity premium. Furthermore, they assume that some incumbent growth firms are able to develop a fraction of new products. Hence their values positively co-move with the aggregate technology shock. Therefore, the securities of growth firms provide a hedge against the displacement risks, while value firms do not innovate and will gradually be displaced. The opposite effect of innovation on the values of growth and value firms generate a large positive value premium.

One possible undesirable feature of this model is that it is a pure labor economy. The value of assets in place is the net present value of future monopolistic profits from existing products. Kogan, Papanikolaou, and Stoffman (2013) modify the model of Gârleanu, Kogan, and Panageas (2012) by incorporating capital investment to endogenously generate the displacement effect. The arrival of a new generation of households brings innovations in the form of blueprints. An intermediate goods firm is a collection of projects. With some positive probability, it can acquire a blueprint and create new projects by purchasing new capital. It then uses the new projects to produce additional intermediate goods. A positive technology shock increases the productivity of new capital. Unlike the additively separable function
in Romer (1990), an increase in the productivity of new capital boosts the total supply of intermediate goods and leads to a decline in price of intermediate goods. This erodes the profits earned by existing capital. Hence, the model endogenously generates opposite effects on the values of new projects and existing projects. The heterogeneous exposure to innovation shocks leads to a positive difference in the average returns between assets in place and growth opportunities through a similar mechanism as illustrated in Gârleanu, Kogan, and Panageas (2012).

The Kogan and Papanikolaou (2013) model contains some features of the Schumpeterian growth framework. Innovation improves the productivity of new capital, while at the same time exerts price pressure on intermediate goods and erodes the profits of existing assets. One weakness of their set-up is that there is no difference among intermediate goods produced by different projects. The intermediate sectors resemble a perfectly competitive market. Kogan and Papanikolaou (2013) still assume that each project earns monopolistic rents and faces decreasing marginal revenue. As a result, in their model, the aggregate supply of intermediate goods can increase and their price can decrease when a new project with same productivity appears.

Although the creative destruction effect induced by technology shocks widens differences in the cross-section of returns, the net impact on aggregate financial market can be small. These studies rely on some imperfect risk-sharing mechanism to prevent existing investors in the financial market to completely hedge out the displacement risk. They also require assumptions like habit utility (Campbell and Cochrane, 1999) to amplify the price of the risk (Gârleanu, Kogan, and Panageas, 2012; Kogan, Papanikolaou, and Stoffman, 2013).

Long-run risk model

The third strand of literature links innovations with the long-run risk model. In these studies R&D is endogenously determined, as illustrated in the endogenous growth theory.
investment, which determines the expected innovation rate, affects the long-run growth rate in equilibrium and could potentially generate long-run risk.

Bansal and Yaron (2004) begin the literature on long-run risk to explain the equity premium puzzle. They model the consumption and dividend growth as containing a small persistent expected growth component and a time-varying volatility component. They show that Epstein-Zin agents with preference for early resolution of uncertainty (i.e., high EIS) demand a large equity premium, since a reduction in expected economic growth or a rise in economic uncertainty leads to high marginal utility of wealth. In Bansal and Yaron (2004), variation in expected consumption growth is exogenously given. Augmenting the long-run risk model with innovation, the long-run expected growth rate can be endogenously determined by profit-driven R&D investment.

The innovation-based long-run risk studies provide a mechanism through which the long-run expected growth rate evolves persistently. Kung and Schmid (2015) incorporate Romer’s product variety model into a standard RBC model. They illustrate that a negative aggregate productivity shock that originates from the final goods sector would reduce the demand for intermediate goods and the profits from supplying intermediate goods. The value of intermediate firms will decrease if low productivity persists. Expectation will self-fulfill through the profit-driven R&D channel. Low profits of intermediate goods reduce the incentive for R&D investment, resulting in a low expected innovation rate and long-run growth rate. In this way, an exogenous productivity shock is transmitted, amplified and prolonged through the economy, driving R&D investment and the aggregate growth into a cyclical manner. As prolonged low economic growth coincides with depressed firm values, investors with recursive preferences will demand a high risk premium for firms’ securities.

Innovation-based long-run risk models also have implications on cross-sectional returns. Kung and Schmid (2015) show that the cash flows generated by existing physical capital are positively correlated with consumption growth and exposed positively to long-run risk,
while growth options are less responsive to consumption growth. This provides an alternative explanation for the positive spread of average returns between assets in place and growth opportunities. Ai, Croce, and Li (2013) and Ai and Kiku (2013) build stochastic endogenous growth models with long-run risk to explain the value premium. In Ai, Croce, and Li (2013), the sensitivity of capital to aggregate productivity shocks is an increasing function of its age. This further increases the dispersion in response to technology shocks among capital vintages. They also assume that unexercized growth opportunities do not expire, so firms may delay adopting new projects in bad times. Therefore, the value of the growth option has less exposure to long-run risk.

As illustrated, technology shocks can affect the real economy and financial markets through various channels. Bena, Garlappi, and Grüning (2014) show that the displacement effect and long-run risk counteract each other. They argue that the value of an incumbent firm is more sensitive to aggregate productivity shocks when the firm enjoys high monopolistic power, since high monopolistic rents will attract more potential entrants and a greater risk of displacement. They assume that potential entrants have higher innovative efficiency than incumbents do. Therefore, compared to incumbents, the R&D investment of potential entrants is less responsive to aggregate shocks. Less volatile aggregate R&D expenditure transmits to less volatile expected economic growth and hence smaller long-run risk. Therefore, the overall impact of innovation risk on the stock returns of incumbent firms is ambiguous, as it increases their exposure to technology shocks but reduces the price of long-run risk.

Research on the joint behavior of macroeconomic quantities and asset prices may help to identify technology shocks more punctually. The heterogeneous impact of technology shocks can be captured by the spread of cross-sectional stock returns. As the financial market is forward-looking and provides data at high a frequency, the models discussed above also assist to construct market-based measures of innovations.
The literature of innovation-based asset pricing has burgeoned recently. Most studies focus on one mechanism of the technology adoption progress and analyzes its impact on stock prices. Whether any of the channels through which technology shocks affect asset prices is economically significant or dominates is still unclear, and requires more empirical investigation.

2.5 Summary

This section discusses the implications of capital reallocation and technology shocks on real economic activities and financial asset prices. Frictions in the real asset markets stem from costly searching and adverse selection and these frictions can distort firms’ investment decisions and interact with financial frictions. In addition, both the investment decisions and financial status of a firm can affect its valuation.

Technology shocks are considered as the force that drives long-run economic growth. There is an increasing body of research that links stock market movement with technology shocks. Several recent papers show that technology shocks can be a source of systematic risk and are priced by the stock market. Though capital reallocation and technology shocks are tightly linked in Schumpeterian growth theory, there is limited research that examines them together. In the remainder of this thesis, I examine how the efficiency in real asset markets affects firms’ exposure to innovation shocks.
Chapter 3

Model

3.1 Introduction

As discussed in the last chapter, economic growth is not only affected by the speed of technological advancement but also the efficiency of the technology adoption process (Lentz and Mortensen, 2008). In this chapter, I focus on capital reallocation as part of the technology adoption process. I build a simple two-period model to explore the impact of capital reallocation frictions on macroeconomic quantities and asset prices. I show that these frictions slow down the asset reallocation process triggered by technology shocks, resulting in a larger value destruction to non-innovating firms than in a frictionless world. In addition, these frictions also amplify the price of risk carried by technology shocks by affecting the consumption growth dynamics.

The model describes a production economy with a competitive and decentralized used asset market. The technology shock is exogenous and arrives in the form of a more productive entrant firm. Differences in firms’ productivity create an incentive to reallocate capital. The less productive non-innovating firm is a potential seller of used assets, while the more productive entrant firm is a potential buyer of used assets. In a frictionless economy, the
entrant can immediately acquire all the capital from the non-innovating firm. Consequently, both aggregate productivity and aggregate consumption will increase rapidly. However, in the presence of capital reallocation costs, the non-innovating firm is less willing to sell capital and the entrant has to build more new capital instead. In this way, reallocation frictions slow down the technology adoption process and can only boost consumption growth with a delay.

In the model, I adopt a convex cost function to capture the reallocation frictions in the used asset market. In the literature, capital reallocation frictions can stem from various sources, such as trading frictions and informational frictions. As a result of these frictions, markets can become illiquid and capital flows can become slow (e.g., Fuchs, Green, and Papanikolaou, 2015; Gavazza, 2011b). The existence of these frictions supports the convex adjustment cost assumption on used capital.

I then consider the household sector to explore the asset pricing implications of reallocation frictions and technology shocks. Frictions affect the non-innovating firm’s exposure to technology shocks as well as the price of risk carried by technology shocks. In a high-friction economy, the non-innovating firm obtains less proceeds from capital sales and the firm value is more negatively affected by technology shocks than in a low-friction economy. The model also shows that technology shocks will carry a negative price of risk. This is because used assets are substitutes for new investment when accumulating capital. In the high-friction economy, there are less used assets being traded and the entrant must build more new capital. This influences the intertemporal substitution between investment and consumption, in that consumption will fall temporarily upon the arrival of the technology shock and then later rise as the entrant grows. This implies that consumption growth can be more volatile in a high-friction economy and that technology shocks will carry a more negative price of risk.

The model is simple in the sense that there is no other uncertainty besides the technology shock. It also has no market or financial frictions besides the capital reallocation frictions. Factors like aggregate demand shocks or financial constraint are important in asset pricing
and have been extensively studied by prior literature. In this chapter, I turn off these factors in my model but consider a simple technology adoption process. Yet the model can still draw qualitative implications on risk premium and cross-sectional returns. Since there is no assumption about firms’ covariance with the aggregate economic condition, for instance their exposure to aggregate demand shocks, the risk and return implications are purely driven by the interactive effect of technology shocks and capital reallocation frictions. In the later chapters, I develop hypothesis and empirically test the model’s predictions.

This model contributes to the recent growing body of literature that explores the asset pricing implications of technology shocks. The most closely related studies are Gârleanu, Kogan, and Panageas (2012) and Kogan, Papanikolaou, and Stoffman (2013). Both papers rely on the creative destruction mechanism of innovation to show that non-innovating firms are negatively exposed to technology shocks. They use the limited intergenerational imperfect risk-sharing mechanism to generate a negative price of risk carried by technology shocks. Gârleanu, Kogan, and Panageas (2012) examine a pure labor economy and Kogan, Papanikolaou, and Stoffman (2013) assume that investments are completely irreversible. My study differs by focusing on the capital reallocation channel and examines the impact of reallocation frictions on the asset returns associated with technology shocks. In addition, the magnitude of capital reallocation frictions is largely determined by the nature of the underlying assets. My study provides a link between heterogeneous assets and cross-sectional stock returns (or cross-sectional beta spread). Lastly, the recent literature emphasizes that resource reallocation is a key part of the technology adoption process. This study explores the implications of the technology adoption process on asset prices.

The remainder of the chapter is organized as follows. Section 2 describes the baseline model, which embeds a used asset market. Section 3 analyzes the model in a two-period form and discusses the relation between capital reallocation frictions and macroeconomic quantities. Section 4 presents a numerical example, and Section 5 concludes.
3.2 Set-up

The model economy has two periods and three dates and consists of a final goods sector, an intermediate goods sector and a representative household. There is one type of final (consumption) good and one type of intermediate good. The production of final goods requires labor and intermediate goods, while the production of intermediate goods requires only physical capital. An exogenous technology shock can occur in the intermediate goods sector when a new firm with a higher productivity enters the market. In addition to new investment in physical capital, there is also a used capital market in the intermediate goods sector where firms can trade capital. Each sector is described in detail below.

3.2.1 Final Goods Sector

The final goods sector is competitive with a representative firm denoted as $F$. It combines labor with intermediate goods to produce final (consumption) goods, denoted as $Y_t$. The aggregate supply of labor $L_t$ is assumed to be inelastic and normalized to $L_t = 1$ for all dates. The production function is

$$Y_t = X_t^\alpha L_t^{1-\alpha}, \quad t = 0, 1, 2$$

(3.2.1)

where the aggregate demand of intermediate goods $X_t$ is:

$$X_t = \sum_{j=1}^{n} x_{j,t}$$

(3.2.2)

and $x_{j,t}$ is the output of intermediate good firm $j$ at time $t$. $\alpha \in (0, 1)$ is the intermediate goods share of inputs in the final output. I describe how firms produce intermediate goods below.
3.2 Set-up

The final goods firm pays a competitive wage $w_t$ and purchases intermediate goods at the price $p_t^x$. It chooses the quantity of intermediate goods to maximize firm profit at each date which is given by:

$$D_{F,t} = X_t^{\alpha} L^{1-\alpha} - p_t^x X_t - w_t L$$  \hspace{1cm} (3.2.3)

3.2.2 Intermediate Goods Sector

The intermediate goods sector starts with one firm at time 0. The firm holds a patent on its production technology and some physical capital. At time 1, a new technology arrives with some probability $\theta \in (0, 1)$, where the technology can improves the productivity of capital. Let $\eta$ denote the state of this technology shock. If the technology shock arrives, $\eta = \bar{\eta} > 1$, and a new firm receives a patent grant for the new technology and enters the market. If no technology shock arrives, $\eta = 1$, and the original firm continues to be the only supplier of intermediate goods at time 1 and time 2. I refer to the original firm and the entrant firm as the non-innovating firm and the innovating firm, respectively. Figure 3 summarizes the timeline of the intermediate goods sector.

[INSERT FIGURE 3 HERE]

The firms combine production technology and physical capital to produce intermediate goods. The production function of intermediate firms is

$$x_{j,t} = A_j K_{j,t} , \quad j \in \{L, H\}$$  \hspace{1cm} (3.2.4)

where $K_{j,t}$ is firm $j$’s capital stock at time $t$ and $A_j$ is the productivity of firm $j$’s capital. I denote the low productivity non-innovating firm as $j = L$ and the high productivity innovating firm as $j = H$.\footnote{I use $H, L$ to denote firm types and use $0, 1, 2$ to denote dates in subscript.} The innovating firm can only exist starting from $t = 1$ if there is a technology shock (see Figure 3).
The production technology $A_j$ is firm specific and fixed over time. It can only be used by firm $j$ who owns the corresponding patent. Note that the original firm does not innovate. If a new patent is granted to the entrant firm, the innovation would improve the productivity of its capital. This feature is also called the vintage effect, where old capital vintage is not automatically installed with the new technology, hence the productivity on the old capital is fixed (Greenwood, Hercowitz, and Krusell, 1997; Solow, 1960). This is one deviation of my model from most existing studies where new technologies are complements to all existing capital (Bena, Garlappi, and Grüning, 2014; Kung and Schmid, 2015).

The step size of the innovation is determined by the state variable of the technology shock $\bar{\eta}$.

$$A_H = \bar{\eta}A_L \tag{3.2.5}$$

In practice, incumbent firms often continue to conduct R&D activities and innovate. However, occasionally they are displaced by entrants with radical innovations (Aghion, Akcigit, and Howitt, 2013). One could think of the step size of the innovation $\bar{\eta}$ as a relative measure of the difference in innovation size between incumbents and entrants.

Capital is the production input of intermediate goods. Firms can increase their capital stock by making new investment $I_{j,t}$ or acquiring used capital, $N_{j,t} > 0$. Firms can reduce their capital stock by selling their used capital, $N_{j,t} < 0$.

If no technology shock arrives at time 1, the non-innovating firm can make new investment over time but cannot trade used capital since it is the only firm that uses physical capital in the market. The capital of the non-innovating firm evolves as

$$K_{L,t+1} = K_{L,t}(1 - \delta) + I_{L,t} \tag{3.2.6}$$

where $\delta$ is the depreciation rate of physical capital.
If the technology shock arrives at time 1, the innovating firm enters the market. It starts with only a new patent but no capital. The innovating firm can build new capital or acquire and upgrade used capital, and the non-innovating firm can sell some capital to the innovating firm but incur a reallocation cost. The capital of the two firms at time 1 evolves as

\[
K_{H,2} = I_{H,1} + \psi N_{H,1}
\]

\[
K_{L,2} = K_{L,1}(1 - \delta) + N_{L,1} - \frac{\gamma N_{L,1}^2}{2 K_{L,1}}
\]

where \( \psi \in (0, 1] \) is called the transformation rate. One unit of used asset can be transformed to \( \psi \) unit of capital embedded with new technology. \( \gamma \) is the size of the reallocation frictions which determines the convexity of the adjustment cost function. It means the cost to sell more used capital increases fast when reallocation frictions are high. The reallocation cost and the transformation cost ensure that firms do not simultaneously purchase and sell capital.

Capital reallocation is triggered if there is a technology shock at time 1. Individual firm decides the optimal amount of capital to trade to maximize their values and the dispersion in firms’ productivity generates an incentive to trade capital. In equilibrium, the market for used capital clears and the price of used capital \( p^N_t \) is endogenously determined.

\[
N_{L,1}(p^N_t) + N_{H,1}(p^N_t) = 0
\]

Overall, the physical capital stock of the intermediate firms evolves as

\[
K_{j,t+1} = K_{j,t}(1 - \delta) + \Phi(N_{j,t}, K_{j,t}) + I_{j,t}
\]

where

\[
\Phi(N_{j,t}, K_{j,t}) = \begin{cases} 
\psi N_{j,t} & \text{for } N_{j,t} \geq 0 \\
N_{j,t} - \frac{\gamma N_{j,t}^2}{2 K_{j,t}} & \text{for } N_{j,t} < 0
\end{cases}
\]
where $\Phi(.)$ is the adjustment cost function of reallocating used capital. When there is no technology shock, there is no reallocation of used capital and $N_{j,t} = 0$.

It takes one period to build new capital and one period to reallocate used assets. I impose the same assumptions as Eisfeldt and Rampini (2006) and Lanteri (2013) in that new investment $I_{j,t}$ does not involve additional costs besides the capital price. Having adjustment costs of investment would make redeploying used assets even more favorable and also make the capital accumulation process more sensitive to changes in reallocation frictions. I also assume that the reallocation of used capital $N_{j,t}$ incurs asymmetric adjustment costs. For capital sellers (i.e. firms that choose $N_{j,t} < 0$), I assume that they directly bear all the convex reallocation costs of capital. For capital buyers (i.e. firms that choose $N_{j,t} > 0$), I assume that they only incur a transformation cost to upgrade used capital.

Intermediate firms choose the quantity of new investment $I_{j,t}$ and capital reallocated $N_{j,t} > 0$ in order to maximize their firm values. The price of one unit of new capital is normalized to one and the price of one unit of used capital is denoted as $p^N_t$. The price of the intermediate good is denoted as $p^x_t$ and is determined by its aggregate supply $X_t = \sum_{j=1}^n x_{j,t}$. The value function of an intermediate firm $j$ is

$$V_{j,t} = \max_{\{I_{j,t},N_{j,t}\}} \sum_{t=0}^2 \mathbb{E}_t(m_{t+s}D_{t+s})$$

s.t. \hspace{1cm} $K_{j,t+1} = K_{j,t}(1 - \delta) + \Phi(N_{j,t},K_{j,t}) + I_{j,t}$

\hspace{1cm} $I_{j,t} \geq 0$ \hspace{1cm} (3.2.11b)

\hspace{1cm} $N_{j,t} \geq -K_{j,t}(1 - \delta)$ , \hspace{0.5cm} when \hspace{0.5cm} $N_{j,t} < 0$ \hspace{1cm} (3.2.11c)
where the firm’s dividends are

\[
D_{j,t} = p^i_tA_jK_{j,t} - I_{j,t} - p^N_tN_{j,t} \quad \text{when } t < 2 \tag{3.2.12a}
\]

\[
D_{j,2} = p^i_tA_jK_{j,2} + K_{j,2}(1 - \delta) \quad \text{when } t = 2 \tag{3.2.12b}
\]

In the above, \( \mathbb{E}_t \) is the expectation operator, and \( m_{t+s} \) is the realization of the stochastic discount factor (SDF) over the period \( t \) to \( t + s \). The SDF is determined by the household’s consumption in equilibrium which I solve in the next section and firms take it as given. Firms cannot have negative capital stock and can only sell their capital up to the total capital stock adjusted for depreciation. The economy terminates at time 2 with \( D_{j,2} \) as the terminal dividend. At this point there is no more investment or capital reallocation and all residual capital is converted to final goods for consumption. In cases where dividends \( D_{j,t} < 0 \), the firm raises equity to fund investment. There are no financial frictions in this economy and the only source of frictions in this model stems from the capital reallocation process in which participants incur extra costs to trade.

In this model, the intermediate firms’ value-maximizing decisions are inter-related in two aspects when the technology shock arrives. First, they compete on the quantity of goods supplied since the price of intermediate goods is determined by their total output. Second, the price and quantity of capital reallocated are jointly determined by firms’ demand and supply of used capital in equilibrium. These are deviations from standard production-based asset pricing models (e.g. Zhang, 2005).

### 3.2.3 Household

The household sector consists of a representative agent with log utility that consumes the final goods. The agent chooses consumption \( C_t \) at dates 0 and 1 to maximize her lifetime
utility, subject to the budget constraint. Her preference is described by the utility function:

$$\max_{\{C_t\}_{t=0}^{1}} \quad U_t = \ln(C_t) + \sum_{s=1}^{2-t} \beta^s \mathbb{E}(\ln(C_{t+s}))$$  \hspace{1cm} (3.2.13a)

s.t. \quad C_t + \sum_j I_{j,t} = Y_t \hspace{1cm} (3.2.13b)

where $\beta$ is the subjective discount factor.

### 3.3 Competitive Equilibrium

I describe a competitive equilibrium of the model in this subsection. In the economy, there is one exogenous state variable $\eta$ and two endogenous state variables $K_{L,t}$ and $K_{H,t}$. Given an initial condition $\{K_{L,0}, K_{H,1}\}$, a competitive equilibrium is a set of relations of prices and quantities such that i) prices clear the markets for final goods, intermediate goods, used assets and labor and ii) quantities solve firms’ and the household’s optimization problems. In the following, I describe the equilibrium conditions, with a particular focus on the firms’ optimal investment and disinvestment at time 1 when a technology shock arrives.

#### 3.3.1 Final Goods Sector

In each period, the final goods firm chooses the quantity of intermediate goods to maximize the firm value and pays competitive wage. The equilibrium price of intermediate goods and wage can be derived from the first order conditions of the profit function (3.2.3) with respect to intermediate goods $X_t$ and labor $L$ at $L = 1$, respectively:

$$p_t^X = \alpha X_t^{\alpha-1}$$  \hspace{1cm} (3.3.1)

$$w_t = (1 - \alpha)X_t^{\alpha}$$  \hspace{1cm} (3.3.2)
The equilibrium price of intermediate goods \( p_t^x \) and wage \( w_t \) are equal to the current marginal productivity of intermediate goods and labor at time \( t \), respectively (Aghion and Howitt, 1992). The equilibrium price decreases as the aggregate supply of intermediate goods increases. The equilibrium wage \( w_t \) increase with the supply of intermediate goods \( X_t \).

The optimal profit of the final goods firm is obtained by substituting (3.3.1) and (3.3.2) back into the profit function (3.2.3). The substitution yields a zero profit for the final goods firm \( D_{F,t} = 0 \) due to perfect competition in the final goods sector.

### 3.3.2 Intermediate Goods Sector

The intermediate goods firm’s problem depends on whether a technology shock arrives at time \( 1 \). I solve for the firms’ problem by backward induction. I first examine the equilibrium conditions of two firms given the state at time \( 1 \). I then solve for the non-innovating firm’s problem at time \( 0 \).

First, the current value Lagrangian function of intermediate firms’ maximization problem can be written as

\[
\mathcal{L}_{j,t} = \{ p_t^x A_j K_{j,t} - I_{j,t} - p_t^N N_{j,t} + \mathbb{E}( \sum_{s=1}^{t-s} m_{t+s} D_{t+s} ) \} \\
- \left( \sum_{s=0}^{T_j-s-1} q_{j,t+s}(K_{j,t+s+1} - K_{j,t+s}(1 - \delta) - I_{j,t+s} - \Phi(N_{j,t+s}, K_{j,t+s})) \right) \\
+ \sum_{s=0}^{T_j-s-1} \left( \mu_{j,t+s} I_{j,t+s} \right) + \sum_{s=0}^{T_j-s-1} \left( \nu_{j,t+s} (K_{j,t+s}(1 - \delta) + N_{j,t+s}) \right) \\
\]  

(3.3.3)

where \( q_{j,t+s}, \mu_{j,t+s} \) and \( \nu_{j,t+s} \) are Lagrangian multipliers for the capital accumulation constraint, the non-negative investment and capital stock conditions at time \( t + s \), respectively.
Technology shock at time 1

When there is a technology shock at time 1, the productivity of capital with the new technology is boosted. The marginal benefit of buying one unit of capital to produce intermediate goods can be obtained by maximizing the Lagrangian function (3.3.3) with respect to capital at $t = 2$ and applying the envelope condition.

$$\frac{\partial V_{H,1}^U}{\partial K_{H,2}^U} = m_2^U [p_2^U A_H + (1 - \delta)] = q_{H,1}^U$$  \hspace{1cm} (3.3.4)

where the price of intermediate goods $p_2^U$ at time 2 is determined by the aggregate intermediate goods produced by the two firms according to equation (3.3.1).

$$p_2^U = \alpha (A_L K_{L,2}^U + A_H K_{H,2}^U)^{\alpha - 1}$$  \hspace{1cm} (3.3.5)

Here, the superscript $U$ denotes the state with a technology shock. The innovating firm’s marginal value of capital is the discounted value of revenue from one unit of capital plus the terminal value of capital at time 2. As the economy terminates at time 2, all capital is converted to consumption. The terminal value of capital equals one. $q_{H,1}^U$ captures the marginal value of capital. The Lagrangian multiplier of the capital accumulation constraint $q_{H,1}^U$ captures the innovating firm’s marginal value of capital at optimality.

The price of intermediate goods is determined by its aggregate supply. I assume intermediate firms have limited monopolistic power to influence the price hence earn zero economic profits. This deviates from the standard Schumpeterian endogenous growth model (Aghion and Howitt, 1992), where at any point in time and within an intermediate product sector, there is only one intermediate firm which has the monopoly power to determine the price of its intermediate goods by varying its supply. The monopoly rents extracted from supplying the intermediate goods provide the ultimate incentive for entrepreneurs to innovate.
On the other hand, in my model technology adoption takes time and the non-innovating firm does not exit immediately upon the arrival of the innovating firm and the two firms compete in the same product market. While it is possible to assume some form of oligopoly structure which could ensure that intermediate firms can still extract some monopolistic rents, multiple equilibria can exist in these oligopoly markets (e.g. Cournot competition v.s. Bertrand competition) and result in highly non-linear equilibrium prices. Given that the focus of this study is the effect of technology shocks on firms’ risk and returns rather than the endogenous mechanism of generating new technologies, I choose to impose the assumption of a competitive intermediate sector which generates a simple equilibrium price, and leave the alternative oligopoly approaches for future studies.

The optimal investment is determined by the first order condition (F.O.C.) of the Lagrangian function (3.3.3) with respect to investment $I_{H,1}$.

$$\frac{\partial V_{U,1}}{\partial I_{H,1}} = -1 + q_{U,1} = 0$$  \hspace{1cm} (3.3.6)

The marginal cost of investment equals the price of new capital, which is one by assumption. In addition, if some capital is being sold in the used asset market at $t=1$, the innovating firm’s decision to buy used capital is determined by the F.O.C. of the Lagrangian function (3.3.3) with respect to investment $N_{H,1}$.

$$\frac{\partial V_{U,1}}{\partial N_{H,1}} = -p_{1}^{N} + q_{U,1} \psi = 0$$  \hspace{1cm} (3.3.7)

The marginal cost of redeploying a unit of used capital includes the price of used capital $p_{1}^{N}$ and the transformation cost to upgrade the capital, $1 - \psi$. 

By substituting equation (3.3.4) into (3.3.6) and (3.3.7), I obtain

\[ q_{H,1}^U = m_2^U \left[ \alpha (A_L K_{L,2}^U + A_H K_{H,2}^U) \alpha^{-1} A_H + (1 - \delta) \right] = 1 \]  

(3.3.8)

\[ p_N^1 = \psi \]  

(3.3.9)

In equilibrium, the innovating intermediate firm uses new and used capital until its marginal value of capital is equal to one. If some used capital is being sold, the market price of used capital equals the transformation rate \( \psi \). Used capital is an imperfect substitute new capital. One unit of used capital can be transformed to \( \psi \) unit of upgraded capital. The innovating firm is indifferent between used capital and new capital as long as the price of used capital equals \( \psi \).

In reality, the transformation rate is likely to be negatively affected by the size of the technology shock. Sometimes, innovations can be radical, and in such cases adopting these innovations could require rebuilding a completely new set of equipment, as it can be difficult to incorporate various new features into the used capital to adapt to the new technologies. Therefore, the transformation rate \( \Psi \) could reduce as the size of innovation increases. It is possible to incorporate this negative relation into the model by specifying the transformation rate of used capital as a function of the size of innovation (\( \Psi(\bar{\eta}) \), where \( \frac{\partial \Psi}{\partial \bar{\eta}} < 0 \)). Intuitively, such an assumption would mean that large technology shocks are more destructive to the non-innovating firms as they push down the transformation rate of existing capital hence their prices, \( p_N^1 = \psi \), compared to a model with a fixed transformation rate. However, without more detailed analysis of the inverse relation between the transformation rate and the innovation size in the data, I choose to model the transformation rate as a free parameter at this stage rather than as a function of technology shocks, and examine its impact on production and asset prices.
Meanwhile, the non-innovating firm’s marginal value of capital falls. Compared to the innovating firm, the non-innovating firm has lower productivity \( A_L < A_H \) and generates less revenue. In equilibrium, the marginal value of capital is also obtained from the F.O.C. of its Lagrangian function with respect to capital at \( t = 2 \).

\[
q_{L,1}^U = m_2^U \left[ \alpha (A_L K_{L,2}^U + A_H K_{H,2}^U) \right]^{\alpha - 1} + (1 - \delta) \right] < q_{H,1}^U = 1 \tag{3.3.10}
\]

Comparing the two intermediate firms’ marginal value of capital (equation (3.3.8) and (3.3.10)), the only difference arises from the productivity of capital, \( A_H = \bar{\eta} A_L \). Hence, the non-innovating firm’s marginal value of capital to continue production is determined by the step size of technology shock. Since the price of new capital is one, the non-innovating firm stops investment which is no longer profitable. Dividing equation (3.3.10) by (3.3.8), I obtain that the non-innovating firm’s marginal value of capital is a function of the technology shock.

\[
q_{L,1}^U = \eta^{-1} + (1 - \eta^{-1})(1 - \delta)m_2^U \tag{3.3.11}
\]

where the first term captures the relative capital productivity ratio between the non-innovating firm and the innovating firm. The second term comes from the terminal value of capital at time 2. If the model has longer or infinite horizon, this term has limited effect.

The non-innovating firm sells capital if its marginal benefit of capital to continue production falls further below the market price of used capital, \( q_{L,1}^U < p_1^N \).

\[
\eta^{-1}(1 + (\eta - 1)(1 - \delta)m_2^U) < \psi \tag{3.3.12}
\]

Hence, the decision for the non-innovating firm to sell used capital or take no action depends on both the size of technology shock and the market price of used capital, which equals to \( \psi \).
The optimal quantity of capital reallocated is determined by the F.O.C. of the non-innovating firm’s Lagrangian function with respect to capital sold $N_{L,1} < 0$

$$\frac{\partial V_{L,1}^U}{\partial N_{L,1}} = -p_{11}^N + q_{L,1}^U \left( 1 - \frac{N_{L,1}}{K_{L,1}} \right) = 0 \quad (3.3.13)$$

Thus, the equilibrium capital reallocated is

$$N_1 = -N_{L,1} = N_{H,1} = \frac{1}{\gamma} \left( \frac{\psi}{q_{L,1}^U} - 1 \right) K_{L,1} \quad (3.3.14)$$

Since the quantity of capital sold by the non-innovating firm equals the quantity of capital purchased by the innovating firm in equilibrium, I use $N_1$ to denote the equilibrium quantity of capital reallocated at time 1 hereafter. In equation (3.3.14), $\frac{\psi}{q_{L,1}^U} - 1$ is the wedge between the innovating firm’s and the non-innovating firm’s marginal benefit of used capital. It is also the total gains from trade of used capital in the absence of reallocation frictions. However, the wedge in the marginal benefit of capital effectively narrows as the size of reallocation frictions $\gamma$ increases.

**No technology shock at time 1**

At time 1 with no technology shock, the non-innovating firm is the only intermediate firm. It can invest until its marginal benefit of capital equals one.

$$q_{L,1}^D = m_2^D [\alpha (K_{L,2}^D)^{\alpha-1} A_L + (1 - \delta)] = 1 \quad (3.3.15)$$

where the superscript $D$ denotes the state with no technology shock.
3.3 Competitive Equilibrium

**Ex ante the technology shock at time 0**

At time 0, the non-innovating firm starts with some capital and makes investment until the marginal benefit of capital equals one. The F.O.C. of the non-innovating firm’s Lagrangian function at $t = 0$ with respect to $K_{L,1}$ implies that

$$q_{L,0} = \theta m_1^U \left[ \alpha K_{L,1}^{\alpha - 1} A_L + q_{L,1}^U \left( \frac{d}{2} \left( \frac{N_1}{K_{L,1}} \right)^2 + 1 - \delta \right) \right] + (1 - \theta) m_1^D \left[ \alpha K_{L,1}^{\alpha - 1} A_L + (1 - \delta) \right] = 1$$

(3.3.16)

The non-innovating firm’s marginal benefit of capital is still the discounted value of revenue generated from production of intermediate goods by one unit of capital plus the expected future value of its capital. As discussed before, the future value of the non-innovating firm’s capital falls below one if there is a technology shock at time 1, otherwise it stays at one. The term $\gamma \left( \frac{N_1}{K_{L,1}} \right)^2$ captures the benefit of having more capital stock at time 1 when selling its used capital. This term is very small and comes from the specification of the adjustment function. For tractability, I omitted this term in later analysis.

One slight deviation in this model from standard production-based asset pricing model (e.g. Zhang (2005)) is that the investment firms’ marginal $q$ is truncated at 1, since investment does not incur additional adjustment costs.

**Household**

The current value Lagrangian function of household’s lifespan utility is

$$\mathcal{L}_t^C = \{ln(C_t) + \beta U_{t+1}\} - \lambda_t (C_t + I_t - Y_t)$$

(3.3.17)
The marginal utility of consuming one unit of final goods at time $t$ and $t+s$ are derived from the F.O.C. of equation (3.3.17), with respect to current and future consumption, respectively.

\[
\lambda_t = U_{C_t} = \frac{1}{C_t} \tag{3.3.18}
\]

\[
\lambda_{t+s} = U_{C_{t+s}} = \beta^s \frac{1}{C_{t+s}} \tag{3.3.19}
\]

Hence, the stochastic discount factor is determined by the marginal rate of substitution between future and current consumption.

\[
m_{t+s} = \beta^s \frac{U_{C_{t+s}}}{U_{C_t}} = \beta^s \frac{C_t}{C_{t+s}} \tag{3.3.20}
\]

$m_{t+s}$ is proportional to the inverse of consumption growth over period $s$.

**Stock returns of the non-innovating firm**

The stock returns of the non-innovating firm over period 1 depends on whether there is a technology shock at time 1. The realized return over period 1 can be obtained by rewritten equation (3.3.16) as

\[
q_{L,0} = E(m_1 r_{L,1}) = 1 \tag{3.3.21}
\]

Hence

\[
r^U_{L,1} = p^x A_L + q^U_{L,1} (1 - \delta) \tag{3.3.22a}
\]

\[
r^D_{L,1} = p^x A_L + (1 - \delta) \tag{3.3.22b}
\]

where $r^U_{L,1}$ is the realized return over period 1 when there is a technology shock and $r^D_{L,1}$ is the realized return over period 1 when there is no technology shock. The return increases with the revenue generated by one unit of capital as well as the marginal value of capital.
The expected return of the non-innovating firm is

\[ E[r_{L,1}] = p_2^L A_L + \theta q_{L,1}^U (1 - \delta) + (1 - \theta)(1 - \delta) \] (3.3.23)

To examine the risk premium in the non-innovating firm’s stock return, I derive the covariance between its returns and the discount factors across states over period 1.

\[ \text{Cov}[r_{L,1}, m_1] = \theta (1 - \theta)(1 - \delta)(m_1^U - m_1^P)(q_{L,1}^U - 1) \] (3.3.24)

The size of covariance between the returns and the discount factors across the states increases as the difference in the discount factors \(m_1^U - m_1^P\) and the returns \(r_{L,1}^U - r_{L,1}^P = q_{L,1}^U - 1\). The covariance is a negative measure of risk premium. The non-innovating firm’s risk premium is positive if the covariance is negative, \textit{vice versa}.

The full set of equilibrium conditions are defined and listed in the next page.
Definition 1 A competitive equilibrium of the decentralized economy is defined as a set of functions \( \{m, w, p^x, p^N, I_j, N_{j}, K^U_j, V^F, V_j, C\} \) that solve the household’s and firm’s optimization problems and clear the markets of the final output, intermediate goods, labor, new investment and used assets.

**Stochastic discount factor:** \( m_{t+s} = \beta^s \frac{C_t}{C_{t+s}} \) (3.3.20)

**Marginal value of capital:** \( q_{j,t} \)

**Time 0:**

Non-innovating firm:

\[
q_{L,0} = \theta m_t \left[ \alpha K^U_{L,1} A_L + q^I_{L,1} \left( \frac{\gamma N_{L,1}}{K^U_{L,1}} \right)^2 + 1 - \delta \right] + (1 - \theta) m_t \left[ \alpha K^U_{L,1} A_L + (1 - \delta) \right] = 1
\]

(3.3.16)

**Time 1 with a technology shock:**

Innovating firm:

\[
q_{H,1}^{U} = m_2 \left[ \alpha (A_L K^U_{L,2} + A_H K^U_{H,2})^{\alpha - 1} A_H + (1 - \delta) \right] = 1
\]

(3.3.8)

Non-innovating firm:

\[
q_{L,1}^{U} = m_2 \left[ \alpha (A_L K^U_{L,2} + A_H K^U_{H,2})^{\alpha - 1} A_L + (1 - \delta) \right] = \frac{\psi}{1 - \gamma N_{L,1}^U}
\]

(3.3.10)

**Time 1 with no technology shock:**

Non-innovating firm:

\[
q_{D,1}^{L} = m_2^{D} \left[ \alpha (K^D_{L,2})^{\alpha - 1} A_L + (1 - \delta) \right] = 1
\]

(3.3.15)

**Market clearing conditions**

Used asset: \( N_{H,1} = -N_{L,1} \)  \( \text{and} \) \( p^N_t = \psi \)

(3.3.9)

Intermediate goods: \( p^x_t = \alpha x_t^\alpha - 1 \)

(3.3.1)

Labor: \( w_t = (1 - \alpha) x_t^\alpha \)

(3.3.2)
3.4 Comparative Statics

In this section, I first explain how technology shocks in a frictionless economy can potentially generate a source of systematic risk through their impact on investment. I then show that capital reallocation frictions further amplify the impact of technology shock on investment and affect firms’ risk exposures to technology shocks. Last, I use a numerical example to check the model’s prediction and the impact of other variables.

3.4.1 Technology Shocks

A new technology can boost capital productivity and consumption but with a delay. The technology only affects productivity and output after it is implemented in new capital or upgraded used capital. Adoption of a new technology through either new investment or capital reallocation takes time. Therefore, the benefit of the new technology is only realized after capital is installed. The delay forces the household to forgo more consumption in the short-term to finance investment, in exchange for high future consumption. As a result, technology shocks alter consumption dynamics and can be a source of systematic risk.

Technology shocks can affect the stochastic discount factor through their impact on investment decisions even in a frictionless world. The stochastic discount factor is a function of consumption growth. Given the budget constraint, consumption growth is determined by investment decisions. Hence, I can rewrite the stochastic discount factor as a function of investment.

\[ m_2 = \beta \frac{Y_1 - I_1}{Y_2 + \sum_{j \in \{L,H\}} K_j \cdot 2 (1 - \delta)} \]  
\[ m_1 = \beta \frac{Y_0 - I_0}{Y_1 - I_1} \]  

(3.4.1)  
(3.4.2)
Therefore, I can study the impact of technology shock on the stochastic discount factor through the impact on equilibrium investment decisions at time 1. I show in the rest of this subsection that investment is higher when there is a technology shock than when there is not. The difference in investment at time 1 across states leads to variations in discount factor.

At time 1, if there is a technology shock, only the innovating firm would make new investment and $I_{1}^{U} = I_{H,1}^{U}$. In a frictionless world (i.e. $\gamma = 0$ and $\psi = 1$)\(^2\), the non-innovating firm sells all of its capital to the innovating firm at a price of one and exits the market, $N_{1} = K_{L,1}(1 - \delta)$. Hence, the innovating firm becomes the only supplier of intermediate goods at time 2. This resembles the case illustrated in Aghion and Howitt (1992) where the entrant completely replaces the incumbent firm. If there is no technology shock, the non-innovating firm continues to invest at time 1 and supplies the intermediate goods alone, $I_{1}^{D} = I_{L,1}^{D}$. The equilibrium conditions of the intermediate firms’ marginal value of capital at time 1 and 0 (i.e. equation (3.3.8) and (3.3.15)) can be simplified to:

\[
\begin{align*}
q_{j,1} &= m_{2}[(A_{j}K_{j,2})^{\alpha-1}A_{j} + (1 - \delta)] = 1 \\
q_{L,0} &= (\theta m_{1}^{U} + (1 - \theta)m_{1}^{D})(\alpha(A_{L}K_{L,1})^{\alpha-1}A_{L} + (1 - \delta)) = 1
\end{align*}
\]

where $j = H$ if there is a technology shock and $j = L$ if there is no technology shock. In the frictionless world, the marginal value of capital stays at one at all times and the technology shock is not destructive to the non-innovating firm.

Investment increases when there is a technology shock at time 1 as the new technology increases the future productivity of capital. In equilibrium, intermediate firms invest in new or used capital until their marginal value of capital equals one. The impact of the technology shock on investment at time 1 can be obtained by applying the Implicit Function Theorem to

\(^2\)There is no reallocation cost and all used capital can be fully redeployed when $\gamma = 0$ and $\psi = 1$. 
the first order condition with respect to capital in equation (3.4.3a).

\[
\frac{dI_1}{d(A_{j,1})} = \frac{dI_{j,1}}{d(A_{j,1})} = \frac{\alpha p_2^m m_2 + (C_2)^{-1} p_2^m K_{j,2}}{m_2 (1 - \alpha) p_2^m A_j^2 + (C_2)^{-1} (1 + \beta)(m_2)^{-1}} > 0 \tag{3.4.4}
\]

Equation (3.4.4) shows that investment increases with the firm’s capital productivity. When there is a technology shock, only the innovating firm invests, \(I_{U,1} = I_{U,1}^U\) and when there is no technology shock, only the non-innovating firm invests \(I_{1} = I_{L,1}^D\). Hence, investment is higher when there is a technology shock as \(A_H > A_L\) and \(I_{1}^U > I_{1}^D\). An increase in the capital productivity leads to an increase in the firm’s revenue and motivates the higher productivity innovating firm to invest more. Meanwhile, increased investment and productivity lead to an increase in the supply of intermediate goods and push down its price.

The increase in investment in response to the technology shock at time 1 raises the discount factor over period 1 since the discount factor is inversely related to consumption growth. Due to the time to build nature of capital and the budget constraint, the household has to forgo consumption to finance the increase in investment in period 1 to adopt the new technology. As a result, consumption growth decreases and the discount factor increases over period 1 when there is a technology shock. The difference between the discount factors with and without technology shock over period 1 is

\[
m_{1}^U - m_{1}^D = \beta(Y_0 - I_0) \left( \frac{1}{Y_1 - I_{1}^U} - \frac{1}{Y_1 - I_{1}^D} \right) \tag{3.4.5}
\]

Here, the output \(Y_1\) is determined by the non-innovating firm’s existing capital at time 1 and does not vary across the two states. In addition, although investment \(I_0\) at time 0 is affected by the possible technology shock at time 1 and hence influences the discount factor, the impact of \(I_0\) on the discount factors are the same across the two states. Hence, the difference between

\(^3\text{Proof: See Appendix B.2}\)
the discount factors with and without a technology shock comes only from the difference in investment at time 1 across the two states. Since investment is higher when there is a technology shock, the discount factor over period 1 is also higher when the technology shock arrives.

The positive correlation between the stochastic discount factor and the technology shock implies that technology shocks can potentially generate a negative risk premium. Firm stock returns contains a negative risk premium if its value exposes positively to technology shocks or contains a positive risk premium if its value exposes negatively to technology shocks. This is consistent with Gârleanu, Kogan, and Panageas (2012) and Kogan, Papanikolaou, and Stoffman (2013). However, in the frictionless world, technology shocks have no destructive effect on the value of the non-innovating firm’s capital. They only affect the interest rate but have no risk implication on the non-innovating firm’s stock returns. In the next subsection I show that costly reallocation and imperfect transformation of used capital are required for technology shocks to affect non-innovating firms’ stock returns.

### 3.4.2 Capital Reallocation Frictions

The technology shock introduces dispersion in firms’ capital productivity and creates an incentive to reallocation capital. The presence of frictions in the used capital market slows the capital reallocation process.

In this subsection, I show that technology shocks can affect firms’ risk and stock returns with the presence of capital reallocation frictions. The size of capital reallocation frictions affects the non-innovating firm’s value through two channels. First, frictions erode the non-innovating firm’s proceeds from capital sale and force the firm to hold more unproductive capital. This amplifies the value destruction caused by the technology shock. I refer to this as the cash flow effect. Second, frictions reduce capital reallocation and amplify the demand
for new investment. This then feeds into the stochastic discount factor as consumption is further sacrificed in the short term to finance investment. As a result, capital reallocation frictions amplify the risk premium of technology shocks. This channel is referred to as the discount factor effect. When capital reallocation frictions are high, the two effects reinforce each other and lead to a higher risk premium in the non-innovating firm’s stock returns.

The cash flow effect

When there is a technology shock, the value of non-innovating firm’s capital depreciates as the price of intermediate goods at time 2 falls. The derivative of intermediate goods’ price with respect to its aggregate supply $X_2$ is obtained from 3.3.1.

$$\frac{dp^U_2}{dX^U_2} = -\alpha(1-\alpha)(A_HK^U_{H,2} + A_LK^U_{L,2})^{\alpha-2} = -(1-\alpha)\frac{p^U_2}{X^U_2} < 0 \quad (3.4.6)$$

The price and quantity of intermediate goods supplied are negatively related. The new technology would boost the production of intermediate goods at time 2 but would push down its price. If the non-innovating firm stops investing at time 1 but continue to supply intermediate goods at time 2, it will generate less revenue. Thus, the negative relation between the price and the supply of intermediate goods endogenously creates a negative spillover effect of the technology shock on the non-innovating firm’s value.

In the absence of reallocation frictions, i.e. when $\gamma = 0$, the non-innovating firm sells all its capital as long as the marginal value of capital falls below the market price of used capital, $q^U_{L,1} < \psi$. The total firm value destroyed $H_{L,1}$ by the technology shock on the non-innovating firm when $\gamma = 0$ is

$$H_{L,1} = (1 - \bar{\eta}) \leq (1 - \psi)(1 - \delta)K_{1,1} \quad (3.4.7)$$
When $\gamma = 0$, the value destruction is only determined by the transformation rate $\psi \in (0, 1]$. In practice, the transformation rate is determined by the nature of new technologies. Some radical innovations like electrification, telephony, and shale oil extraction methods use completely different equipment embedded with new technologies. In these cases, old capital vintage is not redeployable, hence the transformation rate $\psi = 0$. On the other hand, some technological advances are more gradual, such as the smartphone example mentioned earlier in the thesis when Microsoft purchased the hardware device unit of Nokia to produce its own smartphones.

Frictions in the used asset market inhibit the capital reallocation process and amplify the value destruction to the non-innovating firm by the technology shock. The cash flow effect of reallocation frictions on the non-innovating firm is summarized in the following proposition.

**Proposition 1** When there is a technology shock, the magnitude of value destruction caused by the technology shock on the non-innovating firms is higher when the reallocation friction $\gamma$ is higher.

The frictions reduce the amount and net proceeds of capital sale and force the non-innovating firm to hold more unproductive capital at time 2. The overall negative effect of frictions $\gamma$ on the non-innovating firm’s value is obtained by applying the Envelope Theorem to equation (3.3.3).

$$\frac{dV_{L,1}^U}{d\gamma} = -\frac{1}{2}N_1^2q_{L,1}^U < 0 \quad (3.4.8)$$

As shown in the capital accumulation constraint (3.2.9), the total cost of capital reallocation is $\frac{\gamma N_1^2}{2K_{L,1}}$. For any given level of $N_1 > 0$, the total cost to reallocating used capital is higher when the size of reallocation frictions $\gamma$ is large. The marginal cost to reallocating an additional unit of capital also increases faster when $\gamma$ is large. Equation (3.4.8) shows that the non-innovating firm’s value falls as reallocation frictions increase.
3.4 Comparative Statics

The discount factor effect

Reallocation frictions amplify the discount factor effect caused by the technology shock. As explained in the frictionless subsection, a technology shock raises the discount factor due to increased investment and tightened budget constraint. With reallocation frictions, the discount factor over period 1 increases even more. When frictions are high, the innovating firm has to purchase more new capital at time 1 to adopt the new technology, since less used capital is available to be redeployed. As a result, a technology shock in a high-friction economy leads to lower consumption growth and a state of higher marginal utility of consumption.

I study the discount factor effect of reallocation frictions through their impact on investment and capital reallocation at time 1. The discount factor over periods 1 and 2 can be written as

\[
m_2 = \beta \frac{Y_1 - I_1}{Y_2 + \sum_{j \in \{L, H\}} K_{j,2}(1-\delta)}
\]

\[
m_1 = \beta \frac{Y_0 - I_0}{Y_1 - I_1}
\]

(3.4.9)

(3.4.10)

where \(K_{H,2} = 0\) if there is no technology shock. Since final output \(Y_t\) is only a function of capital which is determined by investment and capital reallocation, the effect of reallocation frictions on the discount factors is a function of changes in investment \(\frac{d(I_t)}{d(Y_t)}\) at time 0 and 1 and capital reallocation \(\frac{d(N_t)}{d(Y_t)}\) at time 1 caused by the frictions.

The decisions of investment and capital reallocation are interrelated when there is a technology shock. Used assets are imperfect substitutes for new capital. The negative relation between the new investment and the quantity of used capital reallocated is obtained by applying the Implicit Function Theorem to firms’ equilibrium conditions (3.3.8) and...
Both used and new capital can produce intermediate goods which affect the final output and the discount rate. In equation (3.4.11), the numerator is proportional to the marginal increase in the intermediate goods supply \( A_L(\psi \eta - (1 + \gamma \frac{N_i}{K_{L,1}})) \) by reallocating one unit of used capital. An increase in the supply of intermediate goods raises the final output at time 2 hence reduces the discount factor. The denominator captures the marginal effect of investment on the discount factor. An increase in investment also leads to an increase in the aggregate supply of intermediate goods \( X_2 \), an increase in final output at time 2 and a decrease in the discount factor. In addition, more investment leads to less consumption \( C_1^U \) at time 1 and hence an even lower discount factor over period 2. The marginal increase in the intermediate goods supply \( A_L(\psi \eta - (1 + \gamma \frac{N_i}{K_{L,1}})) > 0 \), otherwise capital reallocation has no gains from trade and would not take place. All of the other terms in equation (3.4.11) are strictly positive and \( \alpha < 1 \). Hence, new investment and capital reallocation are negatively related and used capital is an imperfect substitute for new investment. An increase in the cost of used capital would raise the demand for new investment.

Next, I examine the impact of reallocation frictions on investment, capital reallocation and the stochastic discount factor. The effects are summarized in the following proposition.

**Proposition 2** When there is a technology shock,

i) investment increases more,

ii) capital reallocation reduces more, and

iii) the discount factor increases more

in an economy with higher capital reallocation frictions.

---

\( \text{Proof: see Appendix B.3.1} \)
3.4 Comparative Statics

If the technology shock arrives at time 1, the impact of reallocation frictions on the innovating firm’s investment can be obtained by applying the Implicit Function Theorem to equation (3.3.10):

\[
\frac{d(I_{H,1}^U)}{d(\gamma)} = \frac{N_1}{\psi} \left( \frac{1}{2} \right) (1 + \beta)(1 - \delta)(1 - \tilde{\eta}^{-1})K_{L,1} - \frac{\gamma}{q_{L,1}} \frac{d(N_1)}{d(\gamma)} > 0 \tag{3.4.12}
\]

Equation (3.4.12) shows that investment increases with reallocation frictions, since \( \tilde{\eta}^{-1} < 1 \) and \( \frac{d(N_1)}{d(\gamma)} < 0 \). Investment is higher in the economy with high reallocation frictions for two reasons. First, compared to the frictionless world in which all used capital is redeployed by the innovating firm, reallocation frictions reduce the aggregate supply of intermediate goods by forcing the non-innovating firm to produce intermediate goods with a lower productivity. As a result, the price of intermediate goods is higher in an economy with reallocation frictions. The higher price motivates the innovating firm to invest more until its marginal value of capital falls to one. The increase in reallocation friction also raises the cost of capital reallocation and increases the demand for new capital, since used and new capital are imperfect substitutes. Overall, the presence of reallocation frictions leads to an increase in new investment.

The derivative of capital reallocation \( N_1 \) with respect to the size of reallocation friction \( \gamma \) is obtained by applying the Implicit Function Theorem to the equilibrium capital reallocation function (3.3.14) and substituting equation 3.4.12 into the function:

\[
\frac{d(N_1)}{d(\gamma)} = -\frac{1}{\gamma} \left( N_1 + \psi K_{L,1} \frac{d(q_{L,1}^U)}{(q_{L,1}^U)^2} \frac{d(\gamma)}{d(\gamma)} \right)
\]

\[
= -\frac{1}{\gamma} \left( N_1 + \psi K_{L,1} \frac{d(q_{L,1}^U)}{(q_{L,1}^U)^2} \frac{d(m_{L}^U)}{d(\gamma)} \right) < 0 \tag{3.4.13}
\]

\[5\text{Proof: see Appendix B.3.2}\]
where
\[
\frac{d(m^U_2)}{d(\gamma)} = \frac{d(m^U_2)}{d(I^U_{H,1})} \frac{d(I^U_{H,1})}{d(\gamma)} = -\frac{N_1(C^U_2)^{-1}(1 + \beta)}{C^U_2(q^U_{L,1})^2 (1 + \beta)(1 - \delta)(1 - \bar{\eta}^{-1})K_{L,1} - \frac{\psi}{q^U_{L,1}} d(N_1)} < 0
\]  
(3.4.14)

Equation (3.4.13) shows that the impact of the reallocation friction $\gamma$ on capital reallocation $N_1$ comes from two counteractive terms, but the first term dominates. The first term $-\frac{1}{\gamma}N_1$ shows that the cost of capital sale increases with reallocation frictions and reduces the amount of capital reallocation. The second term comes from the effect of reallocation frictions on the non-innovating firm’s marginal value of capital $q^U_{L,1}$. $q^U_{L,1}$ decreases with reallocation frictions, since it is only a function of $m^U_2$ which decreases with $\gamma$.\(^6\) Equation (3.4.14) shows that reallocation friction reduces the discount rate $m^U_2$ over period 2 when there is a technology shock as it increases new investment. As equation (3.3.14) shows, capital reallocation increases when the wedge between the two firms’ marginal value of used capital $\psi$ widens. As a result, reallocation frictions also reduce $q^U_{L,1}$ and encourage capital reallocation. This counteracts with the effect of the first term, which captures the effect of increasing cost to sell capital due to reallocation frictions. In Appendix B.3.2, I show that the positive effect of reallocation frictions captured by the second term is smaller than the negative effect captured by the first term. The overall effect of reallocation frictions on capital reallocation is negative.

The difference in time 1 investment across states increases with reallocation frictions. In the previous subsection with a frictionless economy, I show that time 1 investment is higher when there is a technology shock than when there is not. Here, I show that investment increases further with reallocation frictions when there is a technology shock. Since reallocation frictions do not affect investment when there is no technology shock

\(^6\)See equation (3.3.11).
$d(l^D) = 0$, the difference in investment at time 1 between the two states $l^U_1 - l^D_1$ increases with the size of reallocation frictions.

Reallocation frictions affect the time 1 discount factor $m_1$ through their impact on investment at time 0 and 1. The discount factor decreases with investment at time 0 and increases with investment at time 1. The total derivatives of the discount factor in the states with and without technology shocks are

\[
d(m^U_1) = -\frac{\beta}{C^U_1} \left[1 + \frac{C_0}{C^U_1} p^A_1 A_L \right] d(I_0) + \frac{\beta C_0}{(C^U_1)^2} d(l^U_1) \quad (3.4.15a)
\]
\[
d(m^D_1) = -\frac{\beta}{C^D_1} \left[1 + \frac{C_0}{C^D_1} p^A_1 A_L \right] d(I_0) + \frac{\beta C_0}{(C^D_1)^2} d(l^D_1) \quad (3.4.15b)
\]

The difference between the discount factors across states is positive and increases with reallocation frictions.

\[
m^U_1 - m^D_1 = \beta (Y_0 - I_0) \left(\frac{1}{Y_1 - l^U_1} - \frac{1}{Y_1 - l^D_1}\right) > 0 \quad (3.4.16)
\]

\[
\frac{d(m^U_1 - m^D_1)}{d(\gamma)} = \frac{d(m^U_1)}{d(\gamma)} - \frac{d(m^D_1)}{d(\gamma)} = \frac{\beta C_0}{(C^U_1)^2} \frac{d(l^U_1)}{d(\gamma)} > 0 \quad (3.4.17)
\]

The positive difference between the discount factors across states suggests that technology shocks carry a negative risk premium. In addition, the difference is affected by investment at time 1 which increases with reallocation frictions if there is a technology shock as $\frac{d(l^U_1)}{d(\gamma)} > 0$ and $\frac{d(l^D_1)}{d(\gamma)} = 0$. Therefore, reallocation frictions increase the difference between the discount factors across states and amplify the negative risk premium created by the uncertainty of the technology shock at time 1.

Lastly, I show that reallocation frictions affect the non-innovating firm’s risk premium for technology shocks by examining the covariance between returns and the stochastic discount factor.
**Proposition 3** The covariance between the returns of non-innovating firms and the stochastic discount factor is negative and the magnitude increases with the size of capital reallocation frictions.

The covariance between the returns of the non-innovating firm and the discount factor over period 1 is negative.

\[ \text{Cov}[r_{L,1}, m_1] = \theta(1 - \theta)(1 - \delta)(m_1^U - m_1^D)(q_{L,1}^U - 1) < 0 \]  \hspace{1cm} (3.4.18)

since \( m_1^U - m_1^D > 0 \) and \( q_{L,1}^U - 1 < 0 \). The value of the non-innovating firms decreases in respond to the technology shock. The non-innovating firm’s stock returns are negatively correlated with the stochastic discount factor hence contains a positive risk premium.

The cash flow effect and the discount factor effect of reallocation frictions together reinforce each other and increase the risk premium in the non-innovating firm’s stock return over period 1.

\[
\begin{align*}
\frac{d(\text{Cov}[r_{L,1}, m_1])}{d(\gamma)} &= \theta(1 - \theta)(1 - \delta) \left[ \frac{d(m_1^U - m_1^D)}{d(\gamma)}(q_{L,1}^U - 1) + (m_1^U - m_1^D) \frac{d(q_{L,1}^U - 1)}{d(\gamma)} \right] \\
&= -(C_2^U)^{-1} \theta(1 - \theta)(1 - \delta) \left[ (1 - q_{L,1}^U)\beta(C_2^U)^{-1} + (1 + \beta)(1 - \bar{\eta}^{-1})(1 - \delta) \right] \frac{d(I_{H,1}^U)}{d(\gamma)} < 0 \\
&= -(C_2^U)^{-1} \theta(1 - \theta)(1 - \delta) \left[ (1 - q_{L,1}^U)\beta(C_2^U)^{-1} + (1 + \beta)(1 - \bar{\eta}^{-1})(1 - \delta) \right] \frac{d(I_{H,1}^U)}{d(\gamma)} < 0 \\
\end{align*}
\]  \hspace{1cm} (3.4.19)

According to (3.3.24), the covariance between the return and the discount factor increases with the differences in returns and the discount factors across states. Reallocation frictions enlarge the differences in both the discount factors and the returns to opposite directions, as \( \frac{d(m_1^U - m_1^D)}{d(\gamma)} > 0 \) and \( \frac{d(q_{L,1}^U - 1)}{d(\gamma)} < 0 \). Thus, the covariance between the non-innovating firm’s return and the discount factor becomes more negative in an economy with higher reallocation.

\footnote{See equation (3.4.17) and (3.4.13).}
frictions. As a result, reallocation frictions increases the risk premium (negative covariance) in the non-innovating firm’s return generated by the technology shock.

3.5 Numerical Results

In this section, I use a numerical example and qualitatively analyze the interactive effect of technology shocks and capital reallocation frictions on macroeconomic quantities and asset returns, as predicted in analytical solutions. In particular, I show that reallocation frictions amplify the destructive effect of the technology shock and the difference in the discount factors across states. Given the simple two-period set-up, this numerical example does not attempt to quantitatively match the moments of macroeconomic quantities and returns.

3.5.1 Parameter Values

I simulate the model at an annual frequency. There are a total of 10 parameters used in the model. They can be divided into two groups. The first group includes the subjective discount factor $\beta$, capital share $\alpha$, depreciation rate $\delta$, initial capital stock of the non-innovating firm $K_{L,0}$ and its firm-specific productivity $A_L$. These parameters are fixed throughout the numerical analysis. I choose the subjective discount factor $\beta = 0.99$ following Papanikolaou (2011). I set the intermediate goods share $\alpha = 0.3$ to match the average level of labor share (Ai, Croce, and Li, 2013; Kogan, Papanikolaou, and Stoffman, 2013). I choose a large depreciation rate $\delta = 0.3$. Because the economy terminates at time 2, households would consume all final goods at that time. No investment would be made and all residual capital stock is converted to final goods. As a result, the final period consumption growth would be significantly pushed up by the residual capital stock. To reduce the impact of residual capital stock on consumption growth and hence asset returns, I choose a high depreciation rate. Nevertheless, I also simulate the numerical example under a depreciation rate $\delta = 0.1$,
which matches the depreciation rate in the data. I report the results in the Appendix. The predicted patterns discussed in this section are still held under the low depreciation rate case, but investment at time 1 becomes negative and the magnitude of asset returns is unreasonably large due to the high capital stock and consumption at time 2. I set the initial capital stock of the non-innovating firm $K_{L,0} = 0.5$ and its firm productivity $A_L = 0.5$. Initial capital stock cannot be too high relative to firm productivity. Since high initial capital stock leads to high residual capital stock, it is optimal for households to disinvest to smooth consumption growth.

The second group of parameters includes the reallocation friction $\gamma$, step size of innovation $\bar{\eta}$, probability of technology shock $\theta$ and transformation rate $\psi$. These parameters characterize the technology shock and the efficiency of the reallocation process. The reallocation friction parameter $\gamma$ is the focus of this study. In the benchmark example, I only vary the value of $\gamma$ to numerically examine the marginal effect of reallocation frictions on macroeconomic quantities and asset returns. I set the step size of innovation $\bar{\eta} = 1.2$ and the probability of technology shock $\theta = 0.1$. Hence, my example is more relevant to large but infrequent technology shocks. In my model, the distribution of the technology shock is discrete and only contains two states. The average annual technology progress is $E[\eta_t] = 2\%$ p.a., which matches the aggregate growth rate. Gârleanu, Kogan, and Panageas (2012) assume a gamma distribution of technology shocks. Compared to my example, the technology shocks calibrated in their study are even larger. Their average technology shock is 2.65% p.a. (i.e., 0.22% p.m.). In addition, a 20% annual technology shock corresponds to a chance of 22.9% that it will occur, while $\theta = 0.1$ in my example. Lastly, the transformation rate $\psi = 1$ in my benchmark example. I assume that used assets can be fully updated and reallocation costs are the only inefficiency in the economy. Table 1 summarizes the full set of parameter values used in the benchmark examples.
3.5.2 Numerical Method

I solve the value functions and utility function from the set of competitive equilibrium conditions for investment and disinvestment (3.3.4), (3.3.10), (3.3.14); market clearing conditions of the used asset market (3.2.8) and the intermediate goods market (3.3.1); the capital accumulation constraint (3.2.9); and the budget constraint (3.2.13b). Eight variables are solved simultaneously from the equation system, including investment at time 0 $I_0$; the capital stock of the non-innovating firm at time 1 $K_{L,1}$; investment at time 1 with and without the technology shock $I_{1}^{U}$ and $I_{1}^{D}$ (i.e., $I_{1}^{U}$ is made by the innovating firm when there is a technology shock. $I_{1}^{D}$ is made by the non-innovating firm when there is no technology shock); the capital reallocation at time 1 when there is a technology shock $N_{1}$; the capital stock of the non-innovating firm at time 2 with and without the technology shock $K_{L,2}^{U}$ and $K_{L,2}^{D}$, respectively; and the capital stock of the innovating firm at time 2 if there is a technology shock at time 1 $K_{H,2}^{U}$. I repeat this process 200 times. For each repetition, I use a different value of the reallocation friction parameter $\gamma$, ranging from $e^{-1.15}$ to $e^{7}$ (i.e., 0.3 – 1096.67). The lower bound $e^{-1.15}$ is chosen because the non-innovating firm can sell all its capital when there is a technology shock if $\gamma = e^{-1.15}$. In the case where $\gamma < e^{-1.15}$, the non-innovating firm can still sell 100% of its capital stock when there is a technology shock at time 1, but at slightly higher net proceeds. However, reallocation frictions would no longer affect the innovating firm’s investment decision. So I cut the lower bound of $\gamma$ at $e^{-1.15}$. Other variables, including consumption, the SDF, and asset returns are computed from these eight directly solved variables. I plot the variables obtained under different sizes of reallocation friction parameters for comparative statics.

8If there is no technology shock, the innovating firm does not enter the market, $K_{H,2}^{D} = 0$. 
3.5.3 The Impact of Capital Reallocation Frictions

I first check the cash flow effect of capital reallocation frictions by examining firms’ realized return over period 1. Next, I study the impact of frictions on investment and capital risk premia in firms’ stock returns.

First, reallocation frictions affect firms’ realized returns over period 1 when there is a technology shock. Figure 4.a plots the non-innovating firm’s period 1 realized excess return over the risk free rate. The blue line plots the returns when there is a technology shock, and the red line plots the returns when there is no shock. When there is a technology shock, the non-innovating firm’s return is negative and monotonically decreasing with reallocation frictions. The loss ranges from $-9\%$ to $-23\%$ in response to a $20\%$ improvement in productivity at time 1. The negative excess return more than doubles when the size of frictions $\gamma$ increases from the lower bound to the upper bound.

[INSERT FIGURE 4 HERE]

For comparison, I also compute the period 1 return of the innovating firm if it enters the market at time 1, as shown in Figure 4.b. The innovating firm only emerges at time 1 if there is a technology shock. Though it does not exist before the technology shock realizes, let us assume that a claim on the shares of the innovating firm was available at time 0. The claim is infinitesimally small, such that its value does not affect the wealth of households. The payoff of such claim resembles an option. If there is a technology shock at time 1, the value of the claim becomes positive. Otherwise, the claim is worth zero.\footnote{This resembles the case that an entrepreneur owns a pending patent. The patent will become valuable if the patent is granted by the United States Patent and Trademark Office (USPTO). However, the ownership of the patent is not available to the public and hence cannot served as a hedging security for a household’s portfolio.} The excess realized return of such an option is positive when there is a technology shock at time 1. The positive return is extremely high, since the likelihood of having a large productivity-enhancing technology shock is low ($p = 10\%$ in this example). The innovating firm’s return also decreases with
3.5 Numerical Results

reallocation frictions, since frictions slow its technology adoption process. Compared with
the non-innovating firm, the innovating firm’s return are less sensitive to changes in the
friction size in percentage terms, as it can grow by investing in new capital as an alternative.

Second, Figure 5.a shows that the impact of frictions on macroeconomic quantities,
including capital reallocation at time 1, distribution of capital at time 2 and investment at
time 1 and 0. Capital reallocation is only triggered when there is a technology shock. Panel
a shows that the reallocation rate $\frac{N_i}{KL_1}$ is a decreasing function of the friction parameter. At
the lower bound of $\gamma$, the non-innovating firm sells all its capital and exits the market. This
resembles the case of mergers and acquisitions (M&A). Higher reallocation frictions slow
down the equilibrium capital reallocation. When $\gamma$ exceeds $e^{4} = 54.6$, the used asset market
freezes completely. The inverse relation between frictions and the capital reallocation rate is
consistent with proposition 1 and the empirical findings documented by Gavazza (2011a)
and Eisfeldt and Rampini (2006). The rate of capital reallocation determines the capital
distribution between firms at time 2, as shown in Panel b. $z = \frac{K_{U2}}{K_{L2} + K_{U2}}$ is the share of the
innovating firm’s capital stock to aggregate capital. It decreases from 100% to approximately
10% as the reallocation friction parameter increases (Figure 5.b). The less the share of capital
is held by the innovating firm, the less capital is installed with the new technology. However,
high reallocation frictions cannot completely prohibit the innovating firm from entering the
sector, since the innovating firm can still grow using new investment as an alternative.

[INSERT FIGURE 5 HERE]

Figure 5 also plots the impact of reallocation frictions on investment rate at time 1 and
0. I scale investment by the beginning-of-period existing total capital stock. As shown in
Panel c, the time 1 investment rate with a technology shock plotted in blue is higher than the
investment rate with no technology shock plotted in red, even when there is no reallocation
friction. As discussed in the model, the new technology boosts investment by enhancing
the future productivity of capital. Panel c also shows that reallocation frictions further raise time 1 investment, as less used capital is reallocated (see Panel a). As a result, the frictions amplify the difference in time 1 investment across states captured by the gap between the blue and the red lines. Panel d shows the impact of reallocation frictions on investment at time 0 which is slightly negative as frictions reduce the future value of capital when there is a technology shock. In B.3.3, I derive the total impact of reallocation frictions on investment before the technology $I_0$. The sign of the derivative is ambiguous, as $I_0$ can be motivated by a low discount rate, since $I_1$ and $m_1^U$ are both higher when reallocation friction is high. This counteractive effect can explain why $I_0$ is less sensitive to the size of reallocation frictions than $I_1^U$ is.

Next, I examine the pricing kernel effect of reallocation frictions and the risk implication of technology shocks. Figure 6 plots the consumption growth, the discount factor and the covariance between returns and discount factors across states. Panel a shows that reallocation frictions reduce consumption growth over period 1 due to their impact on investment. As a result, the discount factor over period 1 increases when there is a technology shock. The gap between the discount factors across states increases as the size of frictions increases.

[INSERT FIGURE 6 HERE]

As a result, reallocation frictions can affect the discount factor by altering consumption dynamics. Figure 6 plots the consumption growth and the stochastic discount factor over period 1 in Panel a and b. Consumption at time 1 is low due to high investment when there is a technology shock and when reallocation frictions are high. Figure 6.a shows that the temporary fall in consumption growth in response to the technology shock increases with $\gamma$. Low consumption growth corresponds to a state with a high marginal utility of consumption and a high discount factor. Panel b plots the discount factor if there is a technology shock
in blue and it increases with $\gamma$. Compared with the discount factor without the technology shock plotted in red, the gap between the discount factors widens as $\gamma$ increases.

In addition, Figure 6 plots the covariances of returns and the stochastic discount factor in panel c and d. Panel c shows that the covariance between the non-innovating firm’s returns and the stochastic discount factor is negative and decreases sharply as the size of reallocation frictions increases. In particular, the negative covariance triples when $\gamma$ increases from the lower bound value to the upper bound value ($\gamma \in [e^{-1.15}, e^7]$). For the innovating firm, the covariance between its return and the pricing kernel is positive. However, the effect of frictions on this positive covariance is ambiguous. On one hand, the frictions reduce the option return if there is a technology shock, since frictions slow the growth of the innovating firm. On the other hand, frictions increase the difference in the discount factors across states. The net effect of reallocation frictions on the positive covariance is unclear. Figure 6.d show that the covariance of the innovating firm’s returns and the stochastic discount factor increases with reallocation friction, suggesting that the discount factor effect dominates.

### 3.5.4 More Comparative Statics

In this section, I use the numerical example to examine the impact of the step size of innovation $\bar{\eta}$, probability of technology shock $\theta$, and transformation rate $\psi$ on the model’s predictions. I study one factor at a time by choosing a set of four different values for the parameter of interest and compute the impact of reallocation frictions on various quantities for each value, *ceteris paribus*. I show that the predicted relations of capital reallocation frictions on macroeconomic quantities and stock returns still hold.
**The step size of innovation**

The step size of innovation $\bar{\eta}$ determines the productivity of the innovating firm. The set of step sizes is $\bar{\eta} \in [1.1, 1.15, 1.2, 1.25]$.

First, a large technology shock causes greater destruction on the value of used capital. Figure 7 shows that the marginal value of the non-innovating firm’s existing capital decreases with the innovation size. This is because a more advanced production method enables the innovating firm to supply more intermediate goods and pushes down the price of intermediate goods and the non-innovating firm’s profit at time 2. As a result, the non-innovating firms’ return is more negative when the innovation size is large and when reallocation frictions are high, as shown in Figure 8.a.

**[INSERT FIGURE 7 and 8 HERE]**

Second, a large technology shock leads to faster capital reallocation and technology adoption. Figure 9.a and b show that the capital reallocation rate at time 1 and the innovating firm’s share of capital at time 2 increase with the innovation size $\bar{\eta}$ but decrease with the frictions $\gamma$. A large technology shock motivates capital reallocation, since the dispersion in capital value between the non-innovating and innovating firms (hence gains from trade) increases with the innovation size. In terms of investment, Panel c shows that a large technology shock leads to more investment at time 1 as the future productivity of capital is higher. This is consistent with the prediction implied by equation 3.4.4. Panel d plots investment at time 0. A large expected technology shock also depresses investment prior to the technology shock as the value of capital will depreciate more when the large expected technology shock arrives.

**[INSERT FIGURE 9 HERE]**

Figure 9 shows that the size of technology shock also affects the pricing kernel and firms’ risk premia. Panel a shows that consumption growth is lower when the size of the technology
3.5 Numerical Results

shock is large, since investment at time 1 increases with the innovation size. As a result, large technology shocks lead to a state with higher marginal utility of consumption and hence a higher discount factor, as shown in Panel b.

Lastly, Panel c shows that the covariance between the non-innovating firm’s return and the pricing kernel across states is more negative when the innovation size is large. Panel d plots the covariance for the innovating firm’s return and the pricing kernel. It becomes less positive when the innovation size is large.

[INSERT FIGURE 10 HERE]

Probability of the technology shock

The probability of the technology shock $\theta$ determines the likelihood that the non-innovating firm will be threatened by the innovating firm at time 1. The set of $\theta$ is [0.06, 0.08, 0.1, 0.12].

The probability of an innovation also affects returns. Figure 11 plots the firm returns over period 1 when there is a technology shock. Panel a presents the returns for the non-innovating firm. The negative return caused by technology shock alleviates slightly when the probability of having the technology shock at time 1 increases. The uncertainty about the technology shock reduces as $\theta$ increases. The non-innovating firm adjusts its investment and its exposure to the technology shock ex-ante. As a result, the excess return is less negative when the technology shock arrives. Panel b plots the excess returns of the innovating firm. It is higher when the probability of the technology shock is small. As discussed above, the large positive return of the option-like technology is partially driven by the small probability of the technology shock.

[INSERT FIGURE 11 HERE]

Figure 12 plots the impact of $\theta$ on macroeconomic quantities. Since $\theta$ is an ex-ante measure of the probability of the technology shock, it only affects variables at time 0 and have
no effect on variables when the technology shock realizes. Hence, the capital reallocation rate at time 1, the innovating firm’s share of capital stock at time 2 as well as investment at time 1 do no vary with $\theta$. Only investment at time 0 decreases as $\theta$ increases.

[INSERT FIGURE 12 HERE]

In terms of risk implications, the probability of innovation $\theta$ has a small effect on consumption growth as well as the pricing kernel, since the investment at time 1 is not affected by $\theta$, as shown in Figure 13.a and b. Regarding the risk premium, Panel c and d show that the covariance for both the non-innovating firm and the innovating firm decreases, since an increase in the likelihood of technology shock reduces the volatility of returns across states. $\theta$ still affects the risk premium as it affects firms’ realized returns.

[INSERT FIGURE 13 HERE]

The transformation rate

The transformation rate $\psi$ affects the marginal value of used capital to the innovating firm and hence the equilibrium price of capital. The set of $\psi$ is $[0.8, 0.867, 0.933, 1]$.

The transformation rate $\psi$ determines the equilibrium price of used capital $p^N$ hence also affects the extent of value destruction caused by a technology shock. Therefore, it has a similar impact on asset returns and macroeconomic quantities as the reallocation frictions do.

One unique feature of the transformation rate $\psi$ is that a cutoff point exists, below which no capital will be traded at time 1, even in a frictionless used asset market. The cutoff point is equal to the marginal $q$ of the non-innovating firms’ capital at time 1 if there is a technology shock. In the benchmark case where the innovation size is $\bar{\eta} = 1.2$, the marginal $q^{U}_{1,2}$ is 0.833 (see Figure 7). When $\psi = 0.8 < q^{U}_{1,2}$, the economy resembles the case that reallocation frictions are infinite, since no capital is reallocated. As a result, reallocation frictions have no further impact on macroeconomic quantities or asset returns. Hence, the
impact of transformation rate on all variables reduces and eventually converges to the infinite friction case as reallocation friction increases.

Figure 14 shows that a low transformation rate leads to lower returns of both the non-innovating and the innovating firms. For the non-innovating firm, a low transformation rate leads to less net proceeds from capital sale. For $\psi = 0.8 < q_1$, the economy resembles the case where reallocation frictions are infinite, since no capital is reallocated. This provides the solution for the upper bound of value destruction. For a 20% technology shock, the realized excess return of the non-innovating firm is $-23\%$. For the innovating firm, a low transformation rate leads to slower technology adoption.

Figure 15 presents the impact of transformation rate on macroeconomic quantities. As shown in Panel a and b, for any given level of reallocation frictions, the capital reallocation rate and the innovating firm’s share of capital stock is lower when $\psi$ is lower. In addition, Panel c shows that the demand for new investment increases when $\psi$ is low and less used capital is available for sale.

In terms of the risk implication of technology shock, Figure 16 plots the impact of the transformation rate on the stochastic discount factor and the risk premium. Panel a and b show that the consumption growth rate is lower and the discount factor is higher when there is a technology shock and the transformation rate is low. Panel c and d plot the covariance generated by the technology shock. The covariance of returns and the stochastic discount factor is more negative for the non-innovating firm and more positive for the innovating firm when the transformation rate is lower, similar to the impact of the reallocation frictions $\gamma$.

The transformation rate is likely to be low when the economy faces radical innovations, i.e. when the size of innovations is very large. This leads to low equilibrium prices of used capital
hence a lower incentive to reallocate used capital. Consequently, the low transformation rate further amplifies the destructive effect of radical innovations on the value of existing non-innovating firms. However, the simple model in this study is restricted by one intermediate sector, hence used capital can only be traded between innovating firms and non-innovating firms within this sector. In reality, some used assets can be reallocated across industries, and this inter-industry capital reallocation partly mitigates the negative impact of radical innovation on the transformation rate. In the empirical sections of this thesis, I further show that the relative size of inter-industry reallocation frictions also affects the non-innovating firms’ negative return response to technology shocks.

[INSERT FIGURE 16 HERE]

### 3.6 Summary

In this section, I present a two-period static general equilibrium model to study the impact of capital reallocation frictions on the asset pricing implications of technology shocks. The model shows that technology shocks are priced by the financial markets and generate a negative risk premium. Capital reallocation frictions affect firms’ returns through two channels. First, frictions erode the remaining proceeds from capital sale and thus amplify the diminution in non-innovating firms’ values induced by technology shocks. This also reduces the benefit obtained by innovating firms from adopting new technologies as it slows the adoption speed. However, the negative effect of frictions on innovating firms’ returns is much less than the effect on non-innovating firms’ returns. Second, reallocation frictions increase the demand for new investment by innovating firms to adopt new technologies and lowers consumption in the short term. This further raises the discount factor when the technology shock realizes, generating an even more negative risk premium. Together, the two forces driven by reallocation frictions increase non-innovating firms’ risk exposure to
technology shocks. The net effect on the risk exposure of innovating firms to technology shocks is ambiguous. Overall, reallocation frictions amplify the risk dispersion among firms induced by technology shocks.

My model emphasizes that technology adoption cannot proceed independently from physical capital accumulation. Technology shocks only boost the productivity of capital embedded with new technologies and benefit the firms that invest in capital (new or upgraded used capital). This feature of technology shocks has been well recognized in the economics literature (Greenwood, Hercowitz, and Krusell, 1997; Solow, 1960). However, most existing asset pricing models that study technology shocks assume that new technologies are complementary to the entire capital stock and boost output immediately. In this study, I allow the technology shocks to directly affect firms’ capital accumulation process. Kogan, Papanikolaou, and Stoffman (2013) incorporate this vintage feature of technology shocks by assuming that new technologies only improve the productivity of new capital. In their model, investment is completely irreversible and investment decisions are made only once for each project. In comparison, firms in my model optimally make investment and disinvestment decisions over time. Investments are partially reversible, with some reallocation costs. However, my model cannot be easily extended to a dynamic general equilibrium, as the capital accumulation and reallocation processes are path-dependent and the model becomes intractable as the horizon increases by a few periods.
Chapter 4

Data and Methodology

4.1 Introduction

As illustrated in Chapter 3, technology shocks benefit innovators at the expense of non-innovating firms, and the magnitude of such creative destruction varies with the intensity of reallocation frictions. In this chapter, I develop hypotheses from models predictions to examine whether and how reallocation frictions affect firms’ risk exposure to technology shocks.

To test the hypotheses, I construct measures for innovation shocks and asset reallocation frictions to empirically examine their interactive effect on firm values. I derive proxies of real technology shocks from patent data, accounting for the heterogeneous economic values of patents. I then estimate the relative size of reallocation frictions across industries based on asset turnovers and capital expenditure. I also discuss the relative strengths and drawbacks of the proxies.

As illustrated in Chapter 3, my model shows that the cash flow effect and the discount factor effect are the two channels through which capital reallocation frictions amplify the impact of technology shocks on firm returns. In the empirical tests I will focus only on
the cash flow channel, which predicts that technology shocks have a more negative impact on non-innovating firms’ values when reallocation frictions are high. The cash flow effect can be examined by testing the impact of realized technology shocks on contemporaneous stock returns. On the other hand, the discount factor effect predicts that the price of risk of technology shocks is more negative when reallocation frictions are high. To test this channel, one needs to examine the impact of reallocation frictions on the discount factor at the aggregate level. Ideally, we could conduct a cross-country analysis where the size of reallocation frictions is likely to vary widely across countries due to different jurisdictions and market structures across countries. However, the ability to conduct such analyses is limited by the information available on both patents and used capital reallocation in countries other than the U.S. Alternatively, if the size of the economy-wide reallocation frictions varies significantly over time (Eisfeldt and Rampini, 2006), one could perform a time-series analysis of the interactive effect of reallocation frictions and technology shocks on the discount factor. This requires constructing a factor mimicking portfolio that captures the time-varying risk premium of technology shocks. I leave this analysis of the discount factor channel for future research and focus only on the cash flow channel here, since identifying technology shocks and measuring reallocation frictions already presents many challenges.

The remainder of the chapter is organized as follows. Section 2 develops the hypotheses and designs empirical tests according to these hypotheses. Section 3 describes the datasets used in the empirical analysis. Section 4 explains the methods used to construct proxies of technology shocks and reallocation frictions. Section 5 reviews the measurements of technology shocks and reallocation frictions in the prior literature.
4.2 Hypotheses and Empirical Specification

This section develops the hypotheses to empirically test the model’s predictions. The model gives several testable predictions about the implications of technology shocks on cross-sectional returns. The empirical tests focus on the interactive effect of technology shocks and capital reallocation frictions on returns of non-innovating and innovating firms. The impact of technology shocks on the aggregate market risk premium is more difficult to empirically examine, since the economy has only one pricing kernel. The average size of industry capital reallocation frictions determines the risk premium of aggregate technology shocks.

The first hypothesis is regarding the effect of technology shocks on non-innovating firms:

**Hypothesis 1** *Technology shocks negatively affect non-innovating firms’ returns, and the effect is stronger in industries with higher reallocation frictions.*

To test Hypothesis 1, I group firms in each industry into either a non-innovating portfolio or an innovating portfolio and compute the value-weighted portfolio returns. I separate the firms based on whether a firm has been granted at least one productive patent for a given year. I use industry asset liquidity as a proxy for reallocation frictions. I conduct separate Fama-MacBeth regressions for non-innovating portfolio returns and innovating portfolio returns on industry technology shocks, industry asset liquidity, and the interaction term of the two, controlling for other portfolio characteristics. The full specifications for the non-innovating portfolio regression and the innovating portfolio regressions are as follows:

\[
R_{s,t}^{p} = \beta_{0} + \beta_{1}A_{s,t} + \beta_{2}\text{AssetLiq}_{s,t} + \beta_{3}A_{s,t} \times \text{AssetLiq}_{s,t} + \beta_{4}Z_{s,t}^{p} + \epsilon_{s,t} \tag{4.2.1}
\]

where the dependent variable \(R_{s,t}^{p} \in \{R_{s,t}^{NI}, R_{s,t}^{I}\}\) is the value-weighted excess returns over the risk-free rate of industry portfolios. \(R_{s,t}^{NI}\) and \(R_{s,t}^{I}\) denote non-innovating portfolio excess
returns and the innovating portfolio excess returns in industry $s$ over period $t$, respectively. $A_{s,t}$ is the industry technology shock. $AssetLiq_{s,t}$ is the measure of industry asset liquidity, which is negatively related to the size of the capital reallocation frictions. $Z^0_{s,t}$ denotes a vector of control variables, which includes the lagged book-to-market ratio, market capitalization, past 12-month returns, market beta, industry concentration, R&D intensity, leverage ratio, and cash-to-asset ratio. I explain the detailed measurement of all variables in the next section.

The main coefficients of interest are $\beta_1$ and $\beta_3$. For the non-innovating portfolio regressions, the model predicts that $\beta_1$ is negative and $\beta_3$ is positive, as non-innovating firm values are negatively affected by technology shocks and the existence of a liquid market for used assets can alleviate the creative destruction effect. For the innovating portfolio regressions, $\beta_1$ is expected to be positive as new technologies improve innovating firms’ competitiveness. The model does not give a conclusive prediction for $\beta_3$, since innovating firms have the alternative to grow with new investment.

The prediction of the effect of asset liquidity alone on stock returns is unclear. In this model, innovation is the only type of shock in the economy that triggers asset sales. After the shock, high-friction industries will have low asset turnover and low values of non-innovating firms. This suggests a positive correlation between non-innovating firms’ returns and asset liquidity. In reality, asset sales can be motivated by shocks from other sources. For example, firms are likely to make fire sales of their capital when they are in distress (Shleifer and Vishny, 2011). This suggests that returns and asset liquidity measured by turnover rates can also be negatively correlated.

The second hypothesis is related to the overall displacement effect:

**Hypothesis 2** The differences in returns between non-innovating firms and innovating firms have a larger response to technology shocks in industries with high capital reallocation frictions, compared to industries with low reallocation frictions.
Hypothesis 2 examines the variation of cross-sectional returns with capital reallocation frictions. I create non-innovating-minus-innovating portfolios (NMI) by taking long positions in shares of non-innovating firms and short positions in shares of innovating firms for each industry. The regression is specified as follows:

\[
R_{s,t}^{NMI} = \beta_0 + \beta_1 A_{s,t} + \beta_2 AssetLiq_{s,t} + \beta_3 A_{s,t} \times AssetLiq_{s,t} + \beta_4 Z_{s,t}^P + e_{s,t} \tag{4.2.2}
\]

The coefficient \(\beta_1\) measures the overall displacement effect induced by technology shocks. The model implies a negative \(\beta_1\), as new technology benefits innovating firms at the expense of non-innovating firms. The coefficient on the interaction term between innovation and industry asset liquidity \(\beta_3\) examines whether non-innovating firms are hurt more in industries with low asset liquidity, compared to innovating firms. I expect \(\beta_3\) to be positive.

In my model, capital reallocation costs are explicitly imposed on the selling side. Innovating firms are less affected by reallocation frictions, since they also have the alternative to grow using new investment. In reality, searching frictions and informational frictions in used asset markets are borne by both sides, and the long-short strategy of non-innovating and innovating firms allows the estimation of the net impact of capital reallocation frictions on portfolio returns.

### 4.3 Data Sources

I use three types of data in my empirical analysis. First, I use patent data constructed by Kogan, Papanikolaou, Seru, and Stoffman (2012) to measure technological innovation. Second, I collect data on asset sales from COMPUSTAT and disaggregated capital expenditures from the 1997 Bureau of Economic Analysis (BEA) capital flow table to construct two measures
of asset reallocation frictions. Third, stock return data and accounting data are from CRSP and COMPUSTAT, respectively.

4.3.1 Patent Data

The new patent dataset employed in my analysis is constructed by Kogan, Papanikolaou, Seru, and Stoffman (2012) (referred to as KPSS data hereafter).\(^1\) The full sample covers the period 1926–2010.

The KPSS patent data is originally collected from Google Patents. It includes only utility patents, which are granted for the invention of a new and useful process, machine, manufacture, or composition of matter, or a new and useful improvement. These patents account for 90% of all patents issued by the USPTO.\(^2\) Patents granted from 1976–2010 are available for bulk downloading from Google Patents. For patents granted prior to 1976, the original patent documents can be downloaded from individual patent web pages on Google Patents. Patent information was extracted from these detailed patent documents by a number of text analysis algorithms (Kogan, Papanikolaou, Seru, and Stoffman, 2012).

The KPSS patent data contain four types of key information. For each patent, the dataset records its unique seven-digit patent number assigned by the USPTO, its granting date and a linking code (PERMNO) matched to a firm in CRSP. In a separate file, KPSS also provides a record of the patent’s citations.

In some of the tests, I control for the patent classes. The patent class is a proxy of the patent’s related technology field. The definition is based on the U.S. Patent Grant Master Classification File, which contains a detailed classification of all patents ever issued by the

\(^{1}\)The data is available from https://iu.app.box.com/patents.

\(^{2}\)There are six types of patents defined in U.S. Code Title 35. Besides utility patents, other types are design patents, plant patents, reissue patents, defensive publications, and statutory invention registrations. Detailed definitions are available from http://www.uspto.gov/web/offices/ac/ido/oeip/taf/patdesc.htm.
4.3 Data Sources

USPTO according to the United States Patent Classification (USPC) system. Each patent has a three-digit primary patent classification code and a six-digit patent subclassification code. I use the three-digit primary code to identify 431 primary utility patent classes in total.

The full sample of patents includes 6.27 million utility patents granted between 1926 and 2010, and 1.93 million of these patents (31%) have a matched PERMNO that can link to firm information (Kogan, Papanikolaou, Seru, and Stoffman, 2012). The testing sample period in my study is from 1987 to 2010, and is determined by the availability of the patent data, the asset sales data and the reliable industry classification. The final sample period of 1987–2010 contains 1.16 million patents with matched PERMNO.

To ensure the quality of the new patent dataset, Table 2 compares patent datasets from three sources: the USPTO patent statistics, the KPSS data, and the NBER data (Hall, Jaffe, and Trajtenberg, 2001). The total patent grants recorded in the three sources are consistent for the period 1976–2006, and the patent-firm matching rates are comparable between the KPSS and NBER data. Over the testing period 1987–2010, 54% of the patents are granted to U.S. innovators, among which 81% are held by U.S. firms and 67% are held by U.S. public firms. Thus, public companies hold the vast majority of the patents granted to U.S. entities.

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3 The file is updated bimonthly and is available from the USPTO’s website: http://www.google.com/googlebooks/uspto-patents-class.html Alternatively, another widely used patent classification system is the International Patent Classification (IPC) system. Its primary objective is to overcome the difficulties caused by using diverse national patent classifications. My study focuses on U.S. patents and their impact on firms listed on the U.S. stock markets. Hence, my study does not face the issues addressed by the IPC. Moreover, the IPC classifies an invention according to its function, whereas the USPC classifies patents not only based on the invention’s function but also on the industry, anticipated use, intended effect, outcome, and structure. Harris, Arens, and Srinivasan (2010) compared the two classification systems and report that the USPC system outperforms the IPC system across the three criteria used in their evaluation.

4 USPTO Patents reports the aggregate number of patents granted to foreign and U.S. entities at an annual frequency. Data is available from 1963 onward.

5 The most comprehensive database available before KPSS patent data, covering the period from 1976 to 2006.
4.3.2 Asset Liquidity Data

I construct two measures of asset reallocation frictions. The first measure is based on asset liquidity and uses sale of plant, property and equipment (SPPE) from COMPUSTAT. The second measure is constructed based on asset redeployability and uses data from the 1997 BEA capital flow table, following Kim and Kung (2014).

To measure asset liquidity, I use the COMPUSTAT data on the SPPE, which records the gross dollar value of asset sales for a given period. The data starts in 1975, and I exclude observations containing negative values or combined data codes, following Eisfeldt and Rampini (2006).

I also construct an alternative proxy for asset reallocation frictions using data from the 1997 BEA capital flow table. The table records capital expenditures of 123 industries on 180 assets, including equipment, software, and structures in 1997. It provides the most updated information on disaggregated capital investment by industry and is available from BEA’s website.\(^6\) Although the 1992 and the 1982 capital flow tables are also available, these earlier year tables break down capital expenditure into more coarse asset classes for more broadly defined industries.\(^7\) To ensure the consistency of the definition of asset classes as well as industries over the sample period, I only use the 1997 capital flow tables, following Kim and Kung (2014).

4.3.3 Stock Return Data and Accounting Data

Stock returns and firm-level accounting information are from the CRSP daily/monthly stock files and COMPUSTAT, respectively. CRSP daily return data is employed to measure patent values. Portfolio returns are computed from CRSP monthly returns. COMPUSTAT

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\(^6\) [http://www.bea.gov/industry/capflow_data.htm](http://www.bea.gov/industry/capflow_data.htm)

\(^7\) The 1992 table contains 163 asset classes for 64 industries and the 1982 table contains 99 asset classes for 79 industries.
accounting data is used to construct the control variables. My sample includes all NYSE-, AMEX-, and NASDAQ-listed securities that are contained in both the CRSP monthly returns files and the COMPUSTAT annual files between July 1987 and June 2010.

The industry classification is based on COMPUSTAT SIC industry codes, which are available from 1987 on. Although CRSP also collects firm SIC code data and the data is available for earlier years, prior studies report considerable discrepancies between the SIC code from the two databases. By comparing the SIC code from two databases, studies have shown that firms have higher intra-industry correlations in monthly stock returns and lower variances of intra-industry financial ratios when the COMPUSTAT SIC code is used (e.g., Guenther and Rosman, 1994; Kahle and Walkling, 1996). Here I use the more reliable COMPUSTAT SIC codes for industry definitions, and this limits the sample to 1987–2010.

4.4 Measurement

In this section, I explain the procedure to construct the two measures of innovation shocks. I then discuss the proxies for asset reallocation frictions.

4.4.1 Measuring Innovation

Innovation shocks are derived from patent data. The relative size of innovation over the period is determined by the volume of patent grants as well as the patents’ economic values. Patents are heterogeneous in terms of their relative importance or contribution to the economy. The raw growth rate from patent counts can be a very imprecise measure of innovation shock,
since it assumes that patents are identical in values. The patent growth rate can also be easily affected by the efficiency of the USPTO and amendments of patent-related legislations. In this study, I use stock market reactions and future citations to account for patent heterogeneity and derive more reliable measures of innovation.

The arrival of new or improved technology is identified at the time of patent grant in my analysis, as the innovating firm has the exclusive rights to use the patent. The economic value of an innovation is estimated by the stock market reaction to the news of the patent grant or the patent’s future citations. Innovations are then weighted by their estimated economic values and aggregated to the firm and industry levels.

The first innovation measure is based on implied market values of patents, following Kogan, Papanikolaou, Seru, and Stoffman (2012). The second measure is based on the number of patent forward citations, which is one of the approaches illustrated in Hall, Jaffe, and Trajtenberg (2001).

**Market-based innovation**

Patent values are estimated from the abnormal stock returns around the patent granting days. The value of patents are then summed up to measure firm and industry-level innovation.

There are three steps to estimating patent values. First, for each patent, I compute the idiosyncratic return around the patent granting day, where the idiosyncratic return $r_{j,d}$ is defined as the excess stock return of firm $j$ that owns the newly granted patent $i$ over the value-weighted market return. The length of the event window $l$ is three days (i.e., $[d, d + 2]$). If the stock market does not open on the patent granting day, I treat the next trading day as the patent granting day, $d$. These patents roughly account for 1% of the total sample.

The obtained raw idiosyncratic return has two components – the abnormal return related to patent news $x_{j,t}$, and the noise term $\varepsilon_{j,d}$ (i.e., $r_{j,d} = x_{j,d} + \varepsilon_{j,d}$). Since the patent value is often relatively small compared to the firm value, other news around the patent granting day
may account for a significant portion of the idiosyncratic return. Patent values computed directly from the raw idiosyncratic return can be very noisy.

To filter out the noise term, the second step is to estimate the average fraction of return variation that is related to the news of patent granting $\hat{\lambda}$.

\[ \lambda_{j,t} = \frac{\sigma_{j,x,t}^2}{\sigma_{j,x,t}^2 + \sigma_{j,\epsilon,t}^2} \]  

(4.4.1)

where $\sigma_{j,x,t}^2$ and $\sigma_{j,\epsilon,t}^2$ are the variances of the patent-related abnormal returns and the variance of the noise term for firm $j$ in year $t$, respectively.\(^{10}\) Assuming that the ratio $\lambda_{j,t}$ does not vary across firms and time,\(^{11}\) I can use the average ratio $\hat{\lambda}$ to filter out the noise term. $\hat{\lambda}$ can be recovered by estimating the average increase in the volatility of firm idiosyncratic returns around patent granting days. Following the procedure of Kogan, Papanikolaou, Seru, and Stoffman (2012), I regress the log squared idiosyncratic returns on a patent granting event dummy variable $I_{j,d}$, controlling for the week-day effect $b_d$ and the firm-year effect $a_{j,t}$.

\[ \ln(r_{j,d}^l)^2 = a_0 + b_d + a_{j,t} + \gamma I_{j,d} + \mu_{j,t} \]  

(4.4.2)

The estimate $\hat{\gamma}$, reported in Table 3, then allows me to compute $\hat{\lambda}$, the average fraction of abnormal return volatility on the patent granting date that is related to patent news. Assuming that the patent-related abnormal return $x_{j,t}$ has a Gaussian distribution $\mathcal{N}(0, \sigma_{j,x})$ truncated at zero\(^{12}\) and the noise term $\epsilon_{j,t}$ has a Normal distribution $\mathcal{N}(0, \sigma_{j,\epsilon})$, the average patent-related fraction of volatility $\hat{\lambda}$ is computed from:

\[ \hat{\lambda} = 1 - \left( 1 + \frac{1}{1 - \Phi(0)} (e^{\hat{\gamma}} - 1) \right)^{-1} \]  

(4.4.3)

---

\(^{10}\)The subscript $d$ denotes for a day, the subscript $t$ denotes for a year.

\(^{11}\)This assumption implies that $\sigma_{j,x,t}^2$ and $\sigma_{j,\epsilon,t}^2$ vary in constant proportions.

\(^{12}\)Patent value is non-negative. Hence the return related to patent news should also be non-negative.
where \( \phi \) and \( \Phi \) are the standard normal distribution pdf and cdf, respectively. My \( \hat{\lambda} \) estimate is approximately 0.05 (with a 95% confidence interval of [0.036, 0.068]). It is comparable to the estimate of 0.04 by Kogan, Papanikolaou, Seru, and Stoffman (2012). The daily volatility of the noise term can also be backed out using the estimates of \( \hat{\gamma} \) from Regression 4.4.2

\[
\sigma_{j,e,t}^2 = \sigma_{j,d}^2 \left( 1 + l \right) \left( 1 + f_{j,t} \left( 1 + l \right) \frac{\hat{\gamma}}{1 - \hat{\gamma}} \right)^{-1}
\]

(4.4.4)

where \( \sigma_{j,d}^2 \) is the total variance of firm \( j \)'s daily idiosyncratic returns in year \( t \) and \( f_{j,t} \) is the fraction of trading days that are patent granting days for firm \( j \) in year \( t \).

In the last step, the conditional expected returns attributable to patent grants \( x_{j,d} \) can be computed by filtering out the average noise term from the raw idiosyncratic returns and adjusting for its truncated normal distribution.

\[
E[x_{j,d}|r_{j,d}] = \lambda_{j,d} r_{j,d} + \sqrt{\lambda_{j,d} \sigma_{j,e,d}^2} \frac{\Phi(R_{j,d})}{1 - \Phi(R_{j,d})},
\]

(4.4.5)

where \( R_{j,d} = \sqrt{\lambda_{j,d}} \frac{r_{j,d}}{\sigma_{j,e,d}} \), \( \lambda_{j,d} = \frac{\sigma_{j,x,t}^2}{\sigma_{j,x,t}^2 + \hat{\lambda}} = \hat{\lambda} \)

The value of a patent is then measured as the product of the patent-related return \( x_{j,d} \) and the lagged market capitalization \( (S_{j,d-1}) \) of firm \( j \) that owns the patent on the patent granting day \( d \). If there are multiple patents granted to the firm on the same day, each patent is assumed to contribute an equal fraction (i.e., \( \frac{1}{N} \)) of the total value.

\[
\hat{A}_t = \frac{1}{N} E[x_{j,d}|r_{j,d}] S_{j,d-1}
\]

(4.4.6)

I then construct the market-based innovation measure at both firm and industry levels, using the estimated patent values. The total value of patents granted to firm \( j \) in year \( t \) is computed and then scaled by the beginning-of-year market capitalization of firm \( j \). Industry-
level innovation is computed by aggregating the values of patents granted to the same industry $s$ and scaled by the beginning market capitalization of the industry $s$.

\[
\hat{A}_{j,t}^m = \frac{\sum_{i \in P_{j,t}} \hat{A}_i}{S_{j,t-1}} \tag{4.4.7a}
\]

\[
\hat{A}_{s,t}^m = \frac{\sum_{i \in P_{s,t}} \hat{A}_i}{S_{s,t-1}} \tag{4.4.7b}
\]

where $P_{j,t}$ and $P_{s,t}$ denote the set of patents owned by firm $j$ and industry $s$ in year $t$, respectively.

This proxy has its own relative strengths and weaknesses. On the positive side, the market-based proxy can provide a timely and forward-looking measure of the expected patent value. If real economic data is employed to measure the realized patent value, I may need to use a long window, as the patented technology often requires a long adoption period before it eventually start affecting the firm’s cash flow. On the negative side, I introduce additional measurement error during the estimation procedure. Filtering this noisy component requires specific assumptions regarding return distributions, and the relative fractions of the patent-related component and the noise component in the returns volatility are assumed to be constant across firms and across time.

To ensure that this measurement error does not drive the main result, I construct another proxy for innovation, based on patent forward citations.

**Citation-weighted patent index**

The second measure of innovation uses citations to account for heterogeneity among patents. It presumes that a patent has a greater economic impact when it influences subsequent innovations. Trajtenberg (1990) studies the medical-related technology and shows that simple patent counts have no correlation with the estimated social surplus attributable to
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...technology improvement, while citation-weighted patent counts have a high correlation with the surplus measure. Hall, Jaffe, and Trajtenberg (2005) find that citation-weighted patents, as a proxy of firm’s knowledge stock, have significant explanatory power for firms’ market value in addition to cumulated R&D expenditure, while raw patent counts do not show significance in the same test. Thus, raw patent counts can lead to unreliable measures of innovation.

Citation is an ex-post measure of a patent’s economic value, whereas the market-implied value of a patent is an expected measure. A patent receives a citation when the citing patent is granted. The majority of citations occur with a significant lag after patent grants (up to 15 years). The average distribution of the citation lag peaks at 3–5 years after patent grants (Hall, Jaffe, and Trajtenberg, 2001). I count the number of citing patents that are granted no more than five years after the cited patents are granted as a measure of the cited patent’s economic value.

The length of the estimation window is chosen to balance these two offsetting concerns. A long window for citation counts can avoid under-weighting those influential patents that have long citation lags. On the other hand, a long estimation window also introduces more severe truncation issues. Newly granted patents with an age less than the estimation window should be excluded from the sample as they automatically receive fewer citations as a consequence of the measurement interval. Following prior literature, I choose a five-year window for citation counts, which includes a majority of the overall citations without foregoing too many recent patent observations.\textsuperscript{13} (e.g., Bena and Li, 2014; Hall, Jaffe, and Trajtenberg, 2005).

Citation counts can also be affected by factors other than a patent’s influence on future innovations. Years with more patent grants can mechanically generate more citations than the years with fewer patent grants. There are also systematic differences in the frequency of citations received and made across patent classes (Bena and Li, 2014; Hall, Jaffe, and Trajtenberg, 2005).

\textsuperscript{13}I obtain quantitatively similar results when a three-year window is chosen.
4.4 Measurement

Trajtenberg, 2005). The year fixed effect and class fixed effect can be filtered out by dividing the five-year forward citation counts by the median citation counts of the cited patent’s class in a given year. Unreported results using the class-year adjusted citation counts are quantitatively consistent with the results obtained using the simple five-year forward citation counts.

The firm-level citation-weighted innovation measure is the sum of the citations received by patents granted to a firm in year $t$. Industry-level innovation is computed from aggregating the citation-weighted innovation of firms within the same industry. I also take logs of the citation counts, as they are highly skewed (Hall, Jaffe, and Trajtenberg, 2001).

$$
\hat{A}_{j,t}^c = \ln \left( 1 + \sum_{i \in P_{j,t}} C_{i,t} \right)
$$

(4.4.8a)

$$
\hat{A}_{s,t}^c = \ln \left( 1 + \sum_{j \in s} \sum_{i \in P_{j,t}} C_{i,t} \right)
$$

(4.4.8b)

where $C_{i,t}$ is the number of citations received by patent $i$ within five years after its grant (i.e., the estimation window is $[t, t+4)$). $P_{j,t}$ and $P_{s,t}$ denote the patent sets granted to firm $j$ and industry $s$, respectively.

4.4.2 Measuring Asset Reallocation Frictions

Reallocation frictions in the real asset market are usually determined by the nature of assets. More specialized assets are less able to be redeployed to other firms and have thinner secondary asset markets (Caballero and Hammour, 1998; Gavazza, 2011b; Ramey and Shapiro, 1998). Ideally, asset reallocation frictions should first be measured at the asset level and then adjusted for the asset’s weight in the firm’s capital stock.
With limited data on the real asset market, I construct two measures for asset reallocation frictions at the industry level. I assume firms within the same industry face the same the asset reallocation frictions, as they produce similar products, using similar assets.

The main measure here is based on actual trading activities in the secondary asset market. As shown by the model in the previous chapter, high reallocation costs lead to low asset sales, *ceteris paribus*. Based on this monotonic negative correlation, I use asset liquidity as an inverse measure of reallocation frictions. A similar approach is also adopted by Eisfeldt and Rampini (2006). For robustness, I also construct a proxy based on asset redeployability, following Kim and Kung (2014). This is an ex-ante measure for reallocation frictions, based on the assumption that assets can be less costly to resell when they are commonly used across firms and industries.

**Asset liquidity**

I construct measures of asset liquidity as proxies of capital reallocation frictions. By asset liquidity, I mean the volume of used asset transactions relative to capital stocks. My model shows that the size of capital reallocation frictions and asset liquidity are inversely related (see Equation (3.4.13) and Figure 5.a). Low asset liquidity is interpreted as high asset reallocation frictions.

Due to data limitation, firm-level asset liquidity is difficult to estimate.\(^\text{14}\) I compute asset liquidity at the industry level. Inter-industry differences are the main sources of the cross-sectional variations in asset liquidity. Shleifer and Vishny (2011) argue that industry insiders are the major buyers of their industries’ used assets due to asset specificity and less information asymmetry. Empirical studies also show that industry condition is one

\(^{14}\text{Firm-level asset liquidity requires a breakdown of information on assets or asset classes. Ideally, a firm’s asset liquidity should be computed as the value-weighted average of its heterogeneous asset liquidity.}\)
determinant of asset reallocation (Acharya, Bharath, and Srinivasan, 2007; Ramey and Shapiro, 2001).

I include sales of property, plant and equipment (PP&E) and acquisitions obtained from COMPUSTAT as transactions of productive used assets across firms. I compute three turnover rates: i) the SPPE rate, defined as industry total sales of PP&E normalized by beginning-period industry total capital stock; ii) the acquisition rate (ACQ), defined as industry total acquisition normalized by beginning-period industry total assets; iii) and the total reallocation rate (REALLOC), defined as the sum of sales of PP&E and acquisition normalized by beginning-period industry total assets.\(^\text{15}\) I take the logarithm of the three turnover rates.

\[
\begin{align*}
SPPE_{s,t} &= \ln \left( 1 + \frac{Sale \ of \ PP&E_{s,t}}{PPENT_{s,t-1}} \right) \quad (4.4.9a) \\
ACQ_{s,t} &= \ln \left( 1 + \frac{Acquisition_{s,t}}{Total \ assets_{s,t-1}} \right) \quad (4.4.9b) \\
REALLOC_{s,t} &= \ln \left( 1 + \frac{SPPE_{s,t} + Acquisition_{s,t}}{Total \ assets_{s,t-1}} \right) \quad (4.4.9c)
\end{align*}
\]

where \(SPPE_{s,t}\), \(ACQ_{s,t}\) and \(REALLOC_{s,t}\) are the SPPE rate, acquisition rate and total reallocation rate of industry \(s\) at time \(t\), respectively.

One potential issue with acquisition is that it is a cash flow item in COMPUSTAT. This means that only cash acquisition will be captured by this item, since share acquisitions often lead to consolidation of financial statements. Thus, this measure omits a large fraction of acquisition deals and could underestimate the turnover rate.

Another drawback of using realized SPPE and M&A data from COMPUSTAT is that it gives the gross dollar value of asset sales. I cannot distinguish whether an increase in asset sales is due to a rise in the price of assets or an increase of the quantity traded. The model

\(^{15}\text{see Eisfeldt and Rampini (2006) for a similar definition of capital reallocation.}\)
only shows the relation between reallocation frictions and quantity of assets reallocated, and is silent on the price effect.

**Asset redeployability**

For robustness, I construct the second measure of asset reallocation frictions based on the availability of potential buyers, following Kim and Kung (2014). It presumes that assets can be more easily resold (i.e., with less search time and cost) when they are more widely deployed among other firms. High asset redeployability is another indication of low asset reallocation frictions.

To construct measures of asset redeployability, data on disaggregated asset expenditure is required. Kim and Kung (2014) adopt the 1997 capital flow table, which contains the most up-to-date breakdown information on asset expenditures. A required assumption is that the composition of an industries’ capital stock remains stationary over time.

For each asset class, the asset redeployability score $RS_{a,t}$ is first computed as the number of industries among the total 123 industries that use the given asset, weighted by each industry’s share of aggregate capital expenditure in year $t$. The underlying rationale is that more investment spent on the given asset indicates a greater number of potential users of the asset.

$$RS_{a,t} = \sum_{s=1}^{123} I_{a,s} \times \frac{CAPEX_{s,t}}{\sum_{s=1}^{123} CAPEX_{s,t}}$$  \hspace{1cm} (4.4.10)

where $I_{a,s}$ is a dummy variable equal to 1 when industry $s$ spends more than 0.1% of its total capital expenditure on asset class $a$ (i.e., $w_{a,s} \geq 0.1\%$). Firm-level capital expenditure ($CAPX$) is summed up to the industry level defined in the 1997 capital table to compute the industry’s share of aggregate investment. The asset redeployability score $RS_{a,t}$ is set to zero if the description of the given asset suggests that it is highly specialized to an individual firm.
For example, “custom computer programs” implies that the programs are customized and have limited ability to be redeployed by other firms.

Industry asset redeployability $AR_{s,t}$ is then calculated as the value-weighted redeployability score of assets obtained in the first step:

$$ AR_{s,t} = \sum_{a=1}^{180} w_{a,s} \times RS_{a,t} $$

(4.4.11)

where $w_{a,s}$ is the fraction of total capital expenditure made by industry $s$ on asset $a$ according to the 1997 capital flow table.

This alternative measure further captures the relative size of reallocation frictions when used capital is reallocated across industries. In particular, inter-industry capital reallocation is crucial when an industry undergoes a large restructuring led by radical innovations. In this case, used capital can hardly be redeployed by the new innovating firms, though some asset classes which are widely used across industries can still be traded with lower costs. Therefore, high asset redeployability can alleviate the destructive effect caused by radical innovations on existing firms.

### 4.4.3 Control Variables

I now explain the control variables used in my tests. Prior studies have shown that these variables affect firms’ expected returns. A cross-sectional study that fails to control for these variable is unlikely to be informative. I adopt the conventional method to construct these control variables and illustrate them as follows.

Firm-level variables are estimated first. The characteristics of each industry portfolio are then computed as the value-weighted average of the firm-level variables.
Research and development

Investment in R&D as an input of technological innovation may affect stock returns (Aghion and Howitt, 1992; Romer, 1990). Successful R&D projects lead to new innovation and high future earnings (Chan, Lakonishok, and Sougiannis, 2001). Other studies further show that high R&D firms have significantly higher average returns than low R&D firms do, suggesting that R&D investment might also affect a firm’s risk (Li, 2011; Lin, 2012). Thus, R&D investment may correlate with both innovation (as measured by patent grants) and stock returns. I control for R&D intensity (denoted as $R&D$), which is computed as the R&D expenditure scaled by total assets.

Industry concentration

I control for industry concentration as it may correlate with both asset liquidity and stock returns. As pointed out in earlier subsections, the real asset market is more liquid when the pool of potential buyers is large (Gavazza, 2011b). Since industry insiders are the key participants, asset liquidity and industry concentration may be negatively associated. Furthermore, Hou and Robinson (2006) document that industry competition significantly affects firms’ future earnings and cross-sectional stock returns. It is possible that the impact of asset liquidity on stock returns may come from its correlation with industry concentration rather than through the mechanism of creative destruction. Failing to control for industry concentration undermines the robustness of the empirical results.

I use the Herfindal index ($Herf$) to measure industry concentration, where a firms’ market share of sales in industry s are squared and added together.

$$Herf_{s,t} = \sum_{j \in s} \text{mktshare}_{j,t}^2$$  \hspace{1cm} (4.4.12)

where $mktshare_{j,t}$ is sales of firm j scaled by the total sales of its industry.
Financial constraint

Prior literature suggests that a firm’s leverage and funding liquidity may affect its risk and expected return. Leverage amplifies the volatility of a firm’s cash flow as well as the volatility of its stock returns (Arditti, 1967; Christie, 1982). Moreover, highly leveraged firms are also prone to financial constraints as they may suffer from debt overhang and have limited ability to raise funds externally (Hennessy, 2004; Livdan, Sapriza, and Zhang, 2009). Funding liquidity measures how much cash the firm reserves and attempts to gauge the ability of a firm to survive a “rainy day” without draining its credit capacity or fire sales of its key assets. Thus, it captures another aspect of financial constraint in addition to leverage.

Leverage \( (\text{lev}) \) is computed as total debt over total assets (i.e., \((\text{long-term debt} + \text{short-term debt})/\text{total assets}\)). Fund liquidity \( f\text{liquid} \) is computed as cash and short-term investment over total assets. All variables are measured at the beginning of each period.

Beta, size, book-to-market and past returns

I include market beta, size, book-to-market ratio, and past returns in the regression, as a vast literature documents that these factors can explain a significant fraction of cross-sectional return spreads (e.g., Carhart, 1997; Daniel and Titman, 1997; Fama and French, 1997). I take one period lag of these four variables to control for their impact on expected returns.

The pre-ranking beta \( (\beta) \) is estimated from a three-year rolling regression. Firms’ monthly excess returns are regressed on market excess returns to obtain the beta estimates (Frazzini and Pedersen, 2014).

Firm size \( (\text{Size}) \) is the market capitalization of a firm at the end of year. A firm’s closing price on the last trading day of year \( t \) is multiplied by the total common shares outstanding.

Book-to-market ratio \( (BM) \) is computed from book equity over market capitalization. Book equity is common stockholder’s equity plus balance sheet deferred taxes and investment
tax credits minus the book value of preferred stock and post-retirement assets (Fama and French, 1997).

Lastly, past returns ($\text{Priorret}$) are firms’ cumulative returns over the past 12 months. This controls for the momentum effect on stock returns (Carhart, 1997; Jegadeesh and Titman, 1993).

### 4.5 Summary Statistics

In this section, I document and discuss the summary statistics of the patent characteristics, the innovation measures, the reallocation friction measures and other key control variables. The data shows that there is considerable inter-industry variation in asset reallocation frictions.

#### 4.5.1 Patent Value and Citations

Table 4 reports the distributions of market-implied patent values and five-year forward citations. Patent values are expressed in 1982 U.S. dollars.\(^{16}\) For the testing sample covering the period 1987–2010, the median patent has an estimated market value of 3.36 million 1982 U.S. dollars, which corresponds to a rise of 0.57% in stock price. The median patent also receives two citations within five years after its granting. As a comparison, the median patent of the full KPSS patent sample is worth 2.79 million (i.e. a 0.5% increase in stock price) and one citation. There is no notable difference in patent characteristics between the full patent sample and the testing sample. The distributions of both patent values and citations are skewed. Raw patent counts fail to capture such heterogeneity among patents and tend to underweight the impact of influential patents.

\(^{16}\)The 1982 price deflater is used in Kogan, Papanikolaou, Seru, and Stoffman (2012). The same price deflater is adopted here to ensure the results are comparable.
4.5 Summary Statistics

The patent value derived from the stock market reaction is an expected measure of the patent’s future impact. I regress the five-year future citations ($\hat{A}^c_j$) on the market-implied patent value ($\hat{A}^m_i$) to check how the market-based measure predicts future citations. The regression results are reported in Table 5. All regression results for the testing sample period and three of the four regression results for the full sample period show positive associations between the estimated market value of patents and the future five-year number of citations. Similar tests are also performed in Kogan, Papanikolaou, Seru, and Stoffman (2012), where they use the total number of citations to measure a patent’s future economic impact, which may underestimate the impact of a new patent.

I further examine the non-linear relation between patent value and citations. Citation counts are regressed on the market value of patents and its squared term. I also control for the same set of variables used in the previous linear regressions. The results are reported in Table 6. For small-value patents, forward citations increase with market value, while for high-value patents, forward citations may decrease with market value. My regression results confirm the findings of Abrams, Akcigit, and Popadak (2013). Abrams, Akcigit, and Popadak (2013) identify an inverted U-shaped relation between patent value and forward citations, and show that strategic patents could be one of the reasons for this. They show that strategic patents that are used to protect firms’ existing patents do not promote the development of future innovation. These patents usually belong to large firms and are extremely valuable, but receive limited numbers of citations.

4.5.2 Measures of Technology Shocks

Patent values and citations are aggregated at the firm, industry and economy-wide levels to construct innovation measures.
Table 7 reports the summary statistics of firm-level innovation measures. Approximately a quarter of the public firms receive at least one patent grant each year. The market-based measure of innovation suggests that patentable technology accounts for 2% of the increase in a firm’s stock value every year, on average. The citation-weighted innovation measure is skewed and has a higher mean and standard deviation than the market measure of innovation, since it is constructed from citation counts. Comparing the distributions of the two measures for the full patent sample and the testing sample reveals no significant differences between them.

Table 8 documents the distributions of the two innovation measures at the three-digit SIC industry level. It also lists the top five most and least innovative industries, ranked according to the two innovation measures. Consistent with expectations, the computer and electronic devices industries produce the most technological innovations. On average, these industries receive more than 2,000 patents a year, and generate more 25% of their total market value from their innovations. Other industries, like photography and chemical products (e.g., plastic materials and synthetic drugs), are also in the top list. These innovative industries are also those that actively engage in R&D investment, which accounts for more than 5% of their total assets. On the other hand, the agricultural, mining and service industries have less exposure to innovation shocks and rarely participate in R&D.

Table 9 reports the distributions and top lists according to the industry classifications defined in the capital flow table. They are consistent with the estimates based on the three-digit SIC industry codes.

Lastly, I aggregate patent values and forward citations at the economy-wide level to examine its time-series feature. As displayed in Figure 17, the market-based innovation measure and citation-weighted innovation measure are mostly positively associated. The citation-weighted measure is more volatile (citation data is available since 1941). Both measures show a large spike in the late 1990s, which coincides with the technology bubble.
The market-based measure of innovation rockets in 1999. The inflated stock prices during the dot-com bubble period may substantially overestimate the patent values.

### 4.5.3 Measures of Asset Reallocation Frictions

Two measures of asset reallocation friction are constructed. The first proxy is based on real asset sales (Eisfeldt and Rampini, 2006) and the second proxy is derived from capital investment across asset classes.

Table 10 displays the summary statistics of the two friction measures. On average, an industry sells 1.2% of its PPE each year. Eisfeldt and Rampini (2006) estimate that the average annual asset turnover is 1.7%. The standard deviation is 3%, suggesting that there is considerable variation across industries. Industries that are capital-intense but deploy standard equipment have more liquid secondary asset markets; for example, trucking services, heavy construction and agriculture. Asset reallocation frictions are expected to be small in those industries. In contrast, more specialized industries, like electronic equipment, have more illiquid asset markets. In terms of asset redeployability, there is also considerable variation across industries. Service industries have the most redeployable assets.

The two reallocation frictions derived from the different sources are positively associated. Asset redeployability is an ex-ante measure of the reallocation frictions in the secondary asset markets, while asset liquidity is an ex-post measure. I regress asset liquidity on lagged asset redeployability for all industries, excluding utilities and financial services. The results show that asset redeployability can significantly predict asset liquidity. Kim and Kung (2014) conducted similar regression for the manufacturing industries. As shown in Table 11, one standard deviation increase in asset redeployability raises future sales of PPE by 0.4% (i.e., $0.123 \times 0.034 = 0.4\%$) This is economically significant, as the average asset turnover is 1.2%.
4.5.4 Portfolio-Level Variables

Table 12 reports the characteristics of the industry portfolios. Firms in the same industries are grouped into non-innovating portfolios and innovating portfolios based on the market-implied measure of innovation. The industry portfolios of the non-innovating firms on average have greater industry concentration, lower growth opportunity, lower Tobin’s Q and higher leverage ratios compared to the industry portfolios of the innovating firms. They also expend less on R&D, sell more used assets and acquire more companies. Bena and Li (2014) document that non-innovating firms are more likely to be acquirers and innovating firms are more likely to be the targets. A similar trend is also found in the summary statistics of industry portfolios based on the citation-weighted innovation measure, which is reported in Table 13.

4.6 Measurements in Prior Literature

4.6.1 Asset Reallocation Frictions

Realized transaction costs in decentralized used asset markets are not directly observable. Most proxies constructed in the literature are still ordinal measures that rely on the qualitative association between the proxy and one specific aspect of the frictions in real asset market. Three approaches are commonly adopted in the prior literature and are summarized in this subsection: i) market liquidity; ii) liquidation value; and iii) availability of potential buyers.

Market liquidity is one direct measure of the intensity of frictions in the used asset market, as the negative relation between market liquidity and reallocation frictions is well established. Successful transactions of used assets are an indication that the mutual benefit from trade is not completely eroded by market frictions. Eisfeldt and Rampini (2006) build a neoclassical model that allows for asset reallocation. They estimate counter-cyclical
parameters of reallocation costs in order to simulate procyclic aggregate capital reallocations. Balasubramanian and Sivadasan (2009) use the fraction of purchases of used assets to total capital expenditure at the industry level to construct an index of capital resalability. They show that the measure can explain the productivity dispersion and industry structure. Realized liquidity measures are sometimes volatile and less informative, and are affected by various shocks to both the sellers and buyers. High trading volumes caused by fire sales indicate high costs of capital reallocation, rather than the predicted low reallocation cost correlation in normal times.

Some studies use the average liquidation value of assets as the measure of costs to reverse investment. Almeida and Campello (2007) and Campello and Hackbarth (2012) use the average asset liquidation values reported in Berger, Ofek, and Swary (1996) to construct firm-level average asset tangibility. Like liquidity measures, realized resale price can be volatile and available at low frequencies. This measure would also underestimate the overall reallocation costs since searching costs and opportunity costs are not considered.

Another widely used type of proxy for asset market frictions is the availability of potential buyers. It relies on the negative correlation between market thickness and search costs. The asset markets are usually defined by industry or asset types, as industry insiders who face less information asymmetry are the majority of potential buyers (Shleifer and Vishny, 1992). Gavazza (2011b) counts the number of operators who use the same type of aircraft to measure the market thickness of a given aircraft market. Ortiz-Molina and Phillips (2014) use the number of rival firms in the industry with debt ratings as the measure of industry-level asset liquidity. Moreover, Kim and Kung (2014) construct an asset redeployability measure based on how commonly an asset class is invested in across industries. The disadvantage of this type of measure is that it is usually sensitive to the definition of industries or asset classes.

Measures of real asset market frictions are far from perfect. Studies often have to use several proxies to ensure the robustness of their empirical findings.
4.6.2 Technology Shocks

It is difficult to measure technology shocks quantitatively. Previous literature in economics and finance has developed various approaches to identify technology shocks. I categorize these approaches into three groups, which might not be comprehensive. The first category estimates technology shocks from macroeconomic quantities. The second category uses relative stock returns between firms with different exposure to innovation shocks. The last category uses micro data of innovation-related activities to construct a direct measure of innovation. Each approach has its own relative advantages and disadvantages.

Proxies derived from aggregate data identify innovation shocks at the time they affect the real economy on a large scale. These measures often rely on macroeconomic theories to recover measures of technology shocks. Early studies use Solow residuals, which are the variations in output that are not explained by variations in capital and employment (Bartelsman and Doms, 2000; Basu and Fernald, 2006). Other studies impose restrictions on vector auto-regressions to identify technology shocks (Justiniano, Primiceri, and Tambalotti, 2010). Output based on sales or revenue is affected by product prices, generating biased measures of productivity (Foster, Haltiwanger, and Syverson, 2008). According to the economic growth literature, changes in the price of new capital is also a candidate for empirical measures of technology shocks (Greenwood, Hercowitz, and Krusell, 1997, 2000). The price of new capital is predicted to decrease in response to positive innovation shocks. Since macroeconomic quantities are only available at low frequencies, this approach may identify technology shocks after a delay.

Market-implied technology shocks rely on the heterogeneous impact of innovation on stock returns. Some studies use the stock return spread between firms in the investment and consumption sectors, as well as the spread between value and growth firms, to measure the technology shocks (Garlappi and Song, 2013; Kogan and Papanikolaou, 2013; Papanikolaou,
4.6 Measurements in Prior Literature

2011). As mention in the previous section, the advantage of market-implied estimates is that forward-looking market prices can quantify the size of an innovation more precisely and identify technology shocks more punctually as the data for stock returns is available at high frequencies. However, there are also concerns that other non-technology shocks can systematically affect return spreads.

The third approach directly measures innovations by aggregation of innovation-related micro data. R&D investment, which is the input of the innovation process, is aggregated to measure technology shocks by several studies (see e.g., Hsu, 2009; Shea, 1999). However, the R&D expenditure of private firms is not widely accessible, and COMPUSTAT only began to record R&D expenditure at quarterly frequencies from 1979 on. Many studies also construct measures of innovation shocks from patent data (see e.g., Bena and Garlappi, 2012; Bena, Garlappi, and Grüning, 2014; Hirshleifer, Hsu, and Li, 2013; Kogan, Papanikolaou, and Stoffman, 2013). The two primary proxies are patent counts and citation-weighted patent counts. The intuition underlying the patent count measure is that a more innovation-active field will have more intellectual property to protect and will do so by applying for more patents. A natural extension to account for heterogeneity in patent value is weighting patents by their future number of citations (Hall, Jaffe, and Trajtenberg, 2005, 2001). Some other methods have been developed to measure patent values. Pakes (1986) and Schankerman and Pakes (1986) examine patent renewal decisions and treat patents as an option to back out their value. Kogan and Papanikolaou (2013) derive the implied market value of patents by estimating firms’ excess returns around the dates of patent granting.

There are a few concerns related to the use of patent data. Firstly, non-patentable technologies are missing from patent data. Secondly, patent grants are significantly affected by changes in patent regulations and the efficiency of the patent office (see Griliches, 1998\textsuperscript{17}). Moreover, strategic patenting is one type of destructive creation and has received a great

\textsuperscript{17}A survey on this topic.
deal of attention in recent years (Abrams, Akcigit, and Popadak, 2013; Farrell and Shapiro, 2008). It identifies the concern that a significant fraction of patents are used as fencing, which expands the range of protection available to previously granted patents. Although these patents are strategically valuable, they do not improve the innovator’s productivity or product quality. They also prevent development of future innovation.

Nevertheless, proxies constructed from patent data provide a relatively direct and model-free measure of innovation. They are increasingly being adopted in the recent finance literature.

## 4.7 Summary

In this chapter, I develop hypotheses and regression specifications to empirically test the model’s predictions. I construct the proxies of real technology shocks with patent data. I also compute two measures of industry capital reallocation frictions.

To measure technology shocks, I use two methods to estimate patent values. First, I adopt a new method based on market information developed by Kogan, Papanikolaou, Seru, and Stoffman (2012). This market-based measure of patent value is constructed from patent-related abnormal returns around patent grants. Second, I use the forward five-year citation counts to proxy for patent values. This method has been widely used in prior literature (Hall, Jaffe, and Trajtenberg, 2005, 2001). The two measures are significantly correlated.

To measure the size of capital reallocation frictions, I also used two approaches. The first approach relies on the realized industry asset turnover with regard to SPPE and M&A. The second approach follows the new measure developed by Kim and Kung (2014), based on the argument that more widely deployed assets are easier to reallocate. The second measure helps to capture cross-industry asset reallocations. In the model, capital is reallocated within
one intermediate sector. In practice, for non-innovating firms, the ability to sell capital to industry outsiders can also reduce their exposure to technology shocks.
Chapter 5

Empirical Results

5.1 Introduction

In this chapter, I examine the interactive effect of technology shocks and capital reallocation frictions on cross-sectional returns at the industry level.

I first examine the industry characteristics that are associated with high capital reallocation frictions. I find that asset turnover increases in industries with large technology shocks. Other industry characteristics, such as capital age, industry concentration, investment rate, and profitability, are also associated with industry asset turnover rate. In addition, I find suggestive evidence that the capital reallocation rate and reallocation frictions are inversely related, as the capital reallocation rate is strongly negatively correlated with the industry dispersion of growth opportunities.

I then test the hypotheses developed in the previous chapter. I find that the impacts of industry asset liquidity on non-innovating firms and innovating firms are asymmetric. Non-innovating firm returns are negatively affected by technology shocks. The negative return responses are stronger in industries with low asset liquidity. Innovating firms are positively affected by technology shocks, but their return responses do not vary with industry
asset liquidity. The overall displacement effect induced by technology shocks is larger in industries with low asset liquidity.

For robustness test, I conduct a placebo test to show that the main returns are not driven by omitted variables. I construct an arbitrary measure of technology shocks. I randomly assign firm abnormal returns of non-patent granting dates to compute patent values. This arbitrary measure contains no information about patent grants but all possible measurement errors contained in the true market-based technology shock measure. I show that all main results disappear when the arbitrary measure is used in the regressions.

The remainder of the chapter is organized as follows. Section 2 examines the industry characteristics that are responsible for high capital reallocation frictions. Section 3 discusses the main results. Section 4 conducts the robustness tests, and Section 5 concludes.

5.2 Industry Characteristics and Capital Reallocation Frictions

This section examines the correlations between industry characteristics and measures of industry asset market frictions. It helps to build a graph of a typical industry that suffers from high asset reallocation frictions.

I perform Fama-MacBeth regressions of the cross-section asset market frictions on industry average characteristics for the period between 1987 and 2010. The regressions equation are specified as:

\[ Frictions_{s,t} = \beta_0 + \sum_{i}^{N} \beta_i X_{s,t} + \epsilon_{s,t} \]  (5.2.1)

where \( Frictions_{s,t} \) are the proxies of the asset reallocation frictions of industry \( s \) at time \( t \), using measures of asset liquidity (\( AL_{s,t} \)) and asset redeployability (\( AR_{s,t} \)). \( X_{s,t} \) denotes industry
characteristics. I include industry weighed-value average characteristics, including the size of technology shocks $A$, R&D intensity, capital age, logged market capitalization, industry Herfindal index, physical capital intensity, investment rate, Tobin’s Q, return on assets (ROA), logged book-to-market ratio, and leverage ratio. I also include industry dispersions of Tobin’s Q and ROA, as capital reallocation is driven by dispersions in productivity and profitability across the firm level (e.g., Balasubramanian and Sivadasan, 2009).

Table 14 reports the regression results using the SPPE rate as the proxy of industry asset liquidity. Both univariate and multivariate regressions are conducted. The univariate analysis, which is reported in Panel A, provides the unconditional average cross-section correlations of asset market frictions and industry characteristics. The multivariate analysis estimates the conditional correlations, which are reported in Panel B. I present the time-series averages of the slope coefficients from the regressions.

[INSERT TABLE 14 HERE]

I first examine the correlation between technology shocks and asset liquidity. Column (1) shows that technology shocks are negatively associated with the SPPE rate in the univariate analysis, but positively associated with the SPPE rate once other industry characteristics are controlled for. This is consistent with my model, which shows that technology shocks trigger asset reallocation by introducing productivity dispersion across firms. In practice, many other shocks could lead to asset reallocation. Column (2) shows that the SPPE rate is negatively correlated with R&D intensity. My model hence gives no prediction of the relation between R&D and industry concentration, as it assumes the exogenous technology progress. Column (3) reports a negative relation between capital age and asset liquidity for both the univariate and multivariate regressions. Older capital faces larger information frictions and is harder to redeploy by innovating firms (Bond, 1983). Column (4) reports that the SPPE rate is higher when the industry’s average market capitalization is small. Foster, Haltiwanger, and Krizan
(2006) document that smaller firms have a lower survival rate. This could be one reason that small firms have a higher demand for asset sales.

Column (5) shows that a high industry concentration results in low asset turnover. This is consistent with the argument of Gavazza (2011b), who states that trading friction is high when the asset market is thin. It also confirms that used capital is mostly reallocated within the same industry, as the turnover rate increases as the number of industry insiders increases. Column (6) shows a strong negative correlation between the SPPE rate and capital intensity. Column (7) shows that capital sales are strongly and positively correlated with investment in the univariate regression, but the significance and the magnitude of the coefficient reduces after controlling for other variables. The positive relation is consistent with my model’s prediction, as used capital is a substitute for new investment. The demand for both types of capital increases when industry expands. This is further confirmed in Columns (8) and (12), which show that industry asset turnover rises with industry Tobin’s Q and falls as the logged book-to-market ratio increases. Tobin’s Q and the book-to-market ratio are commonly used as proxies of firms’ growth opportunities. However, Column (10) shows that the SPPE rate does not covary with industry profitability measure ROA.

In terms of dispersions in firm characteristics, dispersions in both Tobin’s Q and ROA are strongly negatively correlated with the SPPE rate. High dispersions in Tobin’s Q and ROA suggest that the benefit of capital reallocation is high, but is associated with low industry asset turnover. This is consistent with the empirical findings of Eisfeldt and Rampini (2006). They argue that high contractual and informational frictions in the used asset market prohibit firms from exploring such reallocation benefits.

Last, I find that industry cash holdings and leverage ratios have a limited correlated with the SPPE rate.

I then conduct the same set of regressions with the industry acquisition rate, another measure of asset liquidity. The results are reported in Table 15. Compared with the SPPE
rate, similar industry characteristics are found to be correlated with the acquisition rate, with two noticeable differences. First, acquisition as constructed from COMPUSTAT data is not significantly correlated with technology shocks and R&D in the multivariate analysis. This suggests that these transactions are less motivated by technology shocks. In addition, the industry acquisition rate is highly positively associated with the investment rate and industry profitability, but not with Tobin’s Q. It is also higher in industries with a high dispersion of firm profitability.

Next, I examine the industry characteristics that affect industry asset redeployability, which is a proxy for cross-industry capital reallocation. The results are reported in Table 16. First, cross-industry asset redeployability is not affected by industry technology shocks. The measure of asset redeployability increases with industry concentration, investment rate, and growth opportunities, but decreases with industry R&D intensity, capital age, capital intensity, and dispersion in Tobin’s Q. The results show some differences between the asset liquidity measures and the asset redeployability measure.

In this section, I perform the regressions specified in the last chapter to test the interactive effect of industry asset liquidity and technology shocks on cross-sectional returns.

First, I test Hypothesis 1, stated in the previous chapter. I perform Fama-MacBeth cross-sectional regressions on industry portfolios with various specifications according to Equation (4.2.1). I present the time-series averages of the slope coefficients from the regressions and Newey-West estimators of the standard errors with five lags. Table 17 and Table 18
Empirical Results

report the regression results for the non-innovating portfolios and the innovating portfolios, respectively.

[INSERT TABLE 17 HERE]

In Table 17, Column (1) presents the regression results for the non-innovating portfolio returns on all control variables. The book-to-market ratio, market beta and leverage ratio all have significant explanatory power on the cross-sectional returns of non-innovating portfolios. In Column (2), I include the technology shock measure $A_{it}^n$ in the regression and find that the non-innovating portfolio returns are negatively affected by industry technology shocks alone, but that this effect is weak on average.

I then examine the impact of industry asset liquidity and its interactive effect with technology shocks on non-innovating portfolio returns. I use three industry asset turnover measures as proxies for asset liquidity ($Assetliq_{it}$). In particular, I use the SPPE rate ($SPPE$) in Columns (3) and (4); the acquisition rate ($ACQ$) in Columns (5) and (6); and the reallocation rate ($REALLOC$), which is the sum of SPPE and acquisition over industry market capitalization, in Columns (7) and (8). Column (3) shows that the SPPE rate itself does not significantly affect non-innovating firms’ returns.

Column (4) tests the model with the full regression in Equation (4.2.1). The main variables of interest are the technology shock and its interaction term with the SPPE rate. An average technology shock (4.3%) leads to a 1.2 percentage point decrease in the returns of the non-innovating firms in industries with zero asset turnover ($3\% \times -0.274$). All else equal, a one standard deviation (1.7%) increase in asset liquidity significantly reduces the negative effect of technology shocks on returns by 0.61 percentage points ($= 0.36 \times 1.7\%$). Consistent with my model’s prediction, technology shocks negatively affect the values of non-innovating firms, and the magnitude of this destructive effect increases as industry asset liquidity decreases.
Moreover, I examine the impact of the industry acquisition rate ($ACQ$) as a proxy for $Assetliq_{s,t}$ and its interaction term with technology shocks on the non-innovating portfolio returns. Unlike the SPPE rate, inclusion of $A_{m,t}^n \times AssetLiq_{s,t}$ using the $ACQ$ proxy in Column (6) only weakly increases the explanatory power of technology shocks. In the model, acquisition is equivalent to bundle purchase of assets, hence it is similar to SPPE. However, in practice, acquisitions can differ in their means of payment, which dictates how these transactions are reported in financial statements. Acquisitions by cash are recorded in the cash flow statement and captured by COMPUSTAT acquisition, while acquisitions by shares lead to consolidation of financial statements. Innovating firms are often young and have less cash reserves. They are more likely to use their shares than their cash reserves. For this reason, this measure may not properly capture the ability to reallocate capital when there is a technology shock. The descriptive statistics in Table 15 and 13 also suggest that COMPUSTAT acquisitions are only weakly correlated with technology shocks and non-innovating firms tend to acquire more than innovating firms.

Last, I use the total asset turnover ($REALLOC$) as the measure of industry asset liquidity. Column (8) shows that the destructive effect of technology shocks on non-innovating firms varies across industries with industry total asset turnover.

Next, I examine the impact of industry technology shocks on the portfolio returns of innovating firms. The results are summarized in Table 18. As opposed to the non-innovating portfolio results, the technology shock measure $A_{m,t}^n$ has a positive association with the returns of innovating firms for all regression specifications, as reported in Columns (2)–(8). On the other hand, asset liquidity does not affect the sensitivity of the innovating firms’ returns to technology shocks. Other factors, including funding liquidity and industry concentration, also explain the cross-sectional portfolio returns of innovating firms.

[INSERT TABLE 18 HERE]
Empirical Results

The results of the full regression specifications are presented in Columns (4), (6) and (8). The key variable $A_{m,s,t}$ has a statistically and economically significant positive effect on the cross-sectional returns of innovating firms. An average industry technology shock is associated with a 2.3%–3.3% value appreciation of innovating firms. This is consistent with findings documented by Bloom and Van Reenen (2002), which show that patenting has an immediate positive effect on innovating firms’ market value.\(^1\)

The other key variable is the interaction term $A_{m,s,t} \times \text{AssetLiq}_{s,t}$. Unlike non-innovating firms, all three measures of physical asset liquidity $\text{AssetLiq}_{s,t}$ do not affect innovating firms’ return responses to technology shocks. Thus, industry asset liquidity has an asymmetric impact on non-innovating and innovating firms’ exposure to technology shocks. In my model, I show that reallocation frictions weakly affect the return of innovating firms when the technology shock realizes, as innovating firms can adopt the new technology by new investment when used capital is available. In practice, patents are real options that have a positive value even without real investment. The asymmetric effect of asset liquidity reported here is comparable to the findings of Ortiz-Molina and Phillips (2014). These authors examine the impact of asset illiquidity on the cost of equity implied from analyst forecasts. They split firms into industry “leaders” and “followers” according to their market share in sales and show that the illiquidity measures only have a positive association with the industry followers’ cost of equity, but not with the industry leaders’ cost. This study focuses on the return responses of non-innovating and innovating firms to technology shocks and find an asymmetric impact of asset liquidity on the two groups. According to Table 13, innovating firms on average have a significantly higher Tobin’s Q than non-innovating firms. This suggests that innovating firms and non-innovating firms are potential leaders and followers in productivity and profitability, respectively. Both Ortiz-Molina and Phillips

\(^1\)Prior literature documents that patenting feeds into market values immediately but has a slower effect on productivity. This is because patents provide firms exclusive rights to develop their innovations as well as the options to delay investments.
(2014) and my results suggest that transaction costs due to asset market illiquidity are mostly borne by the selling side.

The correlation between the market-based innovation measure and omitted portfolio characteristics is less likely to drive the key findings of the test. First, the filtration process explained in Section 4.4 is designed to minimize the impact of any firm-specific or industry-related factors on the estimation of the marketed-based patent values. As shown in Columns 1 and 2 of Table 17, the market-based industry innovation measure does not affect the returns of non-innovating firms by itself. This suggests that the correlation between the residual noise in the innovation measure and the portfolio returns is not severe. Second, any potential endogenous issue would bias the coefficient of the innovation measure against Hypothesis 1. Hence, the negative effect of technology shocks on non-innovating firms’ value, after controlling for asset liquidity and the interaction term, may even be underestimated. Third, any correlation between the omitted industry factors and the market-based innovation measure should bias the estimates toward the same direction, rather than generating an opposite effect of technology shocks on the returns of non-innovating firms and innovating firms.

Next, I test Hypothesis 2, which analyzes the overall displacement effect of technology shocks. I construct NMI industry portfolios by holding shares of non-innovating firms and selling shares of innovating firms for each industry to capture the displacement effect induced by industry technology shocks. Table 19 reports the cross-sectional regression results according to Equation 4.2.2 with various specifications. I retain only the NMI portfolios that contain at least five non-innovating firms and five innovating firms.

I perform regressions on the NMI industry portfolio returns with various specifications and report estimates of the main variables of interest in Table 19. Column (1) shows that the average displacement effect captured by the NMI return response to technology shocks
Empirical Results

is negative, but weakly significant. Columns (2)–(7) examine the differential displacement effect across industries with industry asset liquidity $Assetliq_{s,t}$, using the $SPPE$ rate, $ACQ$ rate and $REALLOC$ rate as proxies. Columns (2), (4) and (6) show the results for specifications without the control variables. Columns (3), (5) and (7) show the results for the specification of the full regression in Equation (4.2.2). The interaction term $A_{s,t}^m \times AssetLiq_{s,t}$ reduces the return gap between non-innovating and innovating firms with all three proxies of $AssetLiq_{s,t}$. This implies that non-innovating firms are more negatively affected by low asset liquidity. In addition, the overall displacement effect induced by technology shocks is strongest in industries with low asset reallocation (i.e., high reallocation frictions) and weakest in industries with high asset reallocation (i.e., low reallocation frictions). In line with the results of the non-innovating portfolios, the NMI return response to technology shocks associates strongly with the measures $SPPE$ and $REALLOC$, but weakly with $ACQ$.

Overall, the results provide supporting evidence for the model. I show that non-innovating firm stock prices respond most negatively to technology shocks in industries with high reallocation frictions and least negatively in industries with low reallocation frictions. In contrast, innovating firms stock prices appreciate in respond to technology shocks and the sensitivity does not vary with industry reallocation frictions. In addition, I find that non-innovating firms are more affected by reallocation frictions than innovating firms are when there is a technology shock.

5.4 Robustness

5.4.1 Placebo Tests

There are concerns that unobservable variables could drive both the technology shock measure and the portfolio returns, generating spurious results. The impact of the market-based measure
of technology shocks on the returns of the innovating firms could be overestimated in the regression analysis. This is because the proxy of technology shocks is constructed from the implied market value of patents, which are estimated from innovating firms’ daily abnormal returns around their patent granting dates. The reported negative effect of technology shocks on the returns of the non-innovating firms could be driven by a negative industry component in the technology shock measure. Following the method of KPSS, I extract the patent-related abnormal returns from the raw abnormal returns by excluding the estimated average noise term in firms’ idiosyncratic returns. Consequently, this filtering process may subtract a portion of industry average returns from the patent-related abnormal returns. In turn, the resulting measure of technology shocks may carry a component negatively related to industry average returns.

To address these concerns, I perform a set of placebo tests. I re-estimate each patent’s market value from its innovating firm’s abnormal returns, but randomly assign a non-patent granting date within the same year the patent is granted as if it is the true granting date for that patent. I then aggregate the patent values to the industry level and construct the arbitrary measure of technology shocks. The only difference between the arbitrary measure and the true measure of technology shocks is that the former excludes any abnormal returns that are related to the patent granting events. I then perform the set of regressions according to Equation (4.2.1) using the arbitrary measure, *ceteris paribus*. If the main results are driven by the reasons mentioned above, the arbitrary measure of technology shocks should produce similar results. I repeat the exercise 200 times and report the average estimates in Table 20.

[INSERT TABLE 20 HERE]

The placebo tests show that the main results documented are not driven by the two forces addressed above. The average estimates of the placebo tests are reported in Panel A for the non-innovating portfolios and Panel B for the innovating portfolios. The returns of
the non-innovating firms do not respond negatively to arbitrary technology shocks. Hence, the potential negative component of industry average returns does not significantly drive the results. In addition, the interaction terms between the asset turnover measures and the arbitrary technology measure also lose their explanatory power, as the demand for capital reallocation only increases when there is a true technology shock, and reallocation costs will only be important on that occasion. In terms of the innovating firms, their returns only weakly react to the arbitrary measure of technology shocks, even though the measure is constructed from a fraction of those firms’ daily returns.

5.4.2 Citation-Based Technology Shocks

I also construct a proxy of technology shocks from patent citations, which are widely used in the literature on innovation (Bloom and Van Reenen, 2002; Hall, Jaffe, and Trajtenberg, 2005, 2001). The citation-based measure of technology shocks $A_{c,t}$ weights each patent’s value according to the number of citations it receives. Citations are counted over a five-year window from the patent granting date.² In addition, I categorize firms into innovating portfolios only if they are granted a patent that receives at least one citation. Thus, firms that create unproductive patents are recognized as non-innovating firms. I perform same set of regressions on both non-innovating and innovating portfolio returns using the citation-based measure. The new proxy generates consistent results, summarized in Table 21.

[INSERT TABLE 21 HERE]

Panel A reports the regression results of the non-innovating portfolios. Columns (1) and (2) show that the average impact of technology shocks based citations is negative on non-innovating firms, both with and without controls. Column (3) and Column (4) show that

²The results are robust with three-year and ten-year citation windows. The choice of window length is discussed in Hall, Jaffe, and Trajtenberg (2001).
the magnitude of the technology shock’s value impact varies across the industry with industry asset liquidity when using the SPPE rate as the proxy. Consistent with the main test results, non-innovating firms respond most negatively to technology shocks in industries with zero SPPE turnover. An average citation-based technology shock is associated with a decrease in the value of non-innovating firms of 2% \((= 2.6 \times 0.008)\) in industries with zero SPPE, while the same shock would only lead to a 0.1% \((= -2 + 0.008 \times 0.017 \times 2.6)\) decrease in non-innovating firms’ value in industries with average liquidity. Column (5) and Column (6) report similar but weaker results, with ACQ being the proxy of asset liquidity. Columns (7) and (8) show that the sensitivity of non-innovating firms’ returns to technology shocks is associated with the total industry asset turnover, with and without controls.

Panel B reports the regression results of the innovating portfolios. As opposed to the findings on the non-innovating firms, innovating firms respond positively to technology shocks and their response is not affected significantly by all industry asset liquidity measures.

### 5.4.3 Asset Redeployability

Lastly, as another robustness check, I examine whether cross-industry asset redeployability affects firms’ exposure to technology shocks. In my model, capital reallocation only take places between non-innovating firms and innovating firms within an industry. My model remains silent on cross-industry capital reallocations. In reality, non-innovating firms can also sell used assets to industry outsiders, especially when the new technology requires completely different new capital. According to Kim and Kung (2014), cross-industry asset redeployability is also important for investment decisions, especially under high aggregate economic uncertainty. The asset redeployability measure is adopted as the proxy of cross-industry asset reallocation frictions. The results are displayed in Table 22. They are consistent with the findings using the asset liquidity measure. For both measures of innovation, industry
Empirical Results

Asset redeployability is important for non-innovating firms as it reduces the destructive effect of technology shocks. However, asset redeployability is not important for innovating firms. Table 23 shows the impact of asset redeployability on the NMI portfolio returns. Technology shocks negatively affect returns of the NMI portfolios at 10%, and the magnitude of this displacement effect varies weakly with industry asset redeployability.

Table 23 shows the impact of asset redeployability on the NMI portfolio returns. Technology shocks negatively affect returns of the NMI portfolios at 10%, and the magnitude of the displacement effect varies weakly with industry asset redeployability.

5.5 Summary

In this chapter, I empirically test the interactive effect of technology shocks and capital reallocation frictions on portfolio returns. I construct innovation measures using the market-implied value of patents and their future citations. In addition, I use asset liquidity and asset redeployability to measure the intensity of capital reallocation frictions, following Kim and Kung (2014). I perform cross-sectional tests on the returns of non-innovating and innovating firms. I show that technology shocks alone will not necessarily cause value destruction for non-innovating firms; but rather, the effect depends on the efficiency of capital reallocation. Furthermore, by constructing NMI industry portfolios through holding shares of non-innovating firms and selling shares of innovating firms, I find that the return dispersions are significantly and negatively affected by technology shocks. This confirms the displacement effect predicted by Schumpeterian growth theory. In addition, this displacement
effect varies with the measures of capital reallocation frictions. This also suggests that non-innovating firms suffer from reallocation costs more than innovating firms do. The empirical findings reported in this chapter are consistent with the model’s predictions.
Chapter 6

Conclusion

6.1 Chapter Summary

6.1.1 Chapter 2

Chapter 2 reviews three strands of literature related to this thesis: i) capital reallocation frictions in the secondary asset market and its impact on real investment and external financing; ii) developments in the endogenous growth theory; and iii) asset pricing implications of technology shocks. The review provides a background for the asset implications of real economic activities and the role of capital reallocation frictions.

Capital reallocation is economically significant, but costly and slow. The main source of friction is from the trading and information costs incurred when used assets are traded. Search friction is determined by market thickness and occurs when buyers and sellers of used assets incur monetary and time costs to optimally match with their counterparties. Informational friction arises when the quality of assets is uncertain in the secondary market, and the bad drives out the good. Together, these frictions depress the market price of used assets and slow the reallocation process.
Frictions in capital reallocation make investment partially irreversible and debt financing more costly. Under uncertainty, partially irreversible investment are more likely to be delayed. In addition, physical assets are often used as collateral for debt financing. Assets that are hard to resold has low collateral value, hence reduce firms’ debt financing ability and increases firms financial constraint. For these reason, frictions can affect firm values those their impact on investment and financial decisions. But existing literature has only documented weak empirical evidence.

This thesis explores the interactive effect of reallocation frictions and technology shocks on stock returns. The endogenous growth theory provides the background that links these two processes. New technology benefits innovating firms at the expense of non-innovating firms. The dispersion in firm productivity introduced by a technology shock creates an incentive to reallocate resources, including physical capital. Studies show that resource reallocation is strongly associated with technology adoption and economic growth.

The creative destruction effect of a technology shock also has implications for a firm’s assets. Empirically, large movements in the stock markets are associated with major technology advances. Theoretically, the creative destruction effect of technology reduces consumption in the short term for various reasons, and leads to high marginal utility of consumption. As a result, technology shocks generate a negative risk premium and increases the discount rates of non-innovating firms, which are negatively affected by such shocks.

Given the important role of capital reallocation in the technology adoption process, the efficiency of capital reallocation frictions should affect how technology shocks are priced in financial markets. This thesis explores this question using a simple model and empirical tests.
6.1.2 Chapter 3

This chapter uses a two-period general equilibrium model to show the effect of capital reallocation frictions on stock prices. I illustrate the rationale with both an analytical solution and a numerical example. The model describes a production economy with a final goods sector and an intermediate goods sector. The final goods sector has a representative firm. The intermediate goods sector starts with one firm, which does not innovate. With some positive probability, a second type of firm with an innovation enters the market in the next period. After adopting the new technology, the innovating firm has higher productivity capital than the non-innovating firm does.

I show that the impact of technology shocks on cross-sectional returns have two facets. First, when a technology shock arrives the creative destruction effect leads to a positive return for the innovating firm and a negative return for the non-innovating firm. Second, the diminution in the non-innovating firm’s value induced by the technology shock is large when reallocation frictions increase, as these frictions inhibit the non-innovating firm’s ability to sell unproductive capital and exit the market. Reallocation frictions can also erode the innovating firm’s incremental value added after adopting the new technology. However, the effect of reallocation frictions on the innovating firm’s return is small, as innovating firms can make new investment to grow.

In addition, I show that capital reallocation frictions amplify the risk premia in the non-innovating firm’s stock returns for a technology shock. A technology shock creates a negative price of risk even in a frictionless world, as it boosts investment by sacrificing short-term consumption, leading to a state of high marginal utility of consumption. Capital reallocation frictions increase the demand for investment and further drive short-term consumption down. As a result, investors demand a higher risk premia of the non-innovating firm’s shares when reallocation frictions are high. In this case, the return of the non-innovating firm is more
negative when the technology shock realizes, while at the same time the marginal utility of consumption is also very high.

6.1.3 Chapter 4

In this chapter I first develop hypotheses and regression specifications to empirically test the model. I then construct the measures of technology shocks and capital reallocation frictions. I also test the quality of the measures and the descriptive statistics of the sample.

I test the model at the industry level. I use the interactive term of technology shocks and industry capital reallocation frictions to capture the impact of reallocation frictions on firms’ return exposure to technology shocks. I also separate firms into non-innovating portfolios and innovating portfolios to capture the creative destruction effect of technology shocks. For each industry, I split firms into a non-innovating portfolio and an innovating portfolio, based on whether the firm possesses a productive patent.

I use patent data to construct proxies of real technology shocks. I use the implied market values of the patents and their forward citations to account for heterogeneity among them. The market values of the patents are estimated from the patent-related abnormal returns of firms around their patent granting dates. I follow the method of KPSS to filter out average non-patent-related noise in firms’ returns. For citations, I count the number of citations received by each patent with a five-year after the granting date. I construct the technology shock measure by aggregating all the patent market values or citation counts at the industry level.

I use asset liquidity and asset redeployment to measure the size of industry capital reallocation frictions. For asset liquidity, I compute the asset turnover rates using the SPPE, acquisition, and the sum of these two variables. The asset redeployability measure estimates how commonly an industry’s capital is used by other industries. The measure hence mainly
captures cross-industry capital reallocation frictions. I use BEA’s capital flow table to compute the asset redeployability measure.

6.1.4 Chapter 5

In this chapter, I examine the industry characteristics that relate to capital reallocation frictions measured by industry asset liquidity and asset redeployability. I show that industries with high asset turnover and redeployability have low R&D expenditure and capital intensity, and high investment expenditure and growth opportunities. In addition, the industry dispersion in firms’ growth opportunities and profitability is also associated with the asset liquidity measures and the asset redeployability measure.

Next, I perform cross-sectional tests on the returns of non-innovating and innovating firms separately. I show that technology shocks alone will not necessarily cause value destruction for non-innovating firms; but rather, the effect depends on the efficiency of capital reallocation. In particular, using the SPPE measure of asset liquidity, I find that the non-innovating firms in industries with zero asset liquidity respond negatively to technology shocks by twice as much as the non-innovating firms in industries with median asset liquidity. The result provides supporting evidence of the model and highlights the interactive effect of capital reallocation frictions and technology shocks on the cross-sectional returns. In contrast, I find that innovating firms’ stock returns respond positively to technology shock but do not vary with industry asset liquidity or redeployability.

Furthermore, by constructing NMI industry portfolios through holding shares of non-innovating firms and selling shares of innovating firms, I find that the return dispersions between non-innovating and innovating firms are negatively affected by technology shocks. This confirms the displacement effect predicted by Schumpeterian growth theory. In addition, the effect varies with the measures of capital reallocation frictions. This also suggests that
non-innovating firms suffer from reallocation costs more than innovating firms do. The empirical findings reported in this chapter are consistent with the model’s predictions.

6.2 Limitations and Future Research

There are several limitations in my thesis that I would like to acknowledge. First, the model uses a static setup. Both the analytical solutions and the numerical example can provide only qualitative rather than quantitative predictions about the interactive effect of capital reallocation frictions and technology shocks on the cross-sectional returns. The difficulty of extending the model to the dynamic version is that the timing of technology shocks affects the path of capital evolution. The distribution of capital between the non-innovating firm and the innovating firm depends on when the technology shock arrives and the level of existing capital stock at the time the technology shock arrives. Hence, the economy has a path-dependent production tree and the number of possible states expands exponentially.

Most existing studies of the asset pricing implications of technology shocks isolate the capital accumulation process from the technological progress (e.g. Bena, Garlappi, and Grüning, 2014; Kung and Schmid, 2015). In their models, capital accumulation occurs in the final goods sector and technology shocks take place in the intermediate sector. With this setup, technology shocks would affect the productivity of all existing capital. One exception is Kogan, Papanikolaou, and Stoffman (2013) who examine the technology adoption process in capital accumulation and emphasize that new technologies only enhance the productivity of capital that embeds these technologies. However, they assume that the optimal investment for each innovation project is chosen once and completely irreversible. My study focuses on the interaction of technology adoption and capital accumulation, in particular the capital reallocation process. In my model, I allow firms to adjust their capital stock over time and model the reallocation of capital among firms. The path-dependent distribution of capital
stock among firms would complicate the analysis when the model is extended to a dynamic setup.

Second, I use the additive log utility function to simplify the household’s problem in the model. The log utility function can only generate a small risk equity premium as it assumes a small risk aversion. The equity premium in the historical data implies a much higher risk aversion or a different specification of utility function. Existing asset pricing literature shows that the recursive utility function (e.g. Bansal and Yaron, 2004) or habit utility (e.g. Campbell and Cochrane, 1999) are more plausible in matching the moments of historical stock returns. These assumptions of utility functions are important if future research can extend the model to a dynamic version and attempt to quantitatively measure the interactive effect of capital reallocation frictions and technology shocks.

Furthermore, the prediction of a negative price of risk of technology shocks may rely on the form of the household’s utility function, as the sign of the price of risk depends on the household’s attitudes towards consumption smoothing across states versus consumption smoothing over time (i.e. the relative size of risk aversion versus the elasticity of intertemporal substitution, EIS). To better understand the risk premium of technology shocks, a model extended with Epstein-Zin preferences is needed to examine the relative impact of risk aversion and EIS on the pricing of technology shocks.

In addition, I have only examined the cross-sectional effect of reallocation frictions on return responses to technology shocks in my empirical analysis, and have not investigated the impact of reallocation frictions on the pricing kernel. On the latter, the model predicts that the size of reallocation frictions should affect both firms’ exposure to technology shocks as well as the magnitude of risk premium generated by the aggregate technology shocks. The ability to test the pricing kernel effect here is limited since I only use U.S. data, and since one economy has only one universal pricing kernel which captures the average effect of industry
reallocation frictions. Further research may be extended to cross-country analyses to explore the pricing kernel effect of reallocation frictions.

Future work could also explore the impact of capital age on firms’ exposure to technology shocks. The current empirical tests rely on the assumption that industries differ in their reallocation frictions. Capital age is another dimension along which the intensity of frictions could differ, since informational frictions increase with capital age due to larger dispersions in quality (e.g. Bond, 1983). This implies that the returns of firms with older vintage capital may respond more negatively to technology shocks. This is an area worth investigating and I leave it for future research.
Figure 1 The Cumulative Stock Returns of Four Mobile Phone Suppliers for the Period 2007–2014

Figure 1 is retrieved from Google finance. It plots the cumulative stock returns of Apple Inc. (APPL), Samsung Electronics (005935), Nokia Corporation (NOK) and Blackberry Ltd (BBRY) from June 29, 2007 to December 31, 2014. On June 29, 2007, Apple released its first generation of iPhone. Shares of Apple Inc. is traded at NYSE. Share of Blackberry Ltd is traded at NASDAQ. Share of Samsung is traded at Korea stock market. The returns of Nokia showed in the graph is the ADR returns of Nokia traded in NYSE. The red line presents the return time series of Apple. The blue line presents the return time series of Samsung. The green line presents the return time series of Nokia. The yellow line presents the return time series of Blackberry.
Figure 2 The Cumulative Stock Returns of Nokia and Blackberry from April 2013 to December 2014

Figure 2 is retrieved from Google finance. It plots the cumulative stock returns of Nokia Corporation (NOK) and Blackberry Ltd (BBRY) from April 1, 2013 to December 31, 2014. On September 3, 2013, the Microsoft firstly announce their purchase plan of Nokia’s mobile phone business. The blue line presents the return time series of Nokia. The red line presents the return time series of Blackberry. The shaded area highlights the first month after the first announcement of acquisition plan.
Figure 3 describes the timeline of the intermediate sector. At time 0, there is only a non-innovating firm called firm $L$. At time 1, with probability of $\theta$, a new innovating firm with a new technology enters the sector. It has higher productivity and is called firm $H$. If there is no technology shock, the non-innovating firm continues to be the sole supplier of intermediate goods at time 1 and 2. The economy terminates at time 2.
Figure 4 The Impact of Capital Reallocation Frictions on Stock Returns

The x-axis is the friction measure $\log(\gamma)$. The y-axis is the excess returns. The blue line plots the returns when there is a technology shock, and the red line plots the return when there is no shock. Panel a plots the return of the non-innovating firm. Panel b plots the return of the innovating firm.

Figure plots the impact of capital reallocation frictions on firms’ excess returns over risk free rate $R_{jt} = r_{jt} - r^f_t$. The x-axis is the friction measure $\log(\gamma)$. The y-axis is the excess returns. The blue line plots the returns when there is a technology shock, and the red line plots the return when there is no shock. Panel a plots the return of the non-innovating firm. Panel b plots the return of the innovating firm.
Figure 5 The Impact of Frictions on Capital Reallocation and Investment

Figure plots the impact of reallocation frictions on capital reallocation rate \( N_1 / K_{L,1} \) at time 1, capital distribution \( z = \frac{K_{L,2}}{K_{L,2} + K_{H,2}} \) at time 2 and investment rate \( I_t / K_{L,t} \) at time 0 and 1. The x-axis is the friction measure \( \log(\gamma) \). The blue line plots the quantities when there is a technology shock, and the red line plots the quantities when there is no shock.
Figure 6 The Stochastic Discount Factor and its Covariances with Firm Returns

Figure plots the risk implications of the capital reallocation frictions. The x-axis is the friction measure $\log(\gamma)$. Panel a plots the consumption growth $cg_1$ over period 1. Panel b plots the stochastic discount factor $m_1$ over period 1. The blue line plots the quantities when there is a technology shock, and the red line plots the quantities when there is no shock. Panel c plots the covariance of the non-innovating firm’s returns and the stochastic discount factor. Panel d plots the covariance of the innovating firm’s returns and the stochastic discount factor.
Figure 7 The Impact of Innovation Size on the Marginal Value of the Non-innovating Firm’s Capital at Time 1 if there is a Technology Shock

Figure plots the impact of the innovation size and reallocation frictions on the non-innovating firm’s capital value. The x-axis is the friction measure $\log(\gamma)$ and y-axis is the marginal value of the non-innovating firm’s capital at time 1 if there is a technology shock. The set of innovation size is $\eta_1 = [1.1, 1.15, 1.2, 1.25]$. 

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Figure 8 The Impact of Reallocation Frictions and Innovation Size on Stock Returns

Figure plots the interactive effect of capital reallocation frictions and the innovation size on firm’s excess returns over period 1, if there is a technology shock at time 1. The x-axis is the friction measure $\log(\gamma)$. Each curve represents the returns using a different value of innovation size. $\bar{\eta}_1 = [1.1, 1.15, 1.2, 1.25]$. Their corresponding line colors are blue, red, yellow and purple. The gray arrow points upward if the variable values increases monotonically with the innovation size, vice versa.
Figure 9 The Impact of Reallocation Frictions and Innovation Size on Capital Reallocation and Investment

Figure plots the interactive effect of reallocation frictions and the innovation size on capital reallocation rate $N_1/K_{L,1}$ at time 1, capital distribution $z = K_{L,2}/(K_{L,2} + K_{H,2})$ at time 2 and investment rate $I_t/K_{L,t}$ at time 0 and 1, if there is a technology shock. The x-axis is the friction measure log(γ). The x-axis is the friction measure log(γ). Each curve represents a different value of innovation value, $\eta_1 = [1.1, 1.15, 1.2, 1.25]$. Their corresponding line colors are blue, red, yellow and purple. The gray arrow points upward if the variable values increases monotonically with the innovation size, vice versa.
Figure 10 The Impact of Reallocation Frictions and Innovation Size on Risk

- **Panel a:** Consumption growth over period 1 if there is a technology: \( cg_U \)
- **Panel b:** Discount factor if there is a technology shock: \( m_U \)
- **Panel c:** Covariance of the non-innovating firm’s returns and the stochastic discount factor.
- **Panel d:** Covariance of the innovating firm’s returns and the stochastic discount factor.

Each curve represents a different value of innovation value, \( \bar{\eta} = [1.1, 1.15, 1.2, 1.25] \). Their corresponding line colors are blue, red, yellow, and purple. The gray arrow points upward if the variable values increases monotonically with the innovation size, vice versa.
Figure 11 The Impact of Reallocation Frictions and Innovation Probability on Stock Returns

Figure plots the interactive effect of the reallocation frictions and the innovation probability on firms’ excess returns over period 1, if there is a technology shock at time 1. The x-axis is the friction measure $\log(\gamma)$. Each curve represents a different value of innovation probability, $\theta = [0.06, 0.08, 0.1, 0.12]$. The corresponding line colors are blue, red, yellow and purple. The gray arrow points upward if the variable values increases monotonically with the innovation probability, vice versa.
Figure 12 The Impact of Reallocation Frictions and Innovation Probability on Capital Reallocation and Investment

Figure plots the interactive effect of the reallocation frictions and the innovation probability on capital reallocation rate $N_1/K_{L,1}$ at time 1, capital distribution $z = \frac{K_{L,2}}{K_{L,1} + K_{H,2}}$ at time 2 and investment rate $I_i/K_{L,i}$ at time 0 and 1, if there is a technology shock. The x-axis is the friction measure $\log(\gamma)$. Each curve represents a different value of innovation probability. $\theta = [0.06, 0.08, 0.1, 0.12]$. The corresponding line colors are blue, red, yellow and purple. The gray arrow points upward if the variable values increases monotonically with the innovation probability, vice versa.
Figure 13: The Impact of Reallocation Frictions and Innovation Probability on Risk

Figure plots the risk implications of the capital reallocation frictions and the innovation probability on the stochastic discount factor and its covariances with firm returns. The x-axis is the friction measure $\log(\gamma)$. The x-axis is the friction measure $\log(\gamma)$. Panel a plots the consumption growth $c_{g1}$ over period 1 and panel b plots the discount factor $m_1$ over period 1, if there is a technology shock. Panel c plots the covariance of the non-innovating firm’s returns and the stochastic discount factor. Panel d plots the covariance of the innovating firm’s returns and the stochastic discount factor. Each curve represents a different value of innovation probability, $\theta = [0.06, 0.08, 0.1, 0.12]$. The corresponding line colors are blue, red, yellow and purple. The gray arrow points upward if the variable values increases monotonically with the innovation probability, vice versa.
Figure 14 The Impact of Capital Reallocation Frictions and Transformation Rate on Stock Returns

**a. Excess return of the non-innovating firm**
in respond to a technology shock over period 1: $R_{L,1}^U$

**b. Excess return of the innovating firm**
in respond to a technology shock over period 1: $R_{H,1}^U$

Figure plots the interactive effect of the capital reallocation frictions and the transformation rate on firms’ excess returns over risk free rate over period 1, if there is a technology shock. The x-axis is the friction measure $\log(\gamma)$. Each curve represents a different value of transformation rate. $\psi = [0.8, 0.867, 0.933, 1]$. The corresponding line colors are blue, red, yellow and purple. The gray arrow points upward if the variable values increases monotonically with the transformation rate, vice versa.
Figure 15 The Impact of Reallocation Frictions and Transformation Rate on Capital Reallocation and Investment

Figure plots the interactive effect of the capital reallocation frictions and the transformation rate on capital reallocation rate $N_1/K_{L,1}$ at time 1, capital distribution $z = K_{L,2}/(K_{L,2} + K_{H,2})$ at time 2 and investment rate $I_t/K_{L,t}$ at time 0 and 1, if there is a technology shock. The x-axis is the friction measure $\log(\gamma)$. Each curve represents a different value of transformation rate. $\psi = [0.8, 0.867, 0.933, 1]$. Their corresponding line colors are blue, red, yellow and purple. The corresponding line colors are blue, red, yellow and purple. The gray arrow points upward if the variable values increases monotonically with the transformation rate, vice versa.
Figure 16 The Impact of Reallocation Frictions and Transformation Rate on Risk

Figure plots the risk implications of the capital reallocation frictions and the transformation rate on firms’ exposure to technology shock. The x-axis is the friction measure $\log(\gamma)$. The x-axis is the friction measure $\log(\gamma)$. Panel a plots the consumption growth $c_{g1}$ over period 1 and panel b plots the discount factor $m_{1}$ over period 1, if there is a technology shock. Panel c plots the covariance of the non-innovating firm’s returns and the stochastic discount factor. Panel d plots the covariance of the innovating firm’s returns and the stochastic discount factor. Each curve represents a different value of transformation rate. $\psi = [0.8, 0.867, 0.933, 1]$. The corresponding line colors are blue, red, yellow and purple. The gray arrow points upward if the variable values increases monotonically with the transformation rate, vice versa.
Figure 17 The Aggregate Innovations from 1926 to 2010

Figure plots the aggregate market-based innovation measure and the citation-weighted innovation measure in solid blue line and dashed red line, respectively. The market-based innovation measure is computed from the sum of all patent market values scaled by the beginning-of-year total market capitalization. The citation-weighted innovation measure is computed as the total patent counts weighted by five-year forward citations.
Table 1 Parameter Values in the Benchmark Numerical Example

<table>
<thead>
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<th>Parameters</th>
<th>Value</th>
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<tr>
<td>Share of Intermediate goods $\alpha$</td>
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<tr>
<td>Subjective discount factor $\beta$</td>
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<tr>
<td>Depreciation rate $\delta$</td>
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</tr>
<tr>
<td>Firm productivity of the non-innovating firm $A_L$</td>
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</tr>
<tr>
<td>Step size of innovation $\eta$</td>
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</tr>
<tr>
<td>Probability of technology shock $\theta$</td>
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</tr>
<tr>
<td>Transformation rate $\psi$</td>
<td>1</td>
</tr>
<tr>
<td>Size of reallocation frictions $\gamma$</td>
<td>$[e^{-1.15}, e^7]$</td>
</tr>
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</table>
Table 2 Summary Statistics

This table reports aggregate statistics of patents from different patent data sources. The first panel use data from USPTO Patent Statistics. It provides annual number of utility patents owned by different entities. The second panel is for “KPSS data”, which is constructed by Kogan, Papanikolaou, Seru, and Stoffman (2012). It is the data employed in the main analysis of this study. The thrid panel is for “NBER data”, which is constructed by Hall, Jaffe, and Trajtenberg (2001). Patent Granted is total number of utility patents granted during the given sample periods (including patents granted both to U.S. and foreign innovators). US Origin is utility patents granted to U.S. innovators (including U.S. corporation, U.S. individual, U.S. government). US Corp is utility patents granted to U.S. corporations. Patents with Permno is utility patents in KPSS or NBER data with a matching permno code to CRSP. The percentage share of total patents owned by each group is reported under its corresponding patent counts.

<table>
<thead>
<tr>
<th></th>
<th>1. USPTO Patent Statistics</th>
<th>2. KPSS data</th>
<th>3. NBER data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Patents Granted</td>
<td>US Origin</td>
<td>US Corp</td>
</tr>
<tr>
<td>Sample period: 1987-2010</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>No. of patents granted</td>
<td>3,208,569</td>
<td>1,734,285</td>
<td>1,408,527</td>
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<tr>
<td>% of total patent granted</td>
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<td>0.44</td>
<td>0.36</td>
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<tr>
<td>Sample period: 1976-2006</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>No. of patents granted</td>
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<td>1,414,474</td>
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<tr>
<td>% of total patent granted</td>
<td>0.57</td>
<td>0.44</td>
<td>0.35</td>
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</table>
Table 3 Estimation of the Patent Signal-to-noise Ratio

Reported are the regression results of equation (4.4.2): $\ln(r_{jd}^j)^2 = a_0 + b_d + a_{j,t} + \gamma I_{j,d} + \mu_{j,t}$, where $I_{j,d}$ is a dummy variable equals to one when it is a patent-granting day for firm $j$. The control variables are the weekday effect and the firm-year fixed effect. They are denoted as $b_d$ and $a_{j,t}$, respectively. $\hat{\lambda}$ is the average signal-to-noise ratio, and is computed from equation (4.4.3):

$$\hat{\lambda} = 1 - \left(1 + \frac{1}{\phi(0)} \left( e^{\hat{\gamma}} - 1 \right) \right)^{-1}.$$

<table>
<thead>
<tr>
<th></th>
<th>Coefficients</th>
<th>t-stat</th>
<th>95% Conf. Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_{jd}$</td>
<td>0.020</td>
<td>6.28</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.026</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weekday effect $b_d$</td>
<td>$Y$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm-year fixed effect $a_{j,t}$</td>
<td>$Y$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\hat{\lambda}$</td>
<td>0.053</td>
<td>0.036</td>
<td>0.068</td>
</tr>
</tbody>
</table>
### Table 4 Distributions of Market-implied Patent Value and Citations

Reported are summary statistics of patents. $r_{j,d}^f$ is the raw idiosyncratic returns around patent granting day. $E[x_{j,d}]$ is the filtered patent-related return. $\hat{A}_i$ is the value of patent $i$. $C_i$ is total citation received by patent $i$ by 2010. All returns statistics are reported in percentage points. $C^5_i$ is the number of citations received by patent $i$ within five years after its grant. For five-year forward citation counts $C^5_i$, patents granted after 2006 are excluded due to sample truncation. Panel A and panel B report statistics for the testing sample period and the full patent data sample period, respectively.

#### Panel A: The Testing Sample Period: 1987 to 2010

<table>
<thead>
<tr>
<th>Moment</th>
<th>$r_{j,d}^f$</th>
<th>$E[x_{j,d}]$</th>
<th>$\hat{A}_i$</th>
<th>$C_i$</th>
<th>$C^5_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.08</td>
<td>0.68</td>
<td>11.56</td>
<td>11.24</td>
<td>4.48</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>4.44</td>
<td>0.42</td>
<td>16.45</td>
<td>23.09</td>
<td>6.88</td>
</tr>
<tr>
<td>Nobs</td>
<td>1,086,003</td>
<td>1,077,318</td>
<td>1,077,299</td>
<td>1,093,888</td>
<td>8,407,91</td>
</tr>
</tbody>
</table>

| Percentiles | |
|-------------|-------------|------------|------|--------|
| 99%    | 12.94       | 2.24       | 138.73   | 105.00 | 33   |
| 95%    | 6.44        | 1.45       | 45.91    | 45.00  | 16   |
| 90%    | 4.28        | 1.16       | 25.33    | 28.00  | 11   |
| 75%    | 1.82        | 0.80       | 9.91     | 12.00  | 6    |
| 50%    | -0.08       | 0.57       | 3.36     | 4.00   | 2    |
| 25%    | -1.84       | 0.42       | 0.38     | 1.00   | 1    |
| 10%    | -3.98       | 0.33       | 0.05     | 0.00   | 0    |
| 5%     | -5.86       | 0.29       | 0.02     | 0.00   | 0    |
| 1%     | -11.36      | 0.23       | 0.01     | 0.00   | 0    |

#### Panel B: The Full KPSS Sample: 1926 to 2010

<table>
<thead>
<tr>
<th>Moment</th>
<th>$r_{j,d}^f$</th>
<th>$E[x_{j,d}]$</th>
<th>$\hat{A}_i$</th>
<th>$C_i$</th>
<th>$C^5_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.066</td>
<td>0.602</td>
<td>8.895</td>
<td>9.891</td>
<td>2.99021974</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>3.931</td>
<td>0.383</td>
<td>27.384</td>
<td>19.951</td>
<td>5.50</td>
</tr>
<tr>
<td>Nobs</td>
<td>1,820,576</td>
<td>1,808,488</td>
<td>1,808,271</td>
<td>1,927,579</td>
<td>1,647,911</td>
</tr>
</tbody>
</table>

| Percentiles | |
|-------------|-------------|------------|------|--------|
| 99%    | 11.53       | 2.03       | 104.23  | 90.00 | 25   |
| 95%    | 5.74        | 1.29       | 32.82   | 37.00 | 12   |
| 90%    | 3.83        | 1.00       | 18.97   | 24.00 | 8    |
| 75%    | 1.63        | 0.71       | 7.83    | 11.00 | 4    |
| 50%    | -0.09       | 0.50       | 2.79    | 4.00  | 1    |
| 25%    | -1.68       | 0.38       | 0.65    | 1.00  | 0    |
| 10%    | -3.57       | 0.29       | 0.10    | 0.00  | 0    |
| 5%     | -5.16       | 0.25       | 0.04    | 0.00  | 0    |
| 1%     | -9.96       | 0.20       | 0.01    | 0.00  | 0    |
Table 5 The Linear Relation between the Market Implied Patent Value and the Forward Citation Counts

Reported are regression results from regression equation: $ln(1 + C_{i}^5) = a_0 + a_1ln(1 + A_i) + Z_{it}$. The regression examines the linear relation between the estimation of the market-implied patent value and the five-year forward citation counts. $A_i$ is the patent value in 1982 U.S. billion dollars. $C_{i}^5$ denotes five-year forward citation counts. $Z_{it}$ are control variables including firm’s log idiosyncratic volatility ($ivol$), log firm size ($Size$) and log number of patent granted received by firm $j$ on the same day $gday$. Patent class $C$ and patent granting year $T$, as well as receiving firm $F$ fixed effect are also controlled as fixed effect in column 4. Patent class is based on the primary class code from the U.S. Patent Grant Master Classification File (MCF). Standard errors are clustered by patent granting year and are reported in parenthesis. Patent granted after 2006 are excluded from this test for truncation issue inherited by the five-year forward citation counts $C_{i}^5$. Panel A and panel B display regression results for the testing sample period and the full patent data sample period, respectively. *,**, and *** signify results significant at the 10, 5, and 1% levels, respectively.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent: log(1 + C_{i}^5)</td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>$log(1 + \hat{A}_i)$</td>
<td>0.028***</td>
<td>0.016***</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.023</td>
<td>0.044</td>
</tr>
<tr>
<td>NObs</td>
<td>752,572</td>
<td>752,572</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
</tr>
<tr>
<td>iVol</td>
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<td>Y</td>
</tr>
<tr>
<td>Size</td>
<td>-</td>
<td>Y</td>
</tr>
<tr>
<td>gday</td>
<td>-</td>
<td>Y</td>
</tr>
<tr>
<td>Fixed-Effect</td>
<td>T</td>
<td>T</td>
</tr>
<tr>
<td>Dependent: log(1 + C_{i}^5)</td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>$log(1 + \hat{A}_i)$</td>
<td>0.021***</td>
<td>-0.023***</td>
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<tr>
<td>$R^2$</td>
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<td>0.264</td>
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<td>1,399,225</td>
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<tr>
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<tr>
<td>Size</td>
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<td>Y</td>
</tr>
<tr>
<td>gday</td>
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<td>Y</td>
</tr>
<tr>
<td>Fixed-Effect</td>
<td>T</td>
<td>T</td>
</tr>
</tbody>
</table>
Table 6 The Nonlinear Relation between the Market Implied Patent Value and the Forward Citation Counts

Reported are regression results from regression equation: \( C_i^5 = a_0 + a_1A_i + a_2A_i^2 + Z_{i,t} \). The regression examines the nonlinear relation between the estimation of the market-implied patent value and the five-year forward citation counts. \( A_i \) is the patent value in 1982 U.S. billion dollars. \( A_i^2 \) is the squared term of patent value \( A_i \). \( C_i^5 \) denotes five-year forward citation counts. \( Z_{i,t} \) are control variables including firm’s log idiosyncratic volatility (ivol), log firm size (Size) and log number of patent granted received by firm \( j \) on the same day \( gday \). Patent class \( C \) and patent granting year \( T \), as well as receiving firm \( F \) fixed effect are also controlled as fixed effect in column 4. Patent class is based on the primary class code from the U.S. Patent Grant Master Classification File (MCF). Standard errors are clustered by patent granting year and are reported in parenthesis. Patent granted after 2006 are excluded from this test for truncation issue inherited by the five-year forward citation counts \( C_i^5 \). Panel A and panel B display regression results for the testing sample period and the full patent data sample period, respectively. *, **, and *** signify results significant at the 10, 5, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>Panel A: The Testing Sample Period: 1987 to 2006</th>
<th>Dependent: ( C_i^5 )</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \hat{A}_i )</td>
<td>10.183***</td>
<td>4.514***</td>
<td>5.411***</td>
<td>2.380**</td>
<td></td>
</tr>
<tr>
<td>( \hat{A}_i^2 )</td>
<td>( -4.578*** )</td>
<td>( -1.565*** )</td>
<td>( -2.108*** )</td>
<td>( -1.494*** )</td>
<td></td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.016</td>
<td>0.035</td>
<td>0.120</td>
<td>0.389</td>
<td></td>
</tr>
<tr>
<td>NObs</td>
<td>752,572</td>
<td>752,572</td>
<td>752,572</td>
<td>752,572</td>
<td></td>
</tr>
<tr>
<td>Controls</td>
<td>iVol</td>
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<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td></td>
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<tr>
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<td>gday</td>
<td>-</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Fixed-Effect</td>
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<td></td>
<td>T</td>
<td>TxC</td>
<td>TxC,F</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: The Full Patent Sample: 1926 to 2006</th>
<th>Dependent: ( C_i^5 )</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \hat{A}_i )</td>
<td>10.087***</td>
<td>2.370***</td>
<td>5.259***</td>
<td>2.341**</td>
<td></td>
</tr>
<tr>
<td>( \hat{A}_i^2 )</td>
<td>( -3.925*** )</td>
<td>0.186</td>
<td>( -1.995*** )</td>
<td>( -1.461*** )</td>
<td></td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.117</td>
<td>0.130</td>
<td>0.209</td>
<td>0.457</td>
<td></td>
</tr>
<tr>
<td>NObs</td>
<td>1,399,225</td>
<td>1,399,225</td>
<td>1,399,225</td>
<td>1,399,225</td>
<td></td>
</tr>
<tr>
<td>Controls</td>
<td>iVol</td>
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<td>Y</td>
<td>Y</td>
<td>Y</td>
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<tr>
<td></td>
<td>Size</td>
<td>-</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td></td>
<td>gday</td>
<td>-</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Fixed-Effect</td>
<td></td>
<td></td>
<td>T</td>
<td>TxC</td>
<td>TxC,F</td>
</tr>
</tbody>
</table>
Table 7 Summary Statistics of Firm-Level Innovations

Reported are summary statistics of firm-level innovation measures. $r_{j,t}^j$ is the raw idiosyncratic returns around patent granting day. Panel 1 and panel 2 are statistics for the testing sample period and the full patent data sample period, respectively. $n_{j,t}$ is the number of patent received by firm $j$ in year $t$. $\hat{A}_{j,t}^m$ is the market-based innovation measure, which the sum of the values of all patents received by firm $j$ in year $t$ and scaled by the beginning-of-year market capitalization of firm $j$ (i.e. $\hat{A}_{j,t}^m = \sum_{i \in P_{j,t}} \hat{A}_t^i / S_{j,t-1}$). $\hat{A}_t^c$ is citation-weighted innovation measure (i.e. $\hat{A}_t^c = \ln(1 + \sum_{i \in P_{j,t}} C_5^i)$). total citation received by patent $i$ by 2010. $C_5^i$ is the number of citations received by patent $i$ within five years after its grant. Observations of patents granted after 2006 are excluded due to sample truncation issue.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$n_{j,t}$</td>
<td>$\hat{A}_{j,t}^m$</td>
<td>$\hat{A}_t^c$</td>
</tr>
<tr>
<td>Mean</td>
<td>8.83</td>
<td>0.02</td>
</tr>
<tr>
<td>Std</td>
<td>84.10</td>
<td>0.07</td>
</tr>
<tr>
<td>Nobs</td>
<td>119,724</td>
<td>108,769</td>
</tr>
<tr>
<td>95% Percentiles</td>
<td>17</td>
<td>0.13</td>
</tr>
<tr>
<td>90%</td>
<td>5</td>
<td>0.06</td>
</tr>
<tr>
<td>75%</td>
<td>1</td>
<td>0.01</td>
</tr>
<tr>
<td>50%</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>25%</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10%</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5%</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Table 8 Measures of Innovation at Industry Level (SIC three-digit)

Reported are innovation measures at industry level based on SIC three-digit industry classification. Panel A shows the descriptive statistics of patent counts, market-based and citation-weighted innovation measures and R&D intensity. Panel B lists the most and least innovative industries according to the market-based innovation measure $A^m_s$ and the citation-weighted innovation measure $A^c_s$.

Panel A : Descriptive Statistics

<table>
<thead>
<tr>
<th>Moments</th>
<th>$n_s$</th>
<th>$A^m_s$</th>
<th>$A^c_s$</th>
<th>$R&amp;D_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>165</td>
<td>0.03</td>
<td>3.06</td>
<td>0.01</td>
</tr>
<tr>
<td>Std. Dev</td>
<td>778</td>
<td>0.06</td>
<td>3.18</td>
<td>0.02</td>
</tr>
<tr>
<td>Nobs</td>
<td>5,580</td>
<td>5,580</td>
<td>5,580</td>
<td>5,585</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Percentile</th>
<th>$n_s$</th>
<th>$A^m_s$</th>
<th>$A^c_s$</th>
<th>$R&amp;D_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>95%</td>
<td>745</td>
<td>0.176</td>
<td>8.949</td>
<td>0.065</td>
</tr>
<tr>
<td>90%</td>
<td>223</td>
<td>0.126</td>
<td>7.666</td>
<td>0.039</td>
</tr>
<tr>
<td>75%</td>
<td>27</td>
<td>0.039</td>
<td>5.572</td>
<td>0.015</td>
</tr>
<tr>
<td>50%</td>
<td>2</td>
<td>0.003</td>
<td>2.485</td>
<td>0.002</td>
</tr>
<tr>
<td>25%</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10%</td>
<td>0</td>
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<td>0</td>
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<tr>
<td>5%</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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</tbody>
</table>
Panel B: Top Most and Least Innovative Industries

<table>
<thead>
<tr>
<th>Top 5 Most Innovative Industries by $A^m$</th>
<th>Industry Name</th>
<th>$n_s$</th>
<th>$A^m_s$</th>
<th>$A^c_s$</th>
<th>R&amp;$D_s$</th>
<th>Industry Name</th>
<th>$n_s$</th>
<th>$A^m_s$</th>
<th>$A^c_s$</th>
<th>R&amp;$D_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Electronic Components and Accessories</td>
<td>4322</td>
<td>0.27</td>
<td>9.80</td>
<td>0.07</td>
<td>Computer and Office Equipment</td>
<td>7022</td>
<td>0.24</td>
<td>10.40</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>Photographic Equipment and Supplies</td>
<td>1962</td>
<td>0.26</td>
<td>8.85</td>
<td>0.06</td>
<td>Electronic Components and Accessories</td>
<td>4322</td>
<td>0.27</td>
<td>9.80</td>
<td>0.07</td>
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<tr>
<td></td>
<td>Communications Equipment</td>
<td>2312</td>
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<td>9.21</td>
<td>0.10</td>
<td>Communications Equipment</td>
<td>2312</td>
<td>0.26</td>
<td>9.21</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>Computer and Office Equipment</td>
<td>7022</td>
<td>0.24</td>
<td>10.40</td>
<td>0.11</td>
<td>Photographic Equipment and Supplies</td>
<td>1962</td>
<td>0.26</td>
<td>8.85</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>Plastics Materials and Synthetic</td>
<td>742</td>
<td>0.19</td>
<td>7.60</td>
<td>0.02</td>
<td>Motor Vehicles and Equipment</td>
<td>1839</td>
<td>0.19</td>
<td>8.74</td>
<td>0.03</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Top 5 Least Innovative Industries by $A^m$</th>
<th>Industry Name</th>
<th>$n_s$</th>
<th>$A^m_s$</th>
<th>$A^c_s$</th>
<th>R&amp;$D_s$</th>
<th>Industry Name</th>
<th>$n_s$</th>
<th>$A^m_s$</th>
<th>$A^c_s$</th>
<th>R&amp;$D_s$</th>
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<tr>
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<td>Miscellaneous Metal Ores</td>
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<tr>
<td>Misc. General Merchandise Stores</td>
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<td>0</td>
<td>Misc. General Merchandise Stores</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Automotive dealers &amp; service stations</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>Automotive dealers &amp; service stations</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Table 9 Measures of Innovation at Industry Level (The 1997 BEA Capital Flow Table Classification)

Reported are innovation measures at industry level based on 123 industry classification defined in the 1997 BEA capital flow table. Panel A shows the descriptive statistics of patent counts, market-based and citation-weighted innovation measures and R&D intensity. Panel B lists the most and least innovative industries according to the market-based innovation measure $A^m_i$ and the citation-weighted innovation measure $A^c_i$.

### Panel A: Descriptive Statistics

<table>
<thead>
<tr>
<th>Moments</th>
<th>$n_s$</th>
<th>$A^m_s$</th>
<th>$A^c_s$</th>
<th>R&amp;D$_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>1085</td>
<td>0.075</td>
<td>3.04</td>
<td>0.031</td>
</tr>
<tr>
<td>Std. Dev</td>
<td>326</td>
<td>0.051</td>
<td>3.62</td>
<td>0.019</td>
</tr>
<tr>
<td>Nobs</td>
<td>2,595</td>
<td>2,595</td>
<td>2,595</td>
<td>2,622</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Percentile</th>
<th>$n_s$</th>
<th>$A^m_s$</th>
<th>$A^c_s$</th>
<th>R&amp;D$_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>95%</td>
<td>1496</td>
<td>0.204</td>
<td>8.52</td>
<td>0.089</td>
</tr>
<tr>
<td>90%</td>
<td>745</td>
<td>0.158</td>
<td>7.95</td>
<td>0.060</td>
</tr>
<tr>
<td>75%</td>
<td>146</td>
<td>0.085</td>
<td>6.04</td>
<td>0.022</td>
</tr>
<tr>
<td>50%</td>
<td>15</td>
<td>0.011</td>
<td>3.69</td>
<td>0.006</td>
</tr>
<tr>
<td>25%</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10%</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5%</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
### Panel B: Top Most and Least Innovative Industries

<table>
<thead>
<tr>
<th>Top 5 Most Innovative Industries by $A^m_s$</th>
<th>Top 5 Most Innovative Industries by $A^c_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry Name</td>
<td>$n_s$</td>
</tr>
<tr>
<td>Semiconductor and electronic component</td>
<td>4.27</td>
</tr>
<tr>
<td>Audio, video, and communications equipment</td>
<td>4.02</td>
</tr>
<tr>
<td>Computer and peripheral equipment</td>
<td>7.03</td>
</tr>
<tr>
<td>Motor vehicle manufacturing</td>
<td>1.48</td>
</tr>
<tr>
<td>Resin, rubber, and artificial fibers</td>
<td>0.74</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Top 5 Least Innovative Industries by $A^m_s$</th>
<th>Top 5 Least Innovative Industries by $A^c_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pipeline transportation</td>
<td>0 0 0 0</td>
</tr>
<tr>
<td>Nursing and residential care facilities</td>
<td>0 0 0 0</td>
</tr>
<tr>
<td>Social assistance</td>
<td>0 0 0 0</td>
</tr>
<tr>
<td>Performing arts, museums, zoo,parks</td>
<td>0 0 0 0</td>
</tr>
<tr>
<td>Coal mining</td>
<td>0 0 0 0</td>
</tr>
</tbody>
</table>
Table 10 Measures of Asset Liquidity and Asset Redeployability

Reported are the measures of asset reallocation frictions, asset liquidity and asset redeployability. Panel A shows the descriptive statistics of the two measures. Asset liquidity $AL_s$ is computed according to equation (4.4.9): $AL_{s,t} = \ln \left( 1 + \frac{SPPE_{s,t}}{PPENT_{s,t-1}} \right)$. It is based on SIC three-digit industry code. Asset redeployability $AR_s$ is computed according to the procedures (4.4.10) and (4.4.11). It is based on 123 industry defined in the 1997 BEA capital flow table. Panel B list most and least liquid (redeployable) industries according to the asset liquidity measure and the asset redeployability measure.

Panel A : Descriptive Statistics

<table>
<thead>
<tr>
<th>Moments</th>
<th>$AL_s$</th>
<th>$AR_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.012</td>
<td>0.473</td>
</tr>
<tr>
<td>Std</td>
<td>0.029</td>
<td>0.123</td>
</tr>
<tr>
<td>N</td>
<td>5,573</td>
<td>2,633</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Percentile</th>
<th>$AL_s$</th>
<th>$AR_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>95%</td>
<td>0.048</td>
<td>0.661</td>
</tr>
<tr>
<td>90%</td>
<td>0.029</td>
<td>0.620</td>
</tr>
<tr>
<td>75%</td>
<td>0.013</td>
<td>0.536</td>
</tr>
<tr>
<td>50%</td>
<td>0.004</td>
<td>0.485</td>
</tr>
<tr>
<td>25%</td>
<td>0.001</td>
<td>0.425</td>
</tr>
<tr>
<td>10%</td>
<td>0.000</td>
<td>0.313</td>
</tr>
<tr>
<td>5%</td>
<td>0.000</td>
<td>0.215</td>
</tr>
</tbody>
</table>

Panel B: Top Ranks

<table>
<thead>
<tr>
<th>Top 5 Most Liquid Industry</th>
<th>$AL_s$</th>
<th>Top 5 Most Redeployable Industry</th>
<th>$AR_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Farm Product Raw Materials</td>
<td>0.040</td>
<td>Civic, social, professional organizations</td>
<td>0.749</td>
</tr>
<tr>
<td>Trucking and Courier Services, Exc Air</td>
<td>0.033</td>
<td>Legal services</td>
<td>0.724</td>
</tr>
<tr>
<td>Freight Transport Arrangement</td>
<td>0.031</td>
<td>Social assistance</td>
<td>0.698</td>
</tr>
<tr>
<td>Child Day Care Services</td>
<td>0.030</td>
<td>Personal and laundry services</td>
<td>0.674</td>
</tr>
<tr>
<td>Heavy Construction, exc building</td>
<td>0.029</td>
<td>Other professional and technical services</td>
<td>0.668</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Top 5 Most Illiquid Industry</th>
<th>$AL_s$</th>
<th>Top 5 Least Redeployable Industry</th>
<th>$AR_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronic and Other electric equipment</td>
<td>0.000</td>
<td>Water transportation</td>
<td>0.095</td>
</tr>
<tr>
<td>Accounting, Auditing and Bookkeeping</td>
<td>0.000</td>
<td>Oil and gas extraction</td>
<td>0.133</td>
</tr>
<tr>
<td>Paints and Allied Products</td>
<td>0.000</td>
<td>Hospitals</td>
<td>0.185</td>
</tr>
<tr>
<td>Nonferrous Foundries (Castings)</td>
<td>0.000</td>
<td>Water transportation</td>
<td>0.189</td>
</tr>
<tr>
<td>Secondary Nonferrous Metals</td>
<td>0.000</td>
<td>Agriculture and forestry activities</td>
<td>0.217</td>
</tr>
</tbody>
</table>
Table 11 Association between Asset Liquidity and Asset Redeployability

Reported are the results for the regression of asset liquidity on asset redeployability. Asset redeployability is the ex ante measure of reallocation frictions and is lagged for one period in the regression. Fama-MacBath and panel regressions are conducted. For Fama-MacBath regression, standard errors are adjusted for autocorrelation using the Newey-West procedure based on 3 lags. For panel regression, year and industry fixed effect are considered and standard errors are clustered by industry. Standard errors are reported in parenthesis. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>Regression:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression:</td>
<td>FM</td>
<td>OLS</td>
<td>Panel</td>
<td>Panel</td>
</tr>
<tr>
<td>lag(AR_s)</td>
<td>0.045***</td>
<td>0.036*</td>
<td>0.034*</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>(0.0080)</td>
<td>(0.019)</td>
<td>(0.0196)</td>
<td>(0.0374)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.004</td>
<td>-0.000</td>
<td>-0.008</td>
<td>0.027*</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Nobs</td>
<td>2,708</td>
<td>2,708</td>
<td>2,708</td>
<td>2,708</td>
</tr>
<tr>
<td>FE</td>
<td>-</td>
<td>-</td>
<td>Y</td>
<td>Y × Ind</td>
</tr>
<tr>
<td>Std Error</td>
<td>NW</td>
<td>-</td>
<td>-</td>
<td>CL</td>
</tr>
</tbody>
</table>
Table 12 Summary Statistics of Industry Portfolio Variables (Based by Market-implied Innovation Measures)

Reported are the summary statistics of industry portfolio characteristics for the non-innovating and innovating firms. The sample includes all NYSE-, AMEX-, and NASDAQ-listed securities that are contained in both CRSP monthly returns file and the COMPSTAT industrial annual file between July 1987 to June 2010. Portfolios that contain less than five firms are excluded from the sample. *Herf* is the industry concentration measured with Herfindal index. *ln(size)* and *ln(BM)* are the log of value-weighted market capitalization and book-to-market ratio of the portfolios, respectively. lev is the value-weighted book leverage ratio of the portfolios. *fliquid* is the cash holdings and short-term investment scaled by total assets. *β* is the value-weighted market beta of the portfolios. Firm market beta is estimated from the rolling-window regression of the last thirty-six month firm returns on market returns. *Priorret* is the value-weighted past 12-month returns of the portfolios. *R&D* is the value-weighted R&D expenditure scaled by beginning total assets of the portfolio. *Inv* is the value-weighted capital expenditure scaled by beginning plant, property and equipment of the portfolios. *Tobin's Q* is the value-weighted of market-value -to-total assets ratio of the portfolio, where market value equals total assets minus book equity plus market capitalization. *SPPE* and *ACQ* are the value-weighted SPPE (scaled by beginning PPE) and Acquisition (scaled by beginning total assets) of the portfolios, respectively. Variables are winsorized at 1% at firm level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Herf</th>
<th>ln(SIZE)</th>
<th>ln(BM)</th>
<th>lev</th>
<th>fliquid</th>
<th>β</th>
<th>Priorret</th>
<th>R&amp;D</th>
<th>Inv</th>
<th>Tobin’s Q</th>
<th>SPPE</th>
<th>ACQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry portfolios of non-innovating firms</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.283</td>
<td>6.935</td>
<td>-0.469</td>
<td>0.257</td>
<td>0.096</td>
<td>1.061</td>
<td>0.203</td>
<td>0.011</td>
<td>0.267</td>
<td>1.719</td>
<td>0.014</td>
<td>0.034</td>
</tr>
<tr>
<td>Median</td>
<td>0.249</td>
<td>6.969</td>
<td>-0.531</td>
<td>0.242</td>
<td>0.071</td>
<td>1.046</td>
<td>0.160</td>
<td>0.001</td>
<td>0.234</td>
<td>1.555</td>
<td>0.006</td>
<td>0.015</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.160</td>
<td>1.728</td>
<td>0.720</td>
<td>0.120</td>
<td>0.085</td>
<td>0.472</td>
<td>0.384</td>
<td>0.023</td>
<td>0.151</td>
<td>0.715</td>
<td>0.025</td>
<td>0.049</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.333</td>
<td>-0.079</td>
<td>1.616</td>
<td>0.644</td>
<td>1.962</td>
<td>0.490</td>
<td>1.344</td>
<td>3.615</td>
<td>1.960</td>
<td>1.861</td>
<td>4.237</td>
<td>2.889</td>
</tr>
<tr>
<td>Nobs</td>
<td>3529</td>
<td>3529</td>
<td>3529</td>
<td>3529</td>
<td>3529</td>
<td>3529</td>
<td>3529</td>
<td>3529</td>
<td>3525</td>
<td>3522</td>
<td>3528</td>
<td>3527</td>
</tr>
<tr>
<td>Industry portfolios of innovating firms</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.211</td>
<td>8.887</td>
<td>-0.727</td>
<td>0.225</td>
<td>0.102</td>
<td>1.071</td>
<td>0.186</td>
<td>0.045</td>
<td>0.247</td>
<td>1.979</td>
<td>0.012</td>
<td>0.026</td>
</tr>
<tr>
<td>Median</td>
<td>0.179</td>
<td>8.917</td>
<td>-0.750</td>
<td>0.210</td>
<td>0.072</td>
<td>1.056</td>
<td>0.161</td>
<td>0.036</td>
<td>0.221</td>
<td>1.774</td>
<td>0.006</td>
<td>0.013</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.124</td>
<td>1.627</td>
<td>0.656</td>
<td>0.092</td>
<td>0.094</td>
<td>0.406</td>
<td>0.306</td>
<td>0.036</td>
<td>0.111</td>
<td>0.822</td>
<td>0.019</td>
<td>0.036</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.542</td>
<td>-0.192</td>
<td>0.766</td>
<td>0.750</td>
<td>2.234</td>
<td>0.373</td>
<td>1.590</td>
<td>1.291</td>
<td>1.553</td>
<td>1.580</td>
<td>3.816</td>
<td>2.607</td>
</tr>
<tr>
<td>Nobs</td>
<td>926</td>
<td>926</td>
<td>926</td>
<td>926</td>
<td>926</td>
<td>926</td>
<td>926</td>
<td>926</td>
<td>926</td>
<td>926</td>
<td>926</td>
<td>926</td>
</tr>
<tr>
<td>Diff</td>
<td>0.073***</td>
<td>-1.95*</td>
<td>0.26***</td>
<td>0.031***</td>
<td>-0.005</td>
<td>-0.010</td>
<td>0.017</td>
<td>-0.034***</td>
<td>0.020***</td>
<td>-0.26***</td>
<td>0.002***</td>
<td>0.007***</td>
</tr>
<tr>
<td>t-stat</td>
<td>14.97</td>
<td>-32.07</td>
<td>10.45</td>
<td>8.59</td>
<td>-1.58</td>
<td>-0.63</td>
<td>1.44</td>
<td>-27.15</td>
<td>4.45</td>
<td>-8.80</td>
<td>2.44</td>
<td>5.01</td>
</tr>
</tbody>
</table>
Reported are the summary statistics of industry portfolio characteristics for the non-innovating and innovating firms. The sample includes all NYSE-, AMEX-, and NASDAQ-listed securities that are contained in both CRSP monthly returns file and the COMPUSTAT industrial annual file between July 1987 to June 2010. Portfolios that contain less than five firms are excluded from the sample. \( \text{Herf} \) is the industry concentration measured with Herfindal index. \( \ln(\text{size}) \) and \( \ln(\text{BM}) \) are the log of value-weighted market capitalization and book-to-market ratio of the portfolios, respectively. \( \text{lev} \) is the value-weighted book leverage ratio of the portfolios. \( \text{fliquid} \) is the cash holdings and short-term investment scaled by total assets. \( \beta \) is the value-weighted market beta of the portfolios. Firm market beta is estimated from the rolling-window regression of the last thirty-six month firm returns on market returns. \( \text{Priorret} \) is the value-weighted past 12-month returns of the portfolios. \( R&D \) is the value-weighted R&D expenditure scaled by beginning total assets of the portfolio. \( \text{Inv} \) is the value-weighted capital expenditure scaled by beginning plant, property and equipment of the portfolios. \( \text{Tobin's Q} \) is the value-weighted of market-value-to-total assets ratio of the portfolio, where market value equals total assets minus book equity plus market capitalization. \( \text{SPPE} \) and \( \text{ACQ} \) are the value-weighted SPPE (scaled by beginning PPE) and Acquisition (scaled by beginning total assets) of the portfolios, respectively. Variables are winsorized at 1% at firm level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Herf</th>
<th>ln(SIZE)</th>
<th>ln(BM)</th>
<th>Lev</th>
<th>fliquid</th>
<th>( \beta )</th>
<th>Priorret</th>
<th>R&amp;D</th>
<th>Inv</th>
<th>Tobin's Q</th>
<th>SPPE</th>
<th>ACQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry portfolios of non-innovating firms</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.282</td>
<td>6.853</td>
<td>-0.486</td>
<td>0.256</td>
<td>0.094</td>
<td>1.011</td>
<td>0.208</td>
<td>0.011</td>
<td>0.271</td>
<td>1.745</td>
<td>0.015</td>
<td>0.034</td>
</tr>
<tr>
<td>Median</td>
<td>0.247</td>
<td>6.867</td>
<td>-0.543</td>
<td>0.241</td>
<td>0.069</td>
<td>1.006</td>
<td>0.161</td>
<td>0.001</td>
<td>0.239</td>
<td>1.574</td>
<td>0.006</td>
<td>0.015</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.160</td>
<td>1.683</td>
<td>0.699</td>
<td>0.118</td>
<td>0.083</td>
<td>0.433</td>
<td>0.358</td>
<td>0.025</td>
<td>0.153</td>
<td>0.730</td>
<td>0.025</td>
<td>0.048</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.393</td>
<td>-0.045</td>
<td>1.498</td>
<td>0.686</td>
<td>1.993</td>
<td>0.279</td>
<td>1.356</td>
<td>3.520</td>
<td>1.992</td>
<td>1.864</td>
<td>4.123</td>
<td>2.821</td>
</tr>
<tr>
<td>Nobs</td>
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<td>3047</td>
<td>3047</td>
<td>3047</td>
<td>3047</td>
<td>3047</td>
<td>3047</td>
<td>3047</td>
<td>3043</td>
<td>3043</td>
<td>3046</td>
<td>3047</td>
</tr>
<tr>
<td>Industry portfolios of innovating firms</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.208</td>
<td>8.905</td>
<td>-0.745</td>
<td>0.226</td>
<td>0.098</td>
<td>1.065</td>
<td>0.191</td>
<td>0.048</td>
<td>0.250</td>
<td>1.997</td>
<td>0.013</td>
<td>0.026</td>
</tr>
<tr>
<td>Median</td>
<td>0.170</td>
<td>8.947</td>
<td>-0.782</td>
<td>0.209</td>
<td>0.068</td>
<td>1.045</td>
<td>0.160</td>
<td>0.038</td>
<td>0.226</td>
<td>1.770</td>
<td>0.006</td>
<td>0.012</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.123</td>
<td>1.538</td>
<td>0.668</td>
<td>0.092</td>
<td>0.096</td>
<td>0.411</td>
<td>0.292</td>
<td>0.037</td>
<td>0.111</td>
<td>0.862</td>
<td>0.020</td>
<td>0.036</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.519</td>
<td>-0.128</td>
<td>0.886</td>
<td>0.813</td>
<td>2.457</td>
<td>0.461</td>
<td>1.726</td>
<td>1.185</td>
<td>1.565</td>
<td>1.587</td>
<td>3.892</td>
<td>2.792</td>
</tr>
<tr>
<td>Nobs</td>
<td>713</td>
<td>713</td>
<td>713</td>
<td>713</td>
<td>713</td>
<td>713</td>
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<td>713</td>
<td>713</td>
<td>713</td>
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</table>

\[
\text{Diff} = \begin{bmatrix} 0.07^{***} \\ -2.05^{***} \\ 0.26^{***} \\ 0.03^{***} \\ 0.00 \\ -0.05^{***} \\ 0.02 \\ -0.04^{***} \\ 0.02^{***} \\ -0.25^{***} \\ 0.002^{**} \\ 0.008^{***} \end{bmatrix}, \quad \text{t-stat} = \begin{bmatrix} 13.76 \\ -31.48 \\ 9.22 \\ 7.45 \\ -1.13 \\ -3.13 \\ 1.37 \\ -25.04 \\ 4.31 \\ -7.21 \\ 1.99 \\ 5.13 \end{bmatrix}
\]
Table 14 Fama-MacBeth Regressions of SPPE rate on Industry Average Characteristics

Reported are univariate correlation and the multivariate correlation of SPPE rate with industry characteristics. The statistics are estimated from Fama-MacBeth regressions of SPPE rate according to equation (5.2.1). The sample period covers 1987-2010. Panel A reports the statistics of univariate regression of SPPE on each industry characteristics listed separately. Multivariate regressions results for SPPE with various specifications are reported in rows in panel B. The dependent variable is SPPE rate. $A^m$ is the market-based measure of technology shocks. $R&D$ is the industry value-weighted R&D expenditure normalized by beginning-period total assets. $Capage$ is the industry value-weighted average age of capital. It is measured as the difference between gross PP&E (PPEGT) and net PP&E (PPENT) over the depreciation costs (DEP) (i.e. $capage_{st} = \frac{PPEG_{st} - PPENT_{st}}{DEP_{st}}$). $ln(size)$ is the log of industry average market capitalization, respectively. $Herf$ is the industry concentration measured with Herfindal index. $Cap_{int}$ is the value weighted net PP&E over total assets. $Inv$ is the value-weighted capital expenditure normalized by beginning-period net PP&E. Tobin’s $Q$ and $\sigma Q$ are the industry value-weighted average and standard deviation of firms’ market value over total assets, respectively. Firm market value equals to total assets minus book equity plus market capitalization. $ROA$ and $\sigma ROA$ are the industry value-weighted average and standard deviation of return on assets, respectively. Firm ROA equals to the earnings before interest and tax over the beginning total assets. $ln(BM)$ are the log of industry value-weighted average of book-to-market ratio. $fliquid$ is the industry value-weighted average of funding liquidity. $fliquid$ equals to the sum of cash holdings and short-term investment scaled by total assets. $lev$ is the industry value-weighted average of book leverage ratio of the portfolios. Variables are winsorized at 1% at firm level. Standard errors are adjusted for autocorrelation using the Newey-West procedure based on 3 lags and are reported in parenthesis. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>$A^m$</th>
<th>R&amp;D</th>
<th>Capage</th>
<th>ln(Size)</th>
<th>Herf</th>
<th>Cap_int</th>
<th>Inv</th>
<th>Tobin’s $Q$</th>
<th>$\sigma Q$</th>
<th>ROA</th>
<th>$\sigma ROA$</th>
<th>Ln(BM)</th>
<th>fliquid</th>
<th>Lev</th>
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<tr>
<td>Panel A: Univariate Regressions</td>
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</tr>
<tr>
<td>-0.034***</td>
<td>-0.052***</td>
<td>-0.010***</td>
<td>-0.004***</td>
<td>-0.002</td>
<td>-0.015***</td>
<td>0.020***</td>
<td>-0.001**</td>
<td>-0.003***</td>
<td>-0.017*</td>
<td>-0.010</td>
<td>0.001</td>
<td>0.015***</td>
<td>-0.003</td>
</tr>
<tr>
<td>(0.007)</td>
<td>(0.011)</td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.006)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.009)</td>
<td>(0.007)</td>
<td>(0.001)</td>
<td>(0.004)</td>
<td>(0.003)</td>
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<tr>
<td>0.017***</td>
<td>-0.052***</td>
<td>-0.008***</td>
<td>-0.004***</td>
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<tr>
<td>(0.006)</td>
<td>(0.013)</td>
<td>(0.002)</td>
<td>(0.000)</td>
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<tr>
<td>0.018**</td>
<td>-0.083***</td>
<td>-0.005***</td>
<td>-0.004***</td>
<td>-0.005***</td>
<td>-0.008***</td>
<td>0.013*</td>
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<tr>
<td>(0.008)</td>
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<td>(0.002)</td>
<td>(0.000)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.007)</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>0.016**</td>
<td>-0.074***</td>
<td>-0.006***</td>
<td>-0.004***</td>
<td>-0.005**</td>
<td>-0.008***</td>
<td>0.012*</td>
<td>0.001***</td>
<td>-0.004***</td>
<td></td>
<td></td>
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<td>(0.007)</td>
<td>(0.013)</td>
<td>(0.002)</td>
<td>(0.000)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.007)</td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.008)</td>
<td>(0.005)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.015**</td>
<td>-0.054***</td>
<td>-0.007***</td>
<td>-0.004***</td>
<td>-0.006**</td>
<td>-0.007**</td>
<td>0.012*</td>
<td>0.001***</td>
<td>-0.003**</td>
<td>-0.005</td>
<td>-0.027***</td>
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<tr>
<td>(0.007)</td>
<td>(0.013)</td>
<td>(0.002)</td>
<td>(0.000)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.006)</td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.008)</td>
<td>(0.005)</td>
<td></td>
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</tr>
<tr>
<td>0.015**</td>
<td>-0.054***</td>
<td>-0.007***</td>
<td>-0.004***</td>
<td>-0.005**</td>
<td>-0.006**</td>
<td>0.012*</td>
<td>0.001*</td>
<td>-0.003**</td>
<td>-0.007</td>
<td>-0.028***</td>
<td>-0.001*</td>
<td>-0.000</td>
<td>-0.005</td>
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<tr>
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<td>(0.013)</td>
<td>(0.002)</td>
<td>(0.000)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.007)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.009)</td>
<td>(0.005)</td>
<td>(0.000)</td>
<td>(0.004)</td>
<td>(0.003)</td>
</tr>
</tbody>
</table>
Table 15 Fama-MacBeth Regressions of Acquisition rate on Industry Average Characteristics

Reported are univariate correlation and the multivariate correlation of acquisition rate with industry characteristics. The statistics are estimated from Fama-MacBeth regressions of acquisition rate \( ACQ \) according to equation (5.2.1). The sample period covers 1987-2010. Panel A reports the statistics of univariate regression of \( ACQ \) rate on each industry characteristics listed separately. Multivariate regressions results for \( ACQ \) with various specifications are reported in rows in panel B. The dependent variable is SPPE rate. \( A_m \) is the market-based measure of technology shocks. \( R&D \) is the industry value-weighted R&D expenditure normalized by beginning-period total assets. \( Capage \) is the industry value-weighted average age of capital. It is measured as the difference between gross PP&E (PPEGT) and net PP&E (PPENT) over the depreciation costs (DEP) (i.e. \( capage_{i,t} = \frac{PPEGT_s - PPENT_s}{DEP_s} \)). \( ln(size) \) is the log of industry average market capitalization, respectively. \( Herf \) is the industry concentration measured with Herfindal index. \( Cap\_int \) is the value weighted net PP&E over total assets. \( Inv \) is the value-weighted capital expenditure normalized by beginning-period net PP&E. \( Tobin's\ Q \) and \( \sigma Q \) are the industry value-weighted average and standard deviation of firms’ market value over total assets, respectively. Firm market value equals to total assets minus book equity plus market capitalization. \( ROA \) and \( \sigma ROA \) are the industry value-weighted average and standard deviation of return on assets, respectively. Firm ROA equals to the earnings before interest and tax over the beginning total assets. \( ln(BM) \) are the log of industry value-weighted average of book-to-market ratio. \( fliquid \) is the industry value-weighted average of funding liquidity. \( fliquid \) equals to the sum of cash holdings and short-term investment scaled by total assets. \( Lev \) is the industry value-weighted average of book leverage ratio of the portfolios. Variables are winsorized at 1% at firm level. Standard errors are adjusted for autocorrelation using the Newey-West procedure based on 3 lags and are reported in parenthesis. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>( A_m )</th>
<th>R&amp;D</th>
<th>Capage</th>
<th>( ln\text{(Size)} )</th>
<th>Herf</th>
<th>Cap_int</th>
<th>Inv</th>
<th>Tobin’s Q</th>
<th>( \sigma(Q) )</th>
<th>ROA</th>
<th>( \sigma ROA )</th>
<th>( ln(BM) )</th>
<th>( fliquid )</th>
<th>Lev</th>
</tr>
</thead>
<tbody>
<tr>
<td>( -0.087*** )</td>
<td>( -0.081*** )</td>
<td>( -0.022*** )</td>
<td>( -0.006*** )</td>
<td>0.000</td>
<td>( -0.032*** )</td>
<td>( 0.052*** )</td>
<td>0.003*</td>
<td>0.005**</td>
<td>( 0.040*** )</td>
<td>( 0.063*** )</td>
<td>( -0.005*** )</td>
<td>0.014*</td>
<td>( -0.125*** )</td>
</tr>
<tr>
<td>(0.010)</td>
<td>(0.014)</td>
<td>(0.004)</td>
<td>(0.001)</td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.009)</td>
<td>(0.017)</td>
<td>(0.002)</td>
<td>(0.008)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>( -0.033*** )</td>
<td>( 0.105*** )</td>
<td>( -0.020*** )</td>
<td>( -0.006*** )</td>
<td>0.000</td>
<td>( -0.020*** )</td>
<td>( -0.016*** )</td>
<td>( 0.030*** )</td>
<td>0.004*</td>
<td>0.004</td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>(0.005)</td>
<td>(0.019)</td>
<td>(0.004)</td>
<td>(0.001)</td>
<td>( -0.020*** )</td>
<td>( -0.020*** )</td>
<td>( -0.020*** )</td>
<td>( -0.020*** )</td>
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<td>(0.003)</td>
<td>(0.007)</td>
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</tr>
<tr>
<td>( -0.007 )</td>
<td>( -0.035 )</td>
<td>( -0.011*** )</td>
<td>( -0.007*** )</td>
<td>( -0.022*** )</td>
<td>( -0.014*** )</td>
<td>( 0.017*** )</td>
<td>( -0.000 )</td>
<td>( 0.003 )</td>
<td>( 0.066*** )</td>
<td>( 0.038** )</td>
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<tr>
<td>(0.011)</td>
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<td>(0.003)</td>
<td>(0.001)</td>
<td>(0.006)</td>
<td>(0.004)</td>
<td>(0.006)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.012)</td>
<td>(0.018)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( -0.006 )</td>
<td>( 0.010 )</td>
<td>( -0.010*** )</td>
<td>( -0.007*** )</td>
<td>( -0.020** )</td>
<td>( -0.014*** )</td>
<td>( 0.021*** )</td>
<td>( -0.002 )</td>
<td>( 0.003 )</td>
<td>( 0.055*** )</td>
<td>( 0.042** )</td>
<td>( -0.007*** )</td>
<td>( -0.051*** )</td>
<td>( -0.034* )</td>
</tr>
<tr>
<td>(0.010)</td>
<td>(0.034)</td>
<td>(0.003)</td>
<td>(0.001)</td>
<td>(0.007)</td>
<td>(0.003)</td>
<td>(0.007)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.012)</td>
<td>(0.018)</td>
<td>(0.002)</td>
<td>(0.010)</td>
<td>(0.018)</td>
</tr>
</tbody>
</table>
Table 16 Fama-MacBeth Regressions of Asset Redeployability on Industry Average Characteristics

Reported are univariate correlation and the multivariate correlation of acquisition rate with industry characteristics. The statistics are estimated from Fama-MacBeth regressions of asset redeployability $AR_{it}$ according to equation (5.2.1). The sample period covers 1987-2010. Panel A reports the statistics of univariate regression of asset redeployability $AR_{it}$ on each industry characteristics listed separately. Multivariate regressions results for $AR_{it}$ with various specifications are reported in rows in panel B. The dependent variable is SPPE rate. $A^m$ is the market-based measure of technology shocks. $R&D$ is the industry value-weighted R&D expenditure normalized by beginning-period total assets. $Capage$ is the industry value-weighted average age of capital. It is measured as the difference between gross PP&E (PPEGT) and net PP&E (PPENT) over the depreciation costs (DEP) (i.e. $capage_{it} = \frac{PPEGT_{it} - PPENT_{it}}{DEP_{it}}$). $\ln(size)$ is the log of industry average market capitalization, respectively. $Herf$ is the industry concentration measured with Herfindal index. $Cap_{int}$ is the industry value-weighted net PP&E over total assets. $Inv$ is the value-weighted capital expenditure normalized by beginning-period net PP&E. $Tobin's~Q$ and $\sigma_Q$ are the industry value-weighted average and standard deviation of firms’ market value over total assets, respectively. Firm market value equals to total assets minus book equity plus market capitalization. $ROA$ and $\sigma_{ROA}$ are the industry value-weighted average and standard deviation of return on assets, respectively. $\ln(BM)$ are the log of industry value-weighted average of book-to-market ratio. $fliquid$ is the industry value-weighted average of funding liquidity. $lev$ is the industry value-weighted average of book leverage ratio of the portfolios. Variables are winsorized at 1% at firm level. Standard errors are adjusted for autocorrelation using the Newey-West procedure based on 3 lags and are reported in parenthesis. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>$A^m$</th>
<th>R&amp;D</th>
<th>Capage</th>
<th>$\ln(size)$</th>
<th>Herf</th>
<th>$Cap_{int}$</th>
<th>Inv</th>
<th>$Tobin's~Q$</th>
<th>$\sigma(Q)$</th>
<th>ROA</th>
<th>$\sigma(ROA)$</th>
<th>$\ln(BM)$</th>
<th>fliquid</th>
<th>Lev</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.009</td>
<td>-0.178***</td>
<td>-0.085***</td>
<td>-0.007***</td>
<td>0.163***</td>
<td>-0.297***</td>
<td>0.289***</td>
<td>0.020***</td>
<td>0.033***</td>
<td>0.197**</td>
<td>0.131***</td>
<td>-0.027***</td>
<td>0.006</td>
<td>-0.179***</td>
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<td>(0.036)</td>
<td>(0.028)</td>
<td>(0.015)</td>
<td>(0.002)</td>
<td>(0.011)</td>
<td>(0.015)</td>
<td>(0.019)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.078)</td>
<td>(0.040)</td>
<td>(0.005)</td>
<td>(0.033)</td>
<td>(0.025)</td>
</tr>
</tbody>
</table>

Panel A: Univariate Regressions

| 0.340*** | -0.713*** | -0.101*** | -0.017*** |
| (0.074) | (0.109) | (0.014) | (0.003) |
| 0.067 | -1.157*** | -0.022** | 0.008*** | 0.101*** | -0.338*** | 0.161*** |
| (0.055) | (0.083) | (0.010) | (0.002) | (0.016) | (0.015) | (0.036) |
| 0.106* | -1.240*** | -0.026** | 0.007*** | 0.109*** | -0.332*** | 0.148*** | 0.014*** | -0.013* |
| (0.051) | (0.107) | (0.010) | (0.002) | (0.015) | (0.015) | (0.038) | (0.006) | (0.007) |
| 0.089 | -1.201*** | -0.028** | 0.007** | 0.109*** | -0.334*** | 0.158*** | 0.020** | -0.017** | -0.050 | 0.008 |
| (0.052) | (0.097) | (0.010) | (0.003) | (0.014) | (0.017) | (0.046) | (0.009) | (0.008) | (0.093) | -0.063 |
| 0.098* | -0.899*** | -0.062*** | 0.002 | 0.126*** | -0.323*** | 0.179** | 0.034*** | -0.026*** | -0.122 | -0.003 | 0.006 | -0.484*** | -0.220*** |
| (0.055) | (0.106) | (0.010) | (0.003) | (0.013) | (0.017) | (0.065) | (0.011) | (0.006) | (0.089) | (0.049) | (0.007) | (0.076) | (0.025) |

Panel B: Multivariate Regressions
Table 17 The Interactive Effect of Real Asset Liquidity and Technology Shocks on the Cross-Sectional Returns of Non-innovating Firms

Reported are the Fama-MacBeth cross-sectional regression results for non-innovating portfolio returns with various specifications. The sample period covers 1987-2010. The dependent variable is industry portfolio returns of non-innovating firms \( R_{NI,s,t} \). \( \hat{A}_{m,s,t} \) is the market-based measure of technology shocks. \( AssetLiq_{s,t} \) are measures of asset liquidity for industry \( s \) over period \( t \). Three turnover rates are computed as measures of asset liquidity: SPPE rate, Acquisition rate (ACQ) and Reallocation rate (REALLOC). Definitions of controls are in Table 12. Standard errors are adjusted for autocorrelation using the Newey-West procedure based on 5 lags and are reported in parenthesis. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

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<tr>
<th>VARIABLES</th>
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<td>SPPE</td>
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<tr>
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<tr>
<td>( Size_{NI,s-1,f} )</td>
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<tr>
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<td>(0.005)</td>
</tr>
<tr>
<td>( Priorret_{NI,s-1,f} )</td>
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Table 18 The Interactive Effect of Real Asset Liquidity and Technology Shocks on the Cross-Sectional Returns of Innovating Firms

Reported are the Fama-MacBeth cross-sectional regression results for innovating portfolio returns with various specifications. The sample period covers 1987-2010. The dependent variable is industry portfolio returns of innovating firms $R_{Is,t}^I$. $\hat{A}_s^m_t$ is the market-based measure of technology shocks. $\text{AssetLiq}_{s,t}$ are measures of asset liquidity for industry $s$ over period $t$. Three turnover rates are computed as measures of asset liquidity: SPPE rate, Acquisition rate (ACQ) and Reallocation rate (REALLOC). Definitions of controls are in Table 12. Standard errors are adjusted for autocorrelation using the Newey-West procedure based on 5 lags and are reported in parenthesis. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

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<td>(0.079)</td>
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<td>(0.059)</td>
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<td>(0.105)</td>
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<td>$\hat{A}_s^m_t$</td>
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<td>0.670***</td>
<td>0.777***</td>
<td>0.695***</td>
<td>0.570***</td>
<td>0.688***</td>
<td>0.554***</td>
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<td>0.531</td>
<td>0.548</td>
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Table 19 The Interactive Effect of Real Asset Liquidity and Technology Shocks on the Cross-Sectional Returns of NMI portfolios

Reported are the Fama-MacBeth cross-sectional regression results for NMI portfolio returns with various specifications. The sample period is from 1987 to 2010. The dependent variable is the industry NMI portfolio returns $R_{NMI}^{s,t}$. The NMI portfolio is constructed by going long shares of non-innovating firms and selling shares of innovating firms with in an industry. $\hat{A}_{m,s,t}$ is the market-based measure of technology shocks. $AssetLiq_{s,t}$ are measures of asset liquidity for industry s over period t. Three turnover rates are computed as measures of asset liquidity: SPPE rate, Acquisition rate (ACQ) and Reallociation rate (REALLOC). Definitions of controls are in Table 12. In panel A, the asset liquidity measure is a dummy variable. Standard errors are adjusted for autocorrelation using the Newey-West procedure based on 5 lags and are reported in parenthesis. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

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<td>-0.441*</td>
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<td>-0.739**</td>
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<td>-0.337</td>
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<td>(0.320)</td>
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<td>$\hat{A}<em>{m,s,t} * AssetLiq</em>{s,t}$</td>
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<td>98.473**</td>
<td>7.328</td>
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<td>19.958**</td>
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<td>(0.993)</td>
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Controls
N Y N Y N Y N Y
Observations 853 853 853 853 853 853 853 853
R-squared 0.075 0.578 0.138 0.636 0.154 0.648 0.143 0.642
Table 20 Placebo Tests of Market-based Measure of Technology Shocks

Reported are the Fama-MacBeth cross-sectional regression results for non-innovating portfolio returns and innovating portfolio returns on arbitrary measures of technology shocks. The sample period is from 1987 to 2010. The dependent variable is industry portfolio returns of non-innovating firms $R^N_{it}$ in panel A and portfolio returns of innovating firms $R^I_{it}$ in panel B. $\tilde{A}^m_{it}$ is the arbitrary measure of technology shocks constructed in placebo tests. $\text{AssetLiq}_{st}$ are measures of asset liquidity for industry $s$ over period $t$. Three turnover rates are computed as measures of asset liquidity: SPPE rate, Acquisition rate (ACQ) and Reallocation rate (REALLOC). The set of placebo tests are repeated 200 times. Definitions of controls are in Table 12. The statistics reported are the average estimates of regression results. Standard errors are adjusted for autocorrelation using the Newey-West procedure based on 5 lags and are reported in parenthesis. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

### Panel A: Regression on Non-innovating Portfolios

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<td>$\tilde{A}^m_{it}$</td>
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<td>0.106</td>
<td>0.014</td>
<td>0.020</td>
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<td>0.092</td>
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<td>(0.068)</td>
<td>(0.087)</td>
<td>(0.070)</td>
<td>(0.087)</td>
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<td>$\tilde{A}^m_{it} \times \text{AssetLiq}_{st}$</td>
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### Panel B: Regression on Innovating Portfolios

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187
Table 21 The Interactive Effect of Real Asset Liquidity and Citation-based Measure of Technology Shocks on the Cross-Sectional Returns

Reported are the Fama-MacBeth cross-sectional regression results for non-innovating portfolio returns and innovating portfolio returns with various specifications. The sample period is from 1987 to 2006. The dependent variable is industry portfolio returns of non-innovating firms $R_{NI{t}}$ in panel A and portfolio returns of innovating firms $R_{I{t}}$ in panel B. $A_{c{t}}$ is the citation-based innovation measure of technology shocks. $AssetLiq_{s{t}}$ are measures of asset liquidity for industry $s$ over period $t$. Three turnover rates are computed as measures of asset liquidity: SPPE rate, Acquisition rate (ACQ) and Reallocation rate (REALLOC). Definitions of other variables are in Table 12. Standard errors are adjusted for autocorrelation using the Newey-West procedure based on 5 lags and are reported in parenthesis. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

### Panel A: Regression on Non-innovating Portfolios

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<td>-0.008***</td>
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<tr>
<td>$A_{c{t}} \times AssetLiq_{s{t}}$</td>
<td>0.410***</td>
<td>0.436***</td>
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<tr>
<td>$AssetLiq_{s{t}}$</td>
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### Panel B: Regression on Innovating Portfolios

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<td>(0.002)</td>
<td>(0.002)</td>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>$A_{c{t}} \times AssetLiq_{s{t}}$</td>
<td>0.592</td>
<td>0.626</td>
<td>0.917</td>
<td>0.362</td>
<td>0.519</td>
<td>0.402</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.645)</td>
<td>(1.057)</td>
<td>(0.549)</td>
<td>(0.541)</td>
<td>(0.416)</td>
<td>(0.510)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$AssetLiq_{s{t}}$</td>
<td>-3.573</td>
<td>-4.777</td>
<td>-6.010*</td>
<td>-2.491</td>
<td>-3.344</td>
<td>-2.078</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4.180)</td>
<td>(5.573)</td>
<td>(3.189)</td>
<td>(2.875)</td>
<td>(2.238)</td>
<td>(2.406)</td>
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<th>Controls</th>
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<tr>
<td>Observations</td>
<td>803</td>
<td>803</td>
<td>803</td>
<td>803</td>
<td>803</td>
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<td>803</td>
<td>803</td>
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<tr>
<td>R-squared</td>
<td>0.095</td>
<td>0.503</td>
<td>0.166</td>
<td>0.545</td>
<td>0.146</td>
<td>0.537</td>
<td>0.146</td>
<td>0.543</td>
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Table 22 Real Asset Redeployability and Innovation Risk: Multivariate Analysis

Reported are the Fama-MacBeth cross-sectional regression results according to equation (4.2.1) with various specifications. The sample period is 1987-2010 and 1987-2006 for the market-based innovation measure and the citation-weighted innovation measure, respectively. The dependent variable is industry portfolio returns of non-innovating firms \( R_{NI,s,t} \) and innovating firms \( R_{I,s,t} \). \( AR_{s,t} \) is the measure of asset redeployability. \( A_{s,t} \) is the market-based innovation measure in panel A and the citation-weighted innovation measure in panel B. Definitions of other variables are in Table 12. Variables are winsorized at 1% at firm level. Standard errors are adjusted for autocorrelation using the Newey-West procedure based on 5 lags and are reported in parenthesis. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Panel A: Market-based Innovation</th>
<th>Panel B: Citation-weighted Innovation</th>
</tr>
</thead>
<tbody>
<tr>
<td>( A_{s,t} )</td>
<td>-1.107** (0.512)</td>
<td>0.271 (0.434)</td>
</tr>
<tr>
<td>( AR_{s,t} )</td>
<td>-0.075 (0.059)</td>
<td>0.170 (0.143)</td>
</tr>
<tr>
<td>( A_{s,t} \times AR_{s,t} )</td>
<td>2.626** (1.170)</td>
<td>0.720 (1.016)</td>
</tr>
<tr>
<td>( Herf_{s,t} )</td>
<td>0.003 (0.060)</td>
<td>-0.138*** (0.042)</td>
</tr>
<tr>
<td>( Size_{s,t} )</td>
<td>0.006 (0.007)</td>
<td>-0.010 (0.009)</td>
</tr>
<tr>
<td>( BM_{s,t} )</td>
<td>-0.007 (0.007)</td>
<td>-0.016 (0.010)</td>
</tr>
<tr>
<td>( Lev_{s,t} )</td>
<td>-0.087** (0.033)</td>
<td>-0.040 (0.067)</td>
</tr>
<tr>
<td>( \beta_{s,t} )</td>
<td>0.034* (0.017)</td>
<td>0.015 (0.028)</td>
</tr>
<tr>
<td>( Priorret_{s,t} )</td>
<td>0.031 (0.034)</td>
<td>-0.096 (0.088)</td>
</tr>
<tr>
<td>( R&amp;D_{s,t} )</td>
<td>0.338 (0.326)</td>
<td>-0.486 (0.457)</td>
</tr>
<tr>
<td>( fliquid_{s,t} )</td>
<td>-0.223*** (0.053)</td>
<td>0.181 (0.135)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.033 (0.090)</td>
<td>0.034 (0.128)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,145</td>
<td>1,002</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.243</td>
<td>0.516</td>
</tr>
</tbody>
</table>
Table 23 The Interactive Effect of Asset Redeployability and Innovation Risk on Long-Short Industry Portfolios

Reported are the Fama-MacBeth cross-sectional regression results according to equation (4.2.2) with various specifications. The sample period is 1987-2010 and 1987-2006 for the market-based innovation measure and the citation-weighted innovation measure, respectively. The dependent variable is the returns of industry NMI portfolios $R_{NMI}^{s,t}$. The NMI portfolio is constructed by going long shares of non-innovating firms and selling shares of innovating firms within an industry. $AR_{s,t}$ is the measure of asset redeployability. $A_{s,t}$ is the market-based innovation measure in column 1 and the citation-weighted innovation measure in column 2. Definitions of other variables are in Table 12. Variables are winsorized at 1% at firm level. Standard errors are adjusted for autocorrelation using the Newey-West procedure based on 5 lags and are reported in parenthesis. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>1. Market-based Innovation</th>
<th>2. Citation-weighted Innovation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_{s,t}$</td>
<td>-0.768**</td>
<td>-0.026*</td>
</tr>
<tr>
<td></td>
<td>(0.356)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>$AR_{s,t}$</td>
<td>-0.156***</td>
<td>-0.240***</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.063)</td>
</tr>
<tr>
<td>$A_{s,t} * AR_{s,t}$</td>
<td>0.316</td>
<td>0.030*</td>
</tr>
<tr>
<td></td>
<td>(0.701)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Controls</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>1,363</td>
<td>1,157</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.506</td>
<td>0.467</td>
</tr>
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## Appendix A

### List of Variables and Notations

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definitions</th>
<th>Parameters</th>
<th>Definitions</th>
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<tbody>
<tr>
<td>Y</td>
<td>Final goods</td>
<td>$\alpha$</td>
<td>Share of capital</td>
</tr>
<tr>
<td>C</td>
<td>Consumption</td>
<td>$\beta$</td>
<td>Subjective discount factor</td>
</tr>
<tr>
<td>K</td>
<td>Capital</td>
<td>$\delta$</td>
<td>Depreciation rate</td>
</tr>
<tr>
<td>I</td>
<td>Investment</td>
<td>$\psi$</td>
<td>Transformation rate</td>
</tr>
<tr>
<td>D</td>
<td>Payouts of firm</td>
<td>$\gamma$</td>
<td>Size of reallocation frictions</td>
</tr>
<tr>
<td>V</td>
<td>firm value</td>
<td>$\theta$</td>
<td>Probability of the arrival of a innovation</td>
</tr>
<tr>
<td>U</td>
<td>Households' utility</td>
<td>$\bar{\eta}$</td>
<td>Step size of innovation</td>
</tr>
<tr>
<td>N</td>
<td>Reallocated capital</td>
<td>$p^x$</td>
<td>Price of intermediate goods</td>
</tr>
<tr>
<td>X</td>
<td>Intermediate goods</td>
<td>$w_t$</td>
<td>Wage</td>
</tr>
<tr>
<td>$p^N$</td>
<td>Price of used capital</td>
<td>$q_{j,t}$</td>
<td>Marginal value of capital</td>
</tr>
<tr>
<td>$m_{t+1}$</td>
<td>Stochastic discount factor</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$r_{j,t+1}$</td>
<td>Return</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix B

Proofs

B.1 Intermediate firms’ value maximization condition

The current value Lagrangian function of intermediate firms’ maximization problem (3.3.3) is revisited here

\[ L_{jt} = \{p_r^tA_jK_{jt} - I_{jt} - p_r^tN_{jt} + \mathbb{E}\left(\sum_{s=1}^{t-s} m_{t+s}D_{t+s}\right) \}
\]

\[ - \left( \sum_{s=0}^{T_j-s-1} q_{j,t+s}(K_{j,t+s+1} - K_{j,t+s}(1 - \delta) - I_{j,t+s} - \Phi(N_{j,t+s}, K_{j,t+s})) \right) \]

\[ + \sum_{s=0}^{T_j-s-1} (\mu_{j,t+s}I_{j,t+s}) + \sum_{s=0}^{T_j-s-1} (\nu_{j,t+s}(K_{j,t+s}(1 - \delta) + N_{j,t+s})) \]  \hspace{1cm} (3.3.3)

where \( q_{j,t+s}, \mu_{j,t+s} \) and \( \nu_{j,t+s} \) are Lagrangian multipliers for the capital accumulation constraint, the non-negative investment and capital stock conditions at time \( t + s \), respectively.
Marginal benefit of capital

I take the first order condition of the Lagrangian function (3.3.3) with respect to $K_{j,t+1}$ and apply the envelope condition to obtain the marginal benefit of capital.

$$\frac{\partial \mathcal{L}_{j,t}}{\partial K_{j,t+1}} = E m_{t+1} [p_{t+1}^X A_j + q_{j,t+1} (\Phi_{K_{j,t+1}} + 1 - \delta)] - q_{j,t} = 0 \quad (B.1.1)$$

By applying the envelope condition, I get the marginal benefit of capital

$$\frac{\partial V_{j,t}}{\partial K_{j,t+1}} = E m_{t+1} [p_{t+1}^X A_j + q_{j,t+1} (1 - \delta)] = q_{j,t} \quad (B.1.2)$$

Marginal cost of capital

I take the first order condition of the Lagrangian function (3.3.3) with respect to $I_{j,t}$ or $N_{j,t}$ to obtain the marginal cost of capital $q_{j,t}$.

$$\frac{\partial \mathcal{L}_{j,t}}{\partial I_{j,t}} = -1 + q_{j,t} + \mu_{j,t} = 0 \quad (B.1.3)$$

$$\frac{\partial \mathcal{L}_{j,t}}{\partial N_{j,t}} = -p_t^N + q_{j,t} \Phi_{N_{j,t}} + v_{j,t} = 0, \quad \text{if} \quad N_{j,t} \neq 0 \quad (B.1.4)$$

where \ \( \Phi_{N_{j,t}} = \begin{cases} \psi & \text{for} \quad N_{j,t} \geq 0 \\ 1 - \gamma^N_{N_{j,t}} & \text{for} \quad N_{j,t} < 0 \end{cases} \)

By rearranging the equation, the marginal cost of capital $q_{j,t}$ is

$$q_{j,t} = 1 - \mu_{j,t}, \quad \text{if} \quad N_{j,t} \geq 0 \quad (B.1.5)$$

$$q_{j,t} = \frac{p_t^N - v_{j,t}}{\Phi_{N_{j,t}}}, \quad \text{if} \quad N_{j,t} < 0 \quad (B.1.6)$$
When a firm makes new investment, the nonnegative investment constraint is not binding (i.e. $\mu_{j,t} = 0$). Thus, the marginal cost of capital equals one, $q_{j,t} = 1$. If the firm can also purchase used capital, the maximum capital sale constraint is not binding (i.e. $\nu_{j,t} = 0$) and 

$$q_{j,t} = \frac{p^N_{t}}{\psi} = 1.$$ 

When the firm sells its used capital, the nonnegative investment constraint is binding, $\mu_{j,t} > 0$ and $q < 1$. As long as it sells less than its total capital stock after depreciation adjustment, $\nu_{j,t} = 0$. Therefore the marginal cost of capital $q = \frac{p^N_{t}}{1 - \gamma_{K,t}}$.

When there is a technology shock, the respective marginal values of capital of the innovating firm and the non-innovating firm are

$$q_{U,H,1} = m^U_2 \left[ p^2_{AH} + (1 - \delta) \right] = 1 \quad \text{(B.1.7a)}$$

$$q_{U,L,1} = m^U_2 \left[ p^2_{AL} + (1 - \delta) \right] < 1 \quad \text{(B.1.7b)}$$

Here, equation (B.1.7a) implies the discount factor is the inverse of the innovating firm’s future value of capital, $m^U_2 = [p^2_{AH} + (1 - \delta)]^{-1}$, since $q_{U,1} = 1$. In addition, $A_H = \bar{\eta} A_L$. Dividing equation (B.1.7b) by equation (B.1.7a), the marginal value of capital of the non-innovating firm is

$$q_{L,1}^U = \frac{q_{L,1}^U}{q_{L,1}^U} = \frac{p^2_{AL} + (1 - \delta)}{p^2_{AH} + (1 - \delta)}$$

$$= \tilde{\eta}^{-1} \frac{p^2_{AL} + (1 - \delta) + (\bar{\eta} - 1)(1 - \delta)}{p^2_{AH} + (1 - \delta)}$$

$$= \tilde{\eta}^{-1} + \frac{\bar{\eta} - 1}{p^2_{AH} + (1 - \delta)}$$

$$= \tilde{\eta}^{-1} + (1 - \tilde{\eta}^{-1})(1 - \delta)m^U_2 > \tilde{\eta}^{-1} \quad \text{(B.1.8)}$$
If there is a technology shock, the innovating firm starts to invest while the non-innovating firm stops invest. The non-innovating firm starts to sell capital when \( q_{L,1}U < p^N_1 \). Hence, the range of \( q_{L,1}^U \) that has capital reallocation

\[
\bar{\eta}^{-1} < q_{L,1}^U = \bar{\eta}^{-1} + (1 - \bar{\eta}^{-1})(1 - \delta)m_2^U < \psi
\] (3.3.11)

**Stock returns**

The covariance between the non-innovating firm’s returns and the discount factors across states is

\[
\text{Cov}[r_{L,1}, m_1] = \theta(m_1^U - E[m_1])(r_{L,1}^U - E[r_{L,1}]) + (1 - \theta)(m_1^P - E[m_1])(r_{L,1}^P - E[r_{L,1}])
\]

\[
= \theta(m_1^U - \theta m_1^U - (1 - \theta)m_1^P)(A_L p_1^x + q_{L,1}(1 - \delta)) - \theta(A_L p_1^x + q_{L,1}(1 - \delta))
\]

\[
- (1 - \theta)(A_L p_1^x + (1 - \delta)) + (1 - \theta)(m_1^P - \theta m_1^U - (1 - \theta)m_1^P)(A_L p_1^x + (1 - \delta)
\]

\[
- \theta(A_L p_1^x + q_{L,1}(1 - \delta)) - (1 - \theta)(A_L p_1^x + (1 - \delta))
\]

\[
= \theta(1 - \theta)^2(m_1^U - m_1^P)(1 - \delta)(q_{L,1}^U - 1) + \theta^2(1 - \theta)(m_1^U - m_1^P)(1 - \delta)(q_{L,1}^U - 1)
\]

\[
= \theta(1 - \theta)(1 - \delta)(m_1^U - m_1^P)(q_{L,1}^U - 1)
\] (B.1.9)

**B.2 Impact of the technology shock on the SDF in a frictionless economy**

At time 1, the first order condition of investment is determined by

\[
q_{j,1} = m_2[p_2^x A_j + (1 - \delta)] = 1
\] (B.2.1)
where

\[ m_2 = \beta \frac{Y_1 - I_{j,1}}{Y_2 + K_{j,2}(1 - \delta)} = \beta \frac{Y_1 - I_{j,1}}{[A_j(K_{L,1}(1 - \delta) + I_{j,1})]^\alpha + K_{L,1}(1 - \delta)^2 + I_{j,1}(1 - \delta)} \]  

(B.2.2a)

\[ p_2^\alpha = \alpha(A_j K_{j,2})^{\alpha - 1} = \alpha[A_j(K_{L,1}(1 - \delta) + I_{j,1})]^{\alpha - 1} \]  

(B.2.2b)

Here, if there is a technology shock, only the innovating firm invests, \( j = H \). If there is no technology shock, only the non-innovating firm invests, \( j = L \). \( m_2 \) and \( p_2^\alpha \) are functions of only investment \( I_{j,1} \) and the productivity of the investing firm \( A_j \) at time 1, where \( K_{L,1} \) is fixed at time 1. The total derivatives of \( m_2 \) and \( p_2^\alpha \) are

\[ d(m_2) = \beta \left( \frac{d(C_1)}{C_2} - \frac{C_1 d(C_2)}{(C_2)^2} \right) \]
\[ = \frac{\beta}{C_2} \left[ -d(I_{j,1}) - \frac{C_1}{C_2} \left( p_2^\alpha A_j + (1 - \delta) \right) d(I_{j,1}) - \frac{C_1}{C_2} p_2^\alpha K_{j,2} d(A_j) \right] \]
\[ = \frac{\beta}{C_2} \left[ -d(I_{j,1}) - \frac{C_1}{C_2} d(I_{j,1}) \frac{C_2}{\beta C_1} d(I_{j,1}) - \frac{C_1}{C_2} p_2^\alpha K_{j,2} d(A_j) \right] \]
\[ = \frac{\beta}{C_2} \left[ -d(I_{j,1}) - \beta^{-1} d(I_{j,1}) \right] - \frac{BC_1}{(C_2)^2} p_2^\alpha K_{j,2} d(A_j) \]
\[ = -(C_2)^{-1}(1 + \beta) d(I_{j,1}) - \frac{m_2}{C_2} p_2^\alpha K_{j,2} d(A_j) \]  

(B.2.3)

\[ d(p_2^\alpha) = -(1 - \alpha) \alpha(A_j K_{j,2})^{\alpha - 2} A_j d(I_{j,1}) - (1 - \alpha) \alpha(A_j K_{j,2})^{\alpha - 2} K_{j,1} d(A_j) \]
\[ = -(1 - \alpha) \frac{p_2^\alpha}{X_2} A_j d(I_{j,1}) - (1 - \alpha) \frac{p_2^\alpha}{X_2} K_{j,1} d(A_j) \]  

(B.2.4)
To examine the impact of capital productivity on investment, I apply the Implicit Function Theorem to equation (B.2.1) and obtain

\[ d(m_2)[p_2^xA_j + (1 - \delta)] + m_2[p_2^x d(A_j) + A_j d(p_2^x)] = 0 \] (B.2.5)

Substitute (B.2.3) and (B.2.4) into (B.2.5)

\[ \left( C_2 \right)^{-1}(1 + \beta)d(I_{j,1})(m_2)^{-1} + m_2(1 - \alpha)\frac{p_2^x}{X_2}A_j \right) d(I_{j,1}) = \left( p_2^x m_2 - m_2(1 - \alpha)\frac{p_2^x}{X_2} A_{j,2} + (C_2)^{-1} p_2^x K_{j,2} \right) d(A_j) \]

\[ \Rightarrow \frac{dI_1}{d(A_{j,t})} = \frac{dI_{j,1}}{d(A_{j,t})} = \frac{\alpha p_2^x m_2 + (C_2)^{-1} p_2^x K_{j,2}}{m_2(1 - \alpha)\frac{p_2^x}{X_2}A_j + (C_2)^{-1}(1 + \beta)(m_2)^{-1}} > 0 \] (B.2.7)

The inequality follows from the fact that \( \alpha < 1 \) and all of the terms are strictly positive.

**B.3 Impact of the technology shock on the SDF with reallocation frictions**

**B.3.1 Relation between new investment and capital reallocation at time 1**

Revisit the equilibrium marginal value of capital at time 1 if there is a technology shock.

\[ q_{H,1}^U = m_2^U [p_2^x A_H + (1 - \delta)] = 1 \] (3.3.8)

\[ q_{L,1}^U = m_2^U [p_2^x A_L + (1 - \delta)] = \frac{\psi}{1 + \gamma \frac{N_L}{K_{L,1}}} \] (3.3.10)
where

\[ p_2^x = \alpha (A_L K_{L,2}^U + A_H K_{H,2}^U)^{\alpha - 1} \]  
\[ m_2^U = \beta \frac{C_1^U}{C_2^U} = \beta \frac{Y_1 - I_1^U}{Y_2^U + (K_{H,2}^U + K_{L,2}^U)(1 - \delta)} \]

**Lemma 1** The discount factor over period 2 and the market price of used capital are inversely related.

By applying the Implicit Function Theorem to equation (3.3.10) and (3.3.8), I obtain:

\[
\frac{\psi}{q_{L,1}} m_2^U d(p_2^x) A_L + \left( d(\gamma) \frac{N_1}{K_{L,1}} + \frac{\gamma}{K_{L,1}} d(N_1) \right) m_2^U [p_2^x A_L + (1 - \delta)] \\
+ d(m_2^U) \left( p_2^x A_L + (1 - \delta) \right) \left( 1 + \frac{\gamma N_1}{K_{L,1}} \right) m_2^U = 0
\]

\[
\frac{\psi}{q_{L,1}} m_2^U d(p_2^x) A_L + \left( d(\gamma) \frac{N_1}{K_{L,1}} + \frac{\gamma}{K_{L,1}} d(N_1) \right) q_{L,1}^U + d(m_2^U)(m_2^U)^{-1} \psi = 0
\]  

and

\[
m_2^U A_H d(p_2^x) + d(m_2^U) \left( A_H p_2^x + (1 - \delta) \right) = 0
\]

\[
m_2^U A_H d(p_2^x) + d(m_2^U)(m_2^U)^{-1} = 0
\]

\[ \Rightarrow \frac{d(p_2^x)}{d(m_2^U)} = -\frac{(m_2^U)^{-1}}{m_2^U A_H} < 0 \]
The total derivatives of $m_2^U$ and $p_2^x$ are obtained from equation (B.3.1b) and (B.3.1a)

\[
d(m_2^U) = \frac{\beta}{C_2^U} \left[ -d(I_1^U) - \frac{C_1^U}{C_2^U} \left( \frac{p_2^x}{\alpha(A_L K_{L,2}^U + A_H K_{H,2}^U)} \right)^{-1} \left( A_H(d(I_{H,1}^U) + \psi d(N_1)) \right. \\
\left. \quad - A_L \left( 1 + \gamma \frac{N_1}{K_{L,1}} \right) d(N_1) \right) + (1 - \delta) (d(K_{L,2}^U) + d(K_{H,2}^U)) \right] \\
= \frac{\beta}{C_2^U} \left[ -d(I_1^U) - \frac{C_1^U}{C_2^U} \left( \frac{p_2^x}{\alpha(A_L + (1 - \delta))} (d(I_{H,1}^U) + \psi d(N_1)) \right) \right. \\
\left. \quad + (1 - \delta) \left( d(I_{H,1}^U) + \psi d(N_1) \right) - \left( 1 + \gamma \frac{N_1}{K_{L,1}} \right) d(N_1) \right] \\
= \frac{\beta}{C_2^U} \left[ -d(I_1^U) - \frac{C_1^U}{C_2^U} (m_2^U)^{-1} d(I_1^U) \right] \\
= -(C_2^U)^{-1} (1 + \beta) d(I_1^U) \tag{B.3.5}
\]

and

\[
d(p_2^x) = -(1 - \alpha) \alpha (A_L K_{L,2}^U + A_H K_{H,2}^U)^{-2} \left( A_H(d(I_{H,1}^U) + \psi d(N_1)) - A_L \left( 1 + \gamma \frac{N_1}{K_{L,1}} \right) d(N_1) \right) \\
= -(1 - \alpha) \frac{p_2^x}{X_2} \left[ A_H d(I_{H,1}^U) + A_L \left( \eta \psi - \left( 1 + \gamma \frac{N_1}{K_{L,1}} \right) d(N_1) \right) \right] \tag{B.3.6}
\]

**Lemma 2** Used capital is an imperfect substitute of new investment. Capital reallocation and new investment are negatively related.

By substituting equation (B.3.5) and (B.3.6) into (B.3.4) and rearranging the equation, I obtain the relation between $I_{H,1}^U$ and $N_1$. 

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\[
\frac{dI^U_1}{dN_1} = -(1 - \alpha)(p_x^2/X_2)(m_t^U_2)A_HA_L(\psi\eta - (1 + \gamma N_1^{K_L}) \right)
\]
\[
= \frac{m_t^U_2A_H^2(1 - \alpha)p_x^2/X_2 + (C_U^t)^{-1}(1 + B)(m_t^U)^{-1}}{m_t^U_2A_H^2(1 - \alpha)p_x^2/X_2 + (C_U^t)^{-1}(1 + B)(m_t^U)^{-1}}
\]

(3.4.11)

since

\[
A_L(\psi\eta - (1 + \gamma N_1^{K_L}))) = A_L\left(\psi\eta - \frac{\psi}{q_{U,1}}\right)
\]
\[
= A_L\psi\left(\eta - q_{U,1}^{-1}\right) > 0
\]

(B.3.7)

(According to equation (3.3.12), \( q > \eta^{-1} \).)
B.3.2 Impact of reallocation frictions on investment and capital reallocation at time 1

The relation between reallocation frictions with capital reallocation and investment can be obtained by substituting equation (3.4.11) and (B.3.5) into equation (B.3.2).

\[
\left( d(\gamma) \frac{N_1}{K_{L,1}} + \frac{\gamma}{K_{L,1}} d(N_1) \right) q_{L,1}^U = -\frac{\psi}{q_{L,1}^U} m_2 A_L d(p_2^2) - d(m_2^U) \left( m_2^U \right)^{-1} \psi \\
\left( d(\gamma) \frac{N_1}{K_{L,1}} + \frac{\gamma}{K_{L,1}} d(N_1) \right) q_{L,1}^U = -\frac{\psi}{q_{L,1}^U} \left( 1 - \delta \right) \left( 1 - \eta^{-1} \right) d(m_2^U) \\
d(\gamma) \frac{N_1}{K_{L,1}} = -\frac{\psi}{(q_{L,1}^U)^2} \left( 1 - \delta \right) \left( 1 - \eta^{-1} \right) d(m_2^U) - \frac{\gamma}{K_{L,1} q_{L,1}^U} d(N_1) \\
d(\gamma) \frac{N_1}{K_{L,1}} = \frac{\psi}{C_2 (q_{L,1}^U)^2} \left( 1 + \beta \right) \left( 1 - \delta \right) \left( 1 - \eta^{-1} \right) d(I_{H,1}^U) - \frac{\gamma}{K_{L,1} q_{L,1}^U} \frac{d(N_1)}{d(I_{H,1}^U)} d(I_{H,1}^U) \\
d(\frac{I_{H,1}^U}{d(\gamma)}) = \frac{\psi}{C_2 (q_{L,1}^U)^2} \left( 1 + \beta \right) \left( 1 - \delta \right) \left( 1 - \eta^{-1} \right) K_{L,1} - \frac{\gamma}{q_{L,1}^U} \frac{d(N_1)}{d(I_{H,1}^U)} d(I_{H,1}^U) > 0 \\
(3.4.12)
\]

where the denominator is positive, since \( \frac{d(N_1)}{d(I_{H,1}^U)} < 0 \) The derivative of capital reallocated with respect to reallocation frictions is obtained from equation (3.3.14).

\[
d(N_1) = -\frac{1}{\gamma^2} \left( \frac{\psi}{q_{L,1}^U} - 1 \right) K_{L,1} d(\gamma) - \frac{\psi}{\gamma (q_{L,1}^U)^2} d(q_{L,1}^U) \\
= -\frac{1}{\gamma} N_1 d(\gamma) - \frac{1}{\gamma} \frac{\psi K_{L,1}}{\gamma (q_{L,1}^U)^2} (1 - \eta^{-1})(1 - \delta) d(m_2^U) \\
= -\frac{1}{\gamma} \left( N_1 + \frac{\psi K_{L,1}}{(q_{L,1}^U)^2} (1 - \eta^{-1})(1 - \delta) \frac{d(m_2^U)}{d(I_{H,1}^U)} \frac{d(I_{H,1}^U)}{d(\gamma)} \right) d(\gamma) \\
d(\frac{N_1}{d(\gamma)}) = -\frac{1}{\gamma} \left( N_1 + \frac{\psi K_{L,1}}{(q_{L,1}^U)^2} (1 - \eta^{-1})(1 - \delta) \frac{d(m_2^U)}{d(I_{H,1}^U)} \frac{d(I_{H,1}^U)}{d(\gamma)} \right) < 0 \\
(3.4.13)
\]
since

\[
\frac{d(I_{H,1}^U)}{d(\gamma)} < \frac{N_1}{\psi \left( q_{L,1}^U \right)^2 (1 + \beta)(1 - \delta)(1 - \eta)^{-1}K_{L,1}}
\]

\[
\frac{d(m_2^U)}{d(I_{H,1}^U)} \frac{d(I_{H,1}^U)}{d(\gamma)} > -\frac{N_1}{\psi \left( q_{L,1}^U \right)^2 (1 - \delta)(1 - \eta)^{-1}K_{L,1}}
\]

\[
\Rightarrow \frac{d(N_1)}{d(\gamma)} < -\frac{1}{\gamma} \frac{1}{N_1} + \frac{1}{\gamma} \frac{\psi K_{L,1}}{\left( q_{L,1}^U \right)^2 (1 - \delta)(1 - \eta)^{-1}K_{L,1}} \frac{N_1}{\left( q_{L,1}^U \right)^2 (1 - \delta)(1 - \eta)^{-1}K_{L,1}}
\]

\[
\Rightarrow \frac{d(N_1)}{d(\gamma)} < \frac{1}{\gamma} N_1 + \frac{1}{\gamma} N_1 = 0
\]

### B.3.3 Impact of reallocation frictions on $I_0$ and $m_1^U$

At time 0, only the non-innovating firm invests. Its equilibrium investment is determined by

\[
q_{L,0} = \theta m_1^U \left[ p_1^A L + q_{L,1}^U \left( \frac{N_1}{K_{L,t+1}} \right)^2 + 1 - \delta \right] + (1 - \theta) m_1^P [ p_1^A L + (1 - \delta)] = 1
\]

(3.3.16)

where $\frac{1}{2} \left( \frac{N_1}{K_{L,t+1}} \right)^2$ is very small. Approximately,

\[
q_{L,0} = \theta m_1^U \left[ p_1^A L + q_{L,1}^U (1 - \delta) \right] + (1 - \theta) m_1^P [ p_1^A L + (1 - \delta)] = 1
\]

(B.3.8)

By applying the Implicit Function Theorem to equation (B.3.8), I obtain

\[
\theta d(m_1^U) \left( p_1^A L + q_{L,1}^U (1 - \delta) \right) + (1 - \theta) d(m_1^P) \left( p_1^A L + (1 - \delta) \right) + \theta m_1^P \left( p_1^A L \right) + \theta m_1^U \left( q_{L,1}^U \right) (1 - \delta) = 0
\]

(B.3.9)
where

\[ d(q^L_{t,1}) = (1 - \eta^{-1})(1 - \delta)d(m^L_t) = -(c^U_2)^{-1}(1 + \beta)(1 - \eta^{-1})(1 - \delta)d(I^U_t) \]  \hspace{1cm} (B.3.10)

The derivatives of the discount factors over period 1 and the price of intermediate goods at time are

\[ d(m^U_t) = -\frac{\beta}{C^U_1} \left[ 1 + \frac{C_0}{C^U_1} p^I_1 A_L \right] d(I_0) + \frac{\beta C_0}{(C^U_1)^2} d(I^U_t) \]  \hspace{1cm} (B.3.11a)

\[ d(m^P_t) = -\frac{\beta}{C^P_1} \left[ 1 + \frac{C_0}{C^P_1} p^I_1 A_L \right] d(I_0) + \frac{\beta C_0}{(C^P_1)^2} d(I^P_t) \]  \hspace{1cm} (B.3.11b)

\[ d(p^I_1) = -(1 - \alpha) \frac{p^I_1}{X_1} A_L d(I_0) \]  \hspace{1cm} (B.3.11c)

Substituting equations (B.3.10), (B.3.11a), (B.3.11b) and (B.3.11c) into (B.3.9)

\[-(m^U_t)^{-1} \left[ \frac{\beta}{C^U_1} \left[ 1 + \frac{C_0}{C^U_1} p^I_1 A_L \right] d(I_0) + (m^U_t)^{-1} \theta \frac{\beta C_0}{(C^U_1)^2} d(I^U_t) - (1 - \theta) \frac{\beta}{C^U_1} \left[ 1 + \frac{C_0}{C^U_1} p^I_1 A_L \right] d(I_0) \right.\]

\[-(r^I_t)^{-1} (1 - \alpha) \frac{p^I_1}{X_1} A_L d(I_0) - \theta m^U_t (c^U_2)^{-1}(1 + \beta)(1 - \eta^{-1})(1 - \delta)^2 d(I^U_t) = 0\]

By rearranging the equation, I get

\[ LHS = \left( \frac{Z_1}{(m^U_t)^{-1} \theta \frac{\beta}{C^U_1} \left[ 1 + \frac{C_0}{C^U_1} p^I_1 A_L \right] + (1 - \theta) \frac{\beta}{C^U_1} \left[ 1 + \frac{C_0}{C^U_1} p^I_1 A_L \right] + (r^I_t)^{-1} (1 - \alpha) \frac{p^I_1}{X_1} A_L} \right) d(I_0) \]

\[ RHS = \left\{ (m^U_t)^{-1} \theta \frac{\beta C_0}{(C^U_1)^2} - \theta m^U_t (c^U_2)^{-1}(1 + \beta)(1 - \eta^{-1})(1 - \delta)^2 \right\} d(I^U_t) \]

\[ d(I_0) = \frac{(m^U_t)^{-1} \theta \frac{\beta C_0}{(C^U_1)^2} - \theta m^U_t (c^U_2)^{-1}(1 + \beta)(1 - \eta^{-1})(1 - \delta)^2}{\left( Z_1 + (r^I_t)^{-1} (1 - \alpha) \frac{p^I_1}{X_1} A_L \right)} \]  \hspace{1cm} (B.3.12)
Substituting (B.3.12) into (B.3.11a), I obtain the derivative of $m_I^U$ with respect to $I_1^U$

$$d(m_I^U) = \frac{\beta C_0}{(C_I^U)^2} d(I_1^U) - \beta \frac{\beta}{(C_I^U)^2} \left[ 1 + \frac{C_0}{C_I^U} p_i^A L \right] \frac{d(I_0)}{d(I_1^U)} d(I_1^U)$$

$$d(m_I^U) = \frac{\beta C_0}{(C_I^U)^2} d(I_1^U) - \beta \frac{\beta}{(C_I^U)^2} \left[ 1 + \frac{C_0}{C_I^U} p_i^A L \right] \frac{d(I_0)}{d(I_1^U)}$$

$$d(m_I^U) = \frac{\beta C_0}{(C_I^U)^2} d(I_1^U) - \beta \frac{\beta}{(C_I^U)^2} \left[ 1 + \frac{C_0}{C_I^U} p_i^A L \right] \frac{d(I_0)}{d(I_1^U)}$$

$$d(m_I^U) = \frac{\beta C_0}{(C_I^U)^2} d(I_1^U) - \beta \frac{\beta}{(C_I^U)^2} \left[ 1 + \frac{C_0}{C_I^U} p_i^A L \right] \frac{d(I_0)}{d(I_1^U)}$$

$$d(m_I^U) = \frac{\beta C_0}{(C_I^U)^2} d(I_1^U) - \beta \frac{\beta}{(C_I^U)^2} \left[ 1 + \frac{C_0}{C_I^U} p_i^A L \right] \frac{d(I_0)}{d(I_1^U)}$$

Thus

$$\frac{d(m_I^U)}{\gamma} = \frac{d(m_I^U)}{d(I_1^U)} \times \frac{d(I_1^U)}{d(\gamma)} > 0 \quad (B.3.15)$$

**B.3.4 Impact of reallocation frictions on risk premium**

The covariance between the non-innovating firm’s return and the discount factor over period 1 is

$$\text{Cov}[r_{L,1}, m_1] = \theta(1 - \theta)(1 - \delta)(m_1^U - m_1^D)(q_{L,1}^U - 1) < 0 \quad (B.3.16)$$

The derivative of the non-innovating firm’s covariance is

$$\frac{d(\text{Cov}[r_{L,1}, m_1])}{d(\gamma)} = \theta(1 - \theta)(1 - \delta) \left[ \frac{d(m_I^U - m_I^D)}{d(\gamma)} (q_{L,1}^U - 1) + (m_I^U - m_I^D) \frac{d(q_{L,1}^U)}{d(\gamma)} \right]$$

$$= -\theta(1 - \theta)(1 - \delta) \left[ (1 - q_{L,1}^U) \frac{\beta C_0}{(C_I^U)^2} + (C_I^U)^{-1} (1 + \beta) (1 - \bar{\eta}^{-1})(1 - \delta) \right] \frac{d(q_{L,1}^U)}{d(\gamma)}$$

$$= -\theta(1 - \theta)(1 - \delta) \left[ (1 - q_{L,1}^U) \frac{\beta C_0}{(C_I^U)^2} + (C_I^U)^{-1} (1 + \beta) (1 - \bar{\eta}^{-1})(1 - \delta) \right] \frac{d(q_{L,1}^U)}{d(\gamma)}$$

$$< 0 \quad (B.3.17)$$
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Author/s:
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