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INNOVATION IN DECLINING AND DISTRESSED FIRMS

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ABSTRACT

Firms often face performance shortfalls, either relative to their past performance or relative to their competitors' performance. Sometimes, performance shortfalls are so severe that firms are forced into bankruptcy. This dissertation investigates how organizations respond to such performance shortfalls, and how those responses affect their subsequent performance. It focuses on three specific aspects of these responses---the intensity of organizational search, and the roles of intangible asset divestitures and human capital.

The dissertation consists of three essays. The first essay proposes a persistence-based framework of organizational search. This framework connects the relative persistence of social and historical relative performance with the relative persistence of the carryover effects of two types of organizational search, innovative and market search. This essay posits that social relative performance is more persistent than historical relative performance; as a result, social relative performance has a stronger effect on innovative search, which has a more persistent carryover effect than market search. Consistent with the proposed framework, I find that, while a positive social relative performance is associated with a reduction in a firm’s search intensity, a negative social relative performance increases firm search intensity. On the contrary, historical relative performance does not exhibit this differential pattern. Finally, using an industry-level measure of profit persistence, I find that social relative performance has a stronger effect on innovative search in high-persistence industries, compared to its effect in low-persistence industries. Together, these findings highlight persistence as an important mechanism that links historical and social relative performance to innovative and market search.

The second essay investigates the effect of divestiture of technological assets on large bankrupt firms to see whether the divestiture strategy will help them to overcome competitive disadvantages, or if the firm will sink into the mud of competitive disadvantages. I construct a sample containing large patenting public firms that file for bankruptcy in the United States. I build a two-phase framework to examine the antecedents and consequences of divesting technological assets. The first phase focuses on the bankruptcy period and analyzes which kinds of technological assets are more likely to be divested. The second phase relates to the post-bankruptcy period and

explores the performance changes and knowledge utilization associated with divestiture. I analyze two attributes of the technological assets: whether the assets are of high value, and whether the assets are in a firm's core technological areas. As the two attributes contain information about the price of assets when they get liquidated, and the embeddedness of knowledge in the correspondent technological areas respectively, they are naturally connected with a firm's post-bankruptcy profitability, technological function, and knowledge utilization. Specifically, I find that high-value or non-core technological assets are more likely to be divested than their counterparties are. I also find that, while divesting high-value technological assets can improve profitability, divesting non-core ones is associated with worsen technological function and less knowledge utilization in existing and new technological areas. By examining how the attributes of the assets affect the gains and losses in profitability, technological performance, and knowledge utilization associated with the divestiture, I extend the current understanding of resource reconfiguration among bankrupt firms.

The last essay investigates the effect of bankruptcy on the mobility of a firm's skilled human capital. Using a novel data set, I compare the skilled human capital turnover patterns within the bankrupt and non-bankrupt firms over a prolonged period. Adopting propensity score matching and difference-in-difference approach, I find that bankrupt firms have fewer patent inventors enter during the post-bankruptcy period than that of the pre-bankruptcy period, compared to the inventors' entry of non-bankrupt firms during the same timespans. Additionally, I find that bankrupt firms have fewer inventors retained after bankruptcy, compared to that of non-bankrupt firms. I argue that this turnover pattern in bankrupt firms could be driven by lack of ability to attract new inventors and to retain the existing inventors. Furthermore, I find that bankrupt firms have fewer star inventors and more novice inventors remained in the firm after bankruptcy, which implies that the bankrupt firms may suffer from a reduction in innovation capabilities. The findings suggest that the bankrupt firms face unique human capital management problems, compared to non-bankrupt firms.

In sum, this dissertation investigates how an organization copes with different performance shortfalls and how these strategies have an effect on an organization's subsequent economic and innovative performance. The findings shed light on the strategies of distressed or bankrupt firms and their unique challenges in technological assets management and human capital management.

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CHAPTER ONE:

OVERVIEW OF THE DISSERTATION

INTRODUCTION

This dissertation consists of three essays[1] about a firm's resource management strategies in face of performance shortfalls. By acquiring new resources, divesting some other resources, and recombining or redeploying their existing resource, a distressed firm could better align their resources with deteriorating performance situations. Morrow, Sirmon, & Hitt (2007) point out that a proper implementation of those reconfiguration strategies could be the key to the turnaround of distressed firms.

However, balancing different resource management strategies is not an easy task for the distressed firms. As March (1991) points out, different organizational activities compete for scarce resources. This competition is even more intense for firms that have relatively worse performance. Compared to those well-performing firms, distressed firms need to carefully balance the need of reserving resources for the survival between that for the future value creation. Considering the needs of resource reconfiguration as well as the difficulties of implementing these strategies in distressed firms, I would like to investigate how an organization copes with performance shortfalls by reconfiguring their resource base, and how these strategies affect an organization's resource stock, and subsequent economic and innovative performance.

Within a wide range of resources, I am especially interested in a firm's intangible assets. Intangible assets are increasingly important for an organization as the amounts of intangible assets within in a firm have been increasing dramatically over the past years and intangible assets are likely to be a source of competitive advantage due to social complexity and causal ambiguity.

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[1] In the three essays, I use the personal pronoun "we" instead of "I" for reason of the possible collaboration in the future journal submission.

In this dissertation, I focus on the strategies that directly affect the intangible assets in the troubled firms.

Furthermore, I compare the resource reconfiguration in face of different performance shortfalls. In the three essays, I analyze three types of performance shortfalls: whether the performance is below historical performance, rivals' performance, or when the firm goes bankrupt. The three performance shortfalls differ in their severity and duration. For example, previous research in profit persistence literature implies that a firm's profit relative to the industry average persists for long periods of time (Jacobsen, 1988; Waring, 1996; Wiggins & Ruefli, 2002), while a similar persist pattern does not exist in performance relative to its own past performance. Compared to the first two performance shortfalls, the third one, bankruptcy directly threatens the survival of the firm. The differences in different performance shortfalls could trigger a firm to take different resource management strategies. I examine these performance shortfalls' impact on technological assets development, divestiture strategies, and human capital management in the three essays respectively. By examining the different performance shortfalls and different strategies, I aim at gaining a comprehensive understanding of a firm's resources management strategies in face of different types of performance shortfalls.

I intend to make three contributions. First, I add to the discussion of how a firm deals with a competitive disadvantage. The fundamental question of strategic management is how a firm could achieve and sustain competitive advantage. This literature identifies effective strategies that lead to competitive advantages. Among all the strategies, the literature highlights that effective innovation strategy could help a firm to achieve and sustain competitive advantage. In the three essays, I show that just like well-performing firms, declining and distressed firms also rely on various innovation strategies to overcome the performance shortfalls. In the first essay, I show that when the distressed firms are not threatened by bankruptcy but have a prolonged performance shortfall, they actively conduct innovation activities to develop technological assets. In the second and third essay, I show that a firm divests technological assets and reduces skilled labor recruitment when it goes bankrupt. The results suggest that the severity of performance shortfalls indeed affects the technological resource management of the firms. The findings shed light on the strategies of distressed or bankrupt firms and their unique challenges of resource management.

Second, I respond to resource reconfiguration literature (Karim & Capron, 2016) to explore the reconfiguration strategies for non-traditional resources. As Karim and Capron (2016) observe, most reconfiguration studies focus on traditional resources (e.g. Capron, et al., 2001; Xia & Li, 2013). I hope to extend the analysis to technological assets and human capital, two important types of intangible assets that have not been extensively studied before. Further, the context of most previous studies of resource reconfiguration is diversification (e.g, Helfat & Eisenhardt, 2004), and mergers and acquisitions (e.g. Capron et al., 2001; Karim & Mitchell, 2000; Xia & Li, 2013). However, the resource reconfigurations during bankruptcy are likely to be different from those during the post-diversification and post-acquisition period with its prolonged financial distress and an urgent need for survival. Therefore, I intend to contribute to this literature by examining two important types of intangible assets, technological assets and skilled human capital; and a specific context, among bankrupt firms.

Last but not least, I speak to the micro-foundation research in human capital management. This literature highlights the role of firm-specific human capital as a source of sustainable competitive advantage (e.g. Coff & Kryscynski, 2011). They point out that resolution of two human capital related problems, which are the attraction and retention of human capital, creates value for the firm. Furthermore, considering that the turnover of employees makes the otherwise immobile tacit knowledge transferrable across the organizational boundary, investigating employee turnover patterns has implications for managing organizational knowledge and understanding subsequent organizational performance. The findings in the third essay suggest that being bankrupt is an organizational factor that leads to a reduction of skilled human capital stock. By comparing the entry and exit patterns of employees among bankrupt and non-bankrupt firms, I identify the problems faced by bankrupt firms in terms of human capital management, as well as offer more a comprehensive understanding of the skilled labor turnover patterns among bankrupt firms.

SUMMARY OF DISSERTATION

In the first essay of this dissertation, I use the behavior theory of the firm (BTOF) to examine how a firm could respond to performance shortfalls with respect to its social and historical reference group (Cyert & March, 1963). This literature predicts whether a firm's performance will be above or below its aspiration levels acts as a "master switch" in affecting its search behaviors. In BTOF, despite some research considers social and historical relative performance separately (e.g. Greve, 2003b; Chen & Miller, 2007; Iyer & Miller, 2008), how the two differ from each other still has not been extensively studied. As a result, I respond to the call of Bromiley and Harris (2014) and Kim, Finkelstein, and Haleblian (2015) to study the differential effects of performance feedbacks from social and historical relative performances. In order to do so, I incorporate profit persistence literature (Chacar & Vissa, 2005; Mueller, 1986; Waring, 1996) with BTOF to predict how the social and historical relative performance motivate organizational internal resource building activities through conducting innovative and market search.

Using a large panel of data from COMPUSTAT from 1962 to 2015, the empirical results in the first essay support hypotheses that social relative performance is persistent in nature, while historical relative performance is not persistent. In line with the theoretical predictions, I find that social relative performance has a stronger effect on innovative search than on market search. Furthermore, I find that a negative historical relative performance increases both innovative and market search, while a negative social relative performance increases innovative search. In terms of positive relative performance, I find that a positive historical relative performance increases the two searches, while a positive social relative performance reduces the two. Finally, and further buttressing my framework, using an industry-level measure of performance persistence, I find that being in high-persistence industries intensifies the effect of social relative performance on innovative search, compared to being in low-persistence industries.

The first essay of the dissertation suggests how a performance shortfall affects innovative activities largely depends on how I define performance shortfall– whether it is a performance shortfall related to industry peers or a performance shortfall related to its own past performance. This motivates me to look at a more clearly defined situation of performance shortfall: when a firm goes bankrupt.

The second essay explores technological assets divestiture strategies among bankrupt firms and examines the drivers and performance impact of these divestiture strategies. This paper adds to a nascent literature studying the divestiture of technological assets using patent assignment data. I differentiate the divestiture of technological assets from the divestiture of other assets, mostly physical assets. A bankruptcy firm is facing intense competition between liquating technological assets for cash and retaining technological assets for future use. As a result, how to balance these resource reconfiguration strategies matters for whether a firm could effectively utilize its resources and leverage the resources to value creation (Sirmon, Hitt, Ireland, & Gilbert, 2011). I am interested in which types of technological assets are more likely to be sold during bankruptcy: the one in core/non-core technological areas or the ones with high/low value. I contribute to the bankruptcy literature by discussing how divestiture of technological assets are connected to the profitability, technological function, and knowledge utilization changes among bankrupt firms.

Using a sample of large U.S. bankrupt firms that filed for bankruptcy from 1979 to 2014, I find that a bankrupt firm is more likely to divest high-value or non-core technological assets. Additionally, I find that divesting non-core ones is associated with worsened technological function and less knowledge utilization in existing and new technological areas, compared to divesting core ones. I argue this divergence in the effect of the divestiture of technological assets comes from the impact of divestiture on the knowledge that resides in the technological areas. As knowledge is more embedded in core technological areas than that in non-core areas, divesting core technological assets may not affect the knowledge that resides in the firm. On the other hand, divesting non-core technological assets could negatively affect the existing knowledge in the bankrupt firms.

In the second chapter, I propose the idea of separating technological assets from knowledge assets. I would like to further investigate the knowledge gain, loss, and retention patterns in bankrupt firms. The tacit and socially complex knowledge of the firm is likely to reside within the skilled labor of an organization (Almeida & Kogut, 1999). Considering that the turnover of employees makes the otherwise immobile and tacit knowledge transferrable across the organizational boundary, investigating the turnover of employees could explain the how the knowledge is developed and reconfigured in a firm. This leads to the last chapter of the dissertation.

The last chapter examines the skilled human capital turnover patterns in bankrupt firms and non-bankrupt firms. I study whether bankrupt firms have less or more skilled labor enter, exit, and remain after bankruptcy, compared to non-bankrupt firms over the same periods. Furthermore, I would like to investigate the retention pattern of specific skilled labor: novice and star employees. I construct a sample containing the entire patent inventors' movement history in large U.S. bankrupt firms and comparable non-bankrupt firms via propensity score matching. Using difference-in-difference approach, I find that compared to non-bankrupt firms, bankrupt firms have fewer inventors enter and exit after bankruptcy. Additionally, I find that compared to non-bankrupt firms, bankrupt firms have more novice inventors retained and fewer star inventors retained after bankruptcy. These findings suggest that bankrupt firms face unique problems in attracting new talents and retaining their star employees.

Together, the three essays examine the intangible resource development and divestiture strategies among the firms that experience performance shortfalls. By looking at these resource management strategies among declining or distressed firms, I plan to answer how declining or distressed firms manage their resource portfolio to address performance shortfalls, what kinds of resources are retained and what kinds of resources are divested, and how the resource management strategies differ between bankrupt and non-bankrupt firms.

CHAPTER TWO:

PERSISTENCE OF RELATIVE PERFORMANCE AND ORGANIZATIONAL SEARCH

INTRODUCTION

The stream of literature on performance feedback suggests that performance feedback, which is a performance relative to the aspiration level from social comparison or historical comparison, motivates organizational search aimed at improving performance. The behavior theory of the firm (BTOF) highlights two possible performance feedbacks: performance relative to its past performance, which we call historical relative performance; and performance relative to peers, which we call social relative performance. Subsequent empirical models in this literature elaborate on how the social and historical relative performance affect different types of search behaviors. However, most theoretical and empirical work in BTOF tradition still treats the two performance feedbacks similarly, as noted by Bromiley and Harris (2014) and Kim, Finkelstein, and Haleblian (2015). Even when the two performance feedbacks are considered separately (e.g. Greve, 2003b; Chen & Miller, 2007; Iyer & Miller, 2008), the aim is usually not to develop a theory for why they may be different but to demonstrate that they may have different impacts on organization search. Kim et al (2015) is a notable exception that starts to study the effects of different performance feedbacks.

In response to the call of Bromiley and Harris (2014) and Kim et al. (2015) to study the differential effects of performance feedback from social and historical relative performance, this paper points out that historical and social relative performance differ in their level of persistence. We draw from the literature on profit persistence to examine the relative persistence of historical and social relative performance. The key finding from these studies is that the gap between a firm's profits and the industry average profits persists for long periods of time despite a tendency to converge to the mean (Jacobsen, 1988; Waring, 1996; Wiggins & Ruefli, 2002). This literature suggests that because there are industry structure factors (which are similar to Caves and Porter's mobility barriers within industries), superior (inferior) performance relative to industry peers is likely to repeat in the subsequent periods (e.g., Chacar & Vissa, 2005; Mueller, 1986; Wiggins & Ruefli, 2002). Thus, the previous work implies that social relative performance will be persistent. However, those barriers that contribute to the persistence of social relative performance do not exist in the case of historical relative performance, because a firm can (comparatively) more easily adjust its strategies and historical aspiration level based on its past performance. Thus, we expect the historical relative performance to be less persistent than the social relative performance.

We apply this key insight to construct a persistence-based theoretical framework of organizational search that studies how organizational searches are triggered by persistent (or non-persistent) relative performances. Our framework aims to make four contributions. First, we contribute to the performance feedback literature to show that social and historical relative performance differ in their degree of persistence. Using panel data from COMPUSTAT covering 1962-2015, our empirical results support our hypotheses that social relative performances are persistent in nature, while historical relative performances are not persistent.

Second, we advance a theoretical framework that employs insights from the profit persistence literature (Chacar & Vissa, 2005; Mueller, 1986; Waring, 1996) to predict how the two forms of relative performances affect organizational search. In order to answer this question, we focus on two search activities: innovative search, which refers to search in the internal domain to build innovative capacity; and market search, which refers to search in the market domain to increase demand (Vissa, Greve, & Chen, 2010). These two search activities differ in their lasting effects, which allow us to naturally test the effect of persistence. In particular, previous literature suggests that the effects of innovative search last longer than the effects of market search such as promotion and advertising (Bublitz & Ettredge, 1989, Dutta, Narasimhan, & Rajiv, 2005; Eberhart, Maxwell, & Siddiqu, 2002). Hence, we propose that social relative performance (whether positive or negative) will have a stronger effect on innovative search than on market search, considering the degree of persistence of social relative performance and the degree of persistence in the effect of innovative search. Our empirical results support the theoretical predictions.

Third, while prior studies suggest that performance above aspiration level is a point when satisfactory performance stops the search, we argue that persistence or non-persistence in good performance redefines whether the problem of performance shortfall is indeed solved or not. This persistence-based framework of organizational search allows us to differentiate between the impact of positive and negative relative performances. We find that a negative historical relative performance increases both innovative and market search, while a negative social relative performance increases innovative search. In terms of positive relative performances, we find a positive historical relative performance increases the two searches, while a positive social relative performance reduces the two searches. Our finding suggests that social and historical relative performances act as “master switches” in affecting the search directions and intensities.

Finally, and further buttressing our framework, we test whether our findings of search patterns can be generalized to both high-persistence and low-persistence industries. Industries could differ in their profit persistence, and the importance of innovative and market search varies across industries. Cheuvin and Hirshcey (1993) find that advertising and R&D are both concentrated in a few industries, and the latter one has an even higher concentration rate. Previous research suggests that the positive effect of innovative and market search on firm performance is found to be stronger in those intensive industries than less-intensive industries

(Chauvin & Hirschey, 1993; Eberhart et al, 2002). Adding to them, using an industry-level measure of performance persistence, we find that being in high-persistence industries intensifies the effect of social relative performances on innovative search compared with being in low-persistence industries.

THEORY AND HYPOTHESES

Persistence of Relative performances

Broadly, persistence means that the deviation between a firm's current performance and the performance of its reference group converges to zero slowly. In other words, a persistent relative performance implies that a firm's performance relative to a selected benchmark, either social aspiration level or historical aspiration level, endures for a long period of time. The relative performance has two components, one is the current performance of an organization, and the other is the aspiration level. According to BTOF scholars, aspiration level is the "smallest outcome that would be deemed satisfactory by the decision maker" (Scheneider, 1992, p.1053). Whether a relative performance is persistent or not depends on whether a firm could consistently meet or miss its aspiration level easily. Cyert and March (1963) suggest that an organization could adjust its aspiration level according to the recent performance of the focal firm and of comparable organizations. This suggests that aspiration level, either historical or social aspiration, has a nature of being adaptive. Two mechanisms affect the persistence of relative performance: 1) whether a firm could adjust its aspiration easily, so that it makes the firm easier achieve its aspiration; 2) Whether a firm could achieve its aspiration easily, by setting a reasonable aspiration level. The two mechanisms lead a firm to meet a historical aspiration level more consistently than a social aspiration level.

Focusing first on the social relative performance (that is, the deviation between a firm's performance and its social aspiration level), prior literature shows that convergence of firm's profitability to the industry average is very slow (Mueller, 1986; Geroski, 1990; Waring, 1996) (hence, the use of the term "persistence"). Although the degree of convergence, and thus the degree of persistence, varies across industries (Waring, 1996), empirical results confirm a high degree of profit persistence in a wide range of industries.

Broadly, such profit persistence is argued to arise from various rent-generating and sustaining mechanisms at the industry levels (Chacar & Vissa, 2005; Waring, 1996). Specific industry-level factors shown to affect profit persistence include industry structure (Porter, 1980; Stigler, 1968), market share (Jacobsen, 1988; Mueller, 1986), technological complexity (Lippman & Rumelt, 1982), sunk cost (Dixit, 1981; Spence, 1977; Sutton, 1991), and other related factors. These factors act as "mobility barriers" mentioned in Cave and Porter (1977), which prevent under-performing firms from perfectly imitating the strategies of well-performing firms (Chacar & Vissa, 2005; Lippman & Rumelt, 1982; Waring, 1996), and cause the relative performance of a firm to persist. This stream of literature implies that an organization is likely to consistently meet or miss its social aspiration level, thus, has a persistent social relative performance. This stream of literature suggests that the performance persistence indeed exists, for both successful and unsuccessful firms. Thus, we predict:

Hypothesis 1: Social relative performance is likely to persist.

Unlike the social relative performance, the historical relative performance (the difference between a firm's current performance and its historical aspiration) is likely to fluctuate. The fluctuation of historical relative performance comes from the nature of historical aspiration level. Despite the timely adjusted nature of aspiration level, the historical and social aspiration level differ in their degree of stability. Compared to historical aspiration level, social aspiration level is more stable because the only changes to social aspiration level come from relatively stable exogenous shock such as business cycle or environment change. On the other hand, historical aspiration level is more easily adjustable, because there are many internal and external sources of a firm's past performance variation, which lead to the greater variation in historical aspiration level. As a result, we expect that historical aspiration level is more adjustable than social aspiration level. Not only is historical aspiration more easily to be adjusted, but also an organization's response to historical aspiration turns to be faster than its response to social aspiration. Compared to social aspiration, an organization is more likely to access reliable information related to its own performance and it can understand its own sources of performance changes better (Greve, 2003c; Kim, et al., 2015). As a result, a firm should respond to historical aspiration level faster and this increases the chance of meeting aspiration level in the next period. Altogether, if a firm does not achieve its historical aspiration level in the current year, it could lower its aspiration level, and make the aspiration level more easily achievable for the next year; or it could initiate a faster response to historical aspiration. As a result, the performance shortfall regarding historical aspiration level could be easily met by adjusting the aspiration level or timely response. Hence, these arguments predict that:

Hypothesis 2: Historical relative performance is not likely to persist.

Persistence of Relative Performance and Organizational Search

Organizational search is a process involving problems, pre-existing solutions, and a discovery of new solutions (Gavetti, Greve, Levinthal & Ocasio, 2012). This paper focuses on *innovative search* and *market search* because the temporal patterns of returns to innovative and market search are different. Innovative search has a more persistent return compared to the return to market search, because the innovative search has greater causal ambiguity between inputs and outcomes (Aboody & Lev, 2000; Dierickx & Cool, 1989). Causal ambiguity makes it harder for competitors to imitate a firm's strategy, and makes the return to innovative investment lasts longer. In contrast, the market search is usually observable and can be imitated by competitors (Shum, 2004). Considering the difference in the duration of the effects of the two search activities, the persistence of relative performance is likely to affect the two search activities differently.

We expect positive relative social performance reduces innovative and market search for two reasons. First, positive relative social performance reduces the needs to search. Miller and Chen (1994) summarize that search activities are triggered by the motivation to search, the opportunity to search, and the capability to search. Relative performance reflects the need to search (Greve, 1986). One of the key axioms in the BTOF is that poor performance will motivate organizations to undertake activities to solve the problem, while such search will be depressed when the problem is solved (Cyert & March, 1963, p.121). Hence, if a firm has a positive social relative performance, which is very persistent as hypothesized, it will reduce the need for search activities in general. Furthermore, the resource competition among different activities reduces the preference for innovative and market search when a firm could afford more risky but higher return activities. Positive social relative performance enables the firm to accumulate resources and reallocate resources. Persistent good performance buffers the firm from possible failure and makes the decision makers have a greater tolerance for risky projects. Thus, an organization is more likely to shift from routinized search solutions to actions to these have a larger risk as well as a greater probability of higher return, such as merger and acquisition, enter a new market, and launch a new product, etc. The reduced need for searches and increased tolerance for risky activities further reduce the routinized search solutions such as innovative and market search. To sum up, we expect positive social relative performance reduces innovative and market search.

On the contrary, if a firm has a positive historical relative performance, it will expect performance shortfalls in the near future (since historical relative performance is not persistent). The “anticipated failure in the “immediate future” is expected to motivate decision makers of the firm to search for solutions to deal with the problem, even though it is doing well in the current period of time (Cyert & March, 1963, p.121). Cyert and March (1963) give the rule of proximity[2] of selecting search activities in response to performance feedback. Extending their discussion, Greve (2003c) point out that in practice, unless the problem is specific, managers could hardly know who is responsible for search and where to search. As a result, he points out another rule of search: “searching in organizational units whose daily responsibility include search activities” (Greve, 2003c, p.88). Innovative and market search follow this rule as their responsibility is to search in a technological environment and market environment (Greve, 2003c, p.89). Previous research confirms that a firm will increase innovative search (Greve, 2003a; Jacobson, & Park, 1996; Vissa, et al., 2010) and market search (Vissa, et al., 2010) in face of poor performance. Hence, in the case of positive historical relative performances, a firm will conduct innovative or market search to address the incoming performance shortfall.

Hypothesis 3a: Positive social performance has a negative effect on innovative/market search, while positive historical performance has a positive effect on innovative/market search.

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[2] They argue that search initially would occur in proximity of (1) the problem, (2) the current state of the organization, and (3) vulnerable areas of the organization.

Although persistence in a good performance will reduce the needs of innovative and market search, the strength of such reduction will be different for two reasons. First, compared to innovative search, the returns to market search are not persistent. Examining the effect of weekly advertising on sales, Vilcassim, Kadiyali, and Chintagunta (1999) find that the carryover effect of advertising via brand loyalty or consumer habit development does not last long, especially in intensive advertising industries, where consumers are sensitive to advertising and could easily switch between different brands. Bronnenberg, Mahajan, and Vanhonacker (2000) suggest that one reason for the absence of lasting carryover effect of market search is because a firm is less likely to engage in permanent marketing actions, especially in mature markets. Together, these arguments and findings suggest that even though market search could theoretically generate a long-term effect (through consistent advertising and repeated consumer purchases), the persistent effect of market search has been found to be quite small or absent (Pauwels, Hanssens, & Siddarth, 2002).

In addition, the market search is an attention-getting device to inform buyers about its products and thereby overcoming consumer inertia (Kessides, 1986). Thus, market search counteracts the tendency of brand loyalty [to competitors] (Shum, 2004). From that perspective, it is hard for a firm to sustain a performance advantage over long periods through market search because competitors can use similar strategies to attack the market position of the focal firm and it is almost impossible for the focal firm to prevent this kind of imitation behavior. Hence, the positive effect of market search through brand loyalty building is vulnerable to the advertising campaign of competitors. Since the return to market search is short-lived and relies on consistent investment, a firm would be less likely to cut market search considerably; doing so would mean forgoing significant market share to its competitors.

Unlike the return to market search, the return to innovative search is likely to persist (Bublitz & Ettredge, 1989; Dutta, Narasimhan, & Rajiv, 2005; Eberhart et al., 2002). First, innovative search increases a firm's absorptive capacity, which enables the firm to better identify and exploit knowledge from both inside and outside (Cohen & Levinthal, 1989). The capability generated by innovative search enables the firms to extract more benefits than those without such experience (Rothaermel & Deeds, 2006). The capability associated with innovative experience is embedded in a firm and is highly persistent at least for a five-year interval (Dutta et al., 2005). The process of generating innovative capability involves large causal ambiguity, which makes competitors hard to develop similar capabilities. Aboody and Lev (2000) suggest that information asymmetry is higher for R&D investment than other investment decisions. Because firm's innovative capability is an important source of the abnormal returns (Roberts, 2001) and this capability is relatively persistent, the return to innovative search is expected to last for a long period of time. Because of the persistence of innovative capability and its returns, reducing innovative search will not result in immediate performance decline.

Moreover, decision makers' preference for innovative and market search is different. Although managerial preference and firm's profit will affect the resources allocation, in general, the innovative search is not directly related to profit or sales (Thompson, 1967). Also, Bromiley and Washburn (2011) point out that cutting R&D expense may be easier than cutting other costs because it brings no immediate loss. Furthermore, the uncertain and lasting return further reduces the preference to conduct an innovative search (Tipping, 1993). Specifically, Miller and Bromiley (1990) point out that investment in R&D faces technological uncertainty, which is about whether the R&D projects could successfully turn into innovation, and market uncertainty, which is the uncertainty about whether the innovation could be accepted by the market or not. As a result, we expect that decision-makers in a firm will reduce more innovative search than market search.

To sum up, the prior literature suggests that the benefits of innovative search last longer than those of market search. As a result, cutting innovative search will not bring immediate loss to a firm, compared to cutting market search. Also, decision-makers prefer market searches more than innovative searches under good performance. Thus, in the face of persistent good performance, a firm is likely to cut more innovative search than market search. Hence:

Hypothesis 3b: Positive social relative performance has a stronger negative effect on innovative search than on market search.

A negative social relative performance indicates that a firm has not reached its goal, which triggers the firm to engage in search activities to address the performance shortfall (Singh, 1986; Miller & Chen, 2004). Innovative and market search could both be used to deal with potential performance shortfalls, because they both have potential to increase firm's market value and bring profits in the future (Bublitz & Ettredge, 1989; Chauvin & Hirschey, 1993). Those benefits of the two search behaviors make them solutions to performance shortfalls. Also, increasing the innovative and market search enable the firms to better exploit the existing resources, which are accumulated during the good performance. Greve (2003c) point out that an organization could store innovations, which are rejected during the period of good performance, and reexamine them for the possible launching when low performance occurs. As a result, a firm is expected to increase the innovative and market search activities in face of negative social relative performance.

A next question will be, even poor performance requires search, a firm could conduct a budget search, such as cost-cutting, as well as searches that increase expense; then will a firm be more likely to respond with budget search? We argue that there are three mechanisms that direct an organization to increase the innovative and market search instead of cutting them. First, decision-makers of an organization are more likely to attribute poor performance to environmental factors than internal factors. The external attribution makes the managers likely to decide to continue conducting activities the organization does in the past, instead of ceasing current projects. As a result, compared to increasing supports for current activities, reducing supports is a more distant search, which will only happen when current search activities fail. Furthermore, escalation of commitment makes managers keep devoting to current activities in face of loss situation (Bazerman, 1984; Northcraft & Neale, 1986; Whyte, 1986). Escalation of commitment also leads to sunk cost, which further reduces the chance of quitting existing activities. Third, although noticing reducing R&D expenditure could directly increase firm performance, managers are more likely to look for product development as search activities, and hence increase R&D and innovation launches (Gavetti et al; 2012). Considering the three mechanisms, previous research shows that poor performance is likely to trigger the continuation of existing activities than trying new ones (Audia, Locke, & Smith, 2000; Chen & Miller, 2007; Greve, 2003b, 2007; Miller & Chen, 1994; Vissa, et al. 2010). Altogether, we expect an organization will be more likely to increase innovative and market search than reducing them in face of performance shortfalls.

Although a negative historical relative performance implies the firm could improve its performance in the near future, we still expect that the firm to increase both innovative and market search in that situation based on the pressure from shareholders. Research suggests that most stock market participants, particularly transient institutional owners, are myopic, which focus on a quarter-to-quarter or year-to-year based firm performance (Bushess, 1998). As a result, the managers cannot simply wait for the performance to bounce back, and need to take actions to improve the short-term performance of the firm in order to satisfy and maintain its shareholders. The stock market responds to innovative and market search quickly, which makes them good candidates to solve negative historical relative performance problem (Eberhart et al., 2002; Eng & Keh, 2007; Vissa, et al., 2010)[3]. As a result, we expect a firm increases innovative and market search in the face of negative historical relative performance. Together, these arguments predict:

Hypothesis 4a: Negative social/historical relative performance has a positive effect on innovative/market search.

The persistence of the relative performance will affect whether an organization conducts more innovative search or more market search. As discussed before, the pattern of returns to innovative and market search is different. While the effect of innovative search could last for years, the effect of market search converges in weeks (Baye & Morgan, 2009; Shum, 2004; Vilcassim et al., 1999). This implies that when facing a situation to increase search, a firm will increase innovative search more because it will likely bring more persistent returns. This is even truer if the performance shortfall lasts for a long period of time; relying on investments with

[3] Though cutting expenses also works as a way to increase short-term performance, Bushess (1988) suggest that institutional owners are sophisticated and could understand and tolerate R&D investment. This implies that although institutional owners require for a short-term return, they do not necessarily discourage investments such as R&D and advertising.

instant returns may not be as helpful as developing long-term capabilities. Eberhart et al. (2002) find that an unexpected increase in R&D expense exerts positive stock market return over five years. Steenkamp and Fang (2011) find that during economic contractions, a strategy of increasing R&D but reducing advertising brings more profits than the opposite strategies for a firm faces tight budget constraints. Considering the causal ambiguity in building innovative capability and slow decaying of this capability, the innovative search is expected to bring returns that last for a relatively long period of time (Asthana & Zhang, 2006; Dutta et al., 2005; Eberhart et al., 2002). In light of the persistence of social relative performance, we predict:

Hypothesis 4b: Negative social relative performance has a stronger positive effect on innovative search than on market search.

Previous research suggests that there is considerable heterogeneity in persistence across industries (Waring, 1996). Some industries such as automobiles (Warning, 1996), pharmaceuticals (Roberts, 1999), and foods (Hirsch & Gschwandtner, 2013) have been found to have a slower convergence rate of profit than other industries. Hence, social relative performance is even more persistent in such high-persistence industries, while it is less persistent in low-persistence industries.[4] It also then follows that the positive or negative effects of social relative performance will be higher in high-persistence industries. This will be particularly true for innovative search given its more persistent nature. Firms with positive social performance in high-persistence industries will face a more reduced need to conduct innovative search than their

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[4] We do not expect industry-level performance persistence will affect the degree of persistence of historical relative performance, because the historical relative performance is more affected by firm-level factors. Being in high or low persistence industries has little to do with it.

counterparts in low-persistence industries. The effect of negative social performance will be similarly exacerbated in high-persistence industries. As a result, we expect:

Hypothesis 5: The effect of positive/negative social relative performance on innovative search is higher in high-persistence industries compared with low-persistence industries.

METHODS

Data

The sample for this study comes from Standard and Poor's COMPUSTAT database and covers the period from 1962 to 2015. This ensures the maximum possible length of time for our analyses while at the same time avoiding the sparsely populated R&D and advertising variables associated with the pre-1962 data (Fama & French, 1992). To construct our sample, we exclude firms with less than five years of observations in our sample to reduce the noise of short-lived firms (Francis, LaFond, Olsson & Schipper, 2005). We use the COMPUSTAT identifier (GVKEY) and Standard Industrial Classification (SIC) code to identify the organization and industry at each year. Activities such as reorganization, bankruptcy, M&A are usually associated with a change of GVKEY. Those activities will be reflected in its change of primary SIC. This method validates the social comparison and historical comparison in our model specification. Moreover, in line with prior studies (Bates, Kahle & Stulz, 2009; Vafeas, 1999), we exclude firms that do not have their headquarters in the U.S., as well as firms in finance (SIC codes 6000-6999) and utility sectors (SIC codes 4900-4999). We do so because it is difficult to calculate profitability in financial corporations and firm performance in utility sectors are affected by strong regulatory supervision, which makes firm performance in those sectors not comparable to firm performance in other sectors. Furthermore, to deal with influential outliers, we winsorize all variables to the 5^{th} and 95^{th} percentiles (we perform robustness checks to ensure that our results are not sensitive to the selection of percentiles). We also drop observations, if our key variables of interest (relative performances, search intensities, and slack measures) are more than four standard deviations from their means, because these observations are likely to be database errors or unusual outliers (Chen & Miller, 2007). We also drop observations with negative sales, R&D expense, and advertising expense because of possible measurement error with these records. In line with Hirschey, Skiba, and Wintoki (2012), we replace missing values of those expenditures with zero. Last, since there are firms that do not have debt at all and they may not report the debt as a result of that, we substitute the value with zero, if the variable is missing. We treat quick asset and selling, general and administrative expenses (SGAE) similarly. The final sample includes 179,078 firm-year observations from 1962 to 2015.

Modeling Approach

We test our hypotheses using three related models. Our first model specification, *Persistence Model*, is used to test the persistence of social and historical relative performance (*H1* and *H2*). In order to test a firm's decision to search and its search intensity, we model the firm's innovative and market search decisions using a two-stage process similar to the model used in Vissa et al. (2010). We chose Heckman selection model because our main equation has a sample selection bias induced endogeneity. The sample selection bias is because our sample is an incidental truncation sample, which means in this sample, we only observe R&D and advertising expenditure when the firm decides to conduct innovative and market search. This bias will lead us to only include firms, which conduct the two search activities. As a result, we use Heckman selection to correct the bias.

In the first stage (*Selection Model*), the firm decides whether it will engage in a search activity or not; and in the second stage (*Search Intensity Model*), it decides how much the search effort will be. This two-stage estimation is used to test the influence of the social/historical relative performances on innovative search and market search (*H3* and *H4*). Further, we control for industry-year demand shocks and industry-specific age trends using three-digit industry-year fixed effects in all specifications (Balasubramanian & Sivadasan, 2011). We do not include firm fixed effect in the tests because our intention is to compare the effect of social and historical relative performances; using firm fixed effects will make them empirically equivalent.

Persistence model

The profit persistence literature typically measures performance persistence as a first-order autoregressive (AR (1)) difference process (Mueller, 1986; Waring, 1996). Specifically, studies use equations of the following form:

$$\pi_{i,t} = \alpha + \beta * \pi_{i,t-1} + \epsilon_{i,t} \qquad (1)$$

where $\pi_{i,t}$ is a measure of profitability of firm i in year t, typically relative to the industry average. The slope coefficient β then describes the persistence of profit, which is the proportion of a firm's profits "in any period before period t and systematically remains in period t" (Waring, 1996, p. 1225). Generally speaking, the higher the β, the higher is the profit persistence.

We follow the same specification and estimate the persistence of the two relative performances in two separate equations. In each equation, the dependent variable is the relative performance, and the independent variable is the lagged relative performance. Hence, in our model specification, the dependent variable $\pi_{i,t}$ is *social or historical relative performance*, ; and the key independent variable $\pi_{i,t-1}$, is the lagged value of the dependent variable. In addition, we includ four control variables, which are likely to affect persistence of performance: firm size, firm age, growth opportunity (Titman & Wessels, 1988), and industry profitability (Stigler, 1968;

Porter, 1980). The first three variables control for the typical firm-level drivers of profitability, and the last variable controls for a key industry-level driver of profitability.

Selection model

The first stage *Selection Model* is defined as follows:

$$Y_{i,t} = \alpha_0 + \alpha_1 * X_{i,t-1} + \alpha_2 * Z_{i,t-1} + \alpha_3 * C_{i,j,t-1} + \mu_{j,t} + \varepsilon_{i,j,t} \qquad (2)$$

Where $Y_{i,t}$ is a vector, which designates firm i's selection of conducting innovation or market search in period t. $X_{i,t-1}$ is a measure of firm i's performance at period t-1. $Z_{i,t-1}$ is a vector of firm-level controls and $C_{i,j,t-1}$ captures an industry-level control for industry profitability, which implies the external capacity to support organizational search activities (Chen & Miller, 2007). We build the industry level control by subtracting each firm i's revenue from the average industry j's revenue, so that the industry level control will not go way with industry fixed effect. We control for three types of firm slack in $Z_{i,t-1}$. Firm slack is widely used in BTOF and other organizational search literature (Bromiley & Washbum, 2011; Greve, 2003a,b). Firm slack is likely to affect not only firm's selection of search but also search intensity. Hence, firm slack is included in both *Selection Model* and *Search Intensity Model.* Following Greve (2003a), we include three types of slack as controls: absorbed slack, unabsorbed slack, and financial slack. Absorbed slack represents the excess of administrative resources beyond operational needs. Unabsorbed slack is a reflection of the immediately accessible liquid assets available, while potential slack measures the borrowing ability of an organization. $\mu_{j,t}$ captures three-digit industry-year effect and $\varepsilon_{i,j,t}$ is the residual error term.

Search intensity model

In the second stage, which is conditional on the firm engaging in search activities, we test how performance persistence affects the intensity of organizational search intensity. Specifically, we use the following equation:

$$S_{i,t} = \beta_0 + \beta_1 * G_{i,t-1} + \beta_2 * W_{i,t-1} + \beta_3 * N_{i,j,t-1} + \mu_{j,t} + \epsilon_{i,j,t} \qquad (3)$$

Where $S_{i,t}$ is a vector of firm i's innovative/market search intensity in period t. $G_{i,t-1}$ designates firm i's performance relative to aspiration level in period t. $W_{i,t-1}$ is a vector of firm level controls, while $N_{i,j,t-1}$ is a vector of industry level controls. $\mu_{j,t}$ captures three-digit industry-year effects and $\epsilon_{i,j,t}$ is the error term.

In addition to the controls included in the *Selection Model*, we include a set of variables that will affect search intensity. Because firm search activities are usually trended and routinized (Chen & Miller, 2007; Greve, 2003;), we include the lagged dependent variable to reduce the threat of spuriousness and reverse causation (Allison, 1990) and we include the industry innovative/market search (Chen & Miller, 2007; Vissa et al. 2010) to capture the industry search trends. In line with the two-stage nature of the model, we also include the Inverse Mills Ratio from the first stage in order to take search selection into consideration (Greve, 2011; Vissa et al. 2010).

Dependent Variables

Social relative performance is measured as performance relative to social aspiration level, while historical relative performance is measured as performance relative to historical aspiration level. Following Audia and Greve (2006), *social aspiration level* is measured with an average of prior performance (measured by ROA) by all firms except the focal firm in the industry in the previous year. Following Chang and Miller (2007), historical aspiration level is measured by a lag two-period of ROA.

Social relative performance is measured by the difference between the firm return on assets (ROA) and industry average ROA excluding the focal firm's ROA. We chose ROA as a performance measure to be consistent with previous research in BTOF.

Historical relative performance is measured by the difference between current ROA and ROA of the previous year.

Innovative search is equal to one if a firm makes outlay in R&D in that fiscal year, and zero otherwise.

Market search is equal to one if a firm makes outlay in advertising in that fiscal year, and zero otherwise.

Innovative search intensity is computed as R&D expense divided by total assets.

Market search intensity is defined as advertising expense divided by total assets.

Independent Variables

We separate social and historical relative performance into positive and negative social/historical relative performance as follows:

Positive social relative performance equals to zero when the performance is below or equals to social aspiration level and it equals to the value of performance minus social aspiration level when the performance is above social aspiration level.

Negative social relative performance equals to zero when the performance is above social aspiration level and it equals the absolute value of performance minus social aspiration level when performance is below social aspiration level.

Positive historical relative performance equals to zero when the performance is below or equals historical aspiration level and it equals to the value of performance minus the historical aspiration level when performance is above social aspiration level.

Negative historical relative performance equals to zero when performance is above historical aspiration level and it equals the absolute value of performance minus historical aspiration level when performance is below historical aspiration level.

Control Variables

Firm size is measured by a natural logarithm of total sales.

Firm age is proxied by the fiscal year minus the firm's first appearance in COMPUSTAT.

Growth opportunity is measured by capital expense to total assets (Titman & Wessels, 1988).

Absorbed slack is defined as the ratio of SGAE to total sales (Greve, 2003a).

Unabsorbed slack is measured by the ratio of quick assets (cash and marketable securities) to liabilities (Greve, 2003a).

Potential slack is measured by the ratio of debt to equity (Greve, 2003a).

Industry profitability is measured by industry mean revenue excluding the focal firm's revenue.

Industry innovative/market search is computed as the average R&D/market search intensity excluding the focal firm in the three-digit SIC industries.

RESULTS

Baseline Results

Descriptive statistics of the sample are provided in Table 2.1. Results of baseline regressions are in Tables 2.2 to 2.5. From Table 2.1, innovative and market search intensity range from zero to one, which is reasonable. It suggests that firms that have extremely large innovative or market search intensity are not included in the sample. The values of relative performances also seem reasonable with the largest relative performance is at 3.36. As shown in Table 2.1, correlations are consistent with what we expect. As can be seen, we observe low to moderate correlation between social and historical relative performance. The correlation between positive social and historical relative performance is low (0.10), and the correlation between negative social and historical relative performance is moderate (0.47). Also, market search intensity is moderately correlated with prior market search intensity (-0.64) and industry market search intensity (0.41). Furthermore, innovative search intensity has the small correlation coefficients with most variables, except for lagged innovative search intensity (0.77), industry innovative search (0.58), and lagged market search intensity (0.51). Overall, we conclude that multicollinearity is not a concern in this study and our sample construction is appropriate.

Insert Table 2.1 here

Results of test performance persistence specification are shown in Table 2.2. Before running the AR (1) model, we test the stationary of historical and social relative performance.

The augmented Dickey-Fuller test result[5] rejects the null hypothesis that all panels contain a unit root at 1% level of statistical significance and suggests that historical and social relative performance are both stationary.

In our persistence model specification, the coefficient on the independent variable social/historical relative performance describes the percentage of firm's rent remains from period t-1 to period t. The larger value of that coefficient, the higher level of persistence is expected. From Table 2.2, the previous social relative performance has a significant positive effect (0.13) on the current social relative performance, while the previous historical relative performance has a significant negative effect (-0.05) on the current historical relative performance. The results suggest that if a firm has a positive social relative performance, this superior performance is likely to be sustained; whereas, if a firm has a positive historical relative performance, this superior performance in the past won't lead to the superior performance at the current period of time. As a result, H1 and H2 are supported.

Insert Table 2.2 here

Table 2.3 reports the results of firms' decisions to engage in innovative and market search. From Table 2.3, as a firm's performance increases, the firm has a larger propensity to engage in innovative and market search. In the innovative search selection equation, absorbed slack and unabsorbed slack have a positive significant effect on the propensity of engaging in innovative search; while potential slack does not exert a significant effect on the propensity of

[5] We use Fisher-type unit-root test to conduct the augmented Dickey-Fuller test for historical and social relative performance separately. The P-values of our four statistics, P statistic, Z statistic, L* statistic, and Pm statistic, are all smaller than 0.01.

innovative search. This suggests that the likelihood of conducting innovative is affected by possessing an excess of administrative or financial resources. For market search, there is a positive significant effect of absorbed slack and a negative significant effect of unabsorbed slack, which suggests the selection of doing market investments is more reliant on possessing an excess of administrative resources; while holding more cash reduces the tendency of firms to engage in market search.

Insert Table 2.3 here

Table 2.4 reports the results for search intensity models. Consistently with our prediction of positive relative performances (*Hypothesis 3a*), we find that as positive social relative performance increases by 1 unit, a firm will decrease innovative search intensity by 0.10 percentage units, while a firm will decrease market search intensity by over 0.002 percentage units. As the positive historical relative performance increases by one unit, a firm will increase innovative search intensity by 3 percentage units and the firm will increase market search intensity by 0.2 percentage units. The effect is not small because the variance and mean of both search intensities are quite small, especially for the market search intensity. Our F-test statistics reject the equality of the estimated coefficients of positive relative performances on innovative and market search intensity. Comparing the magnitude of coefficients, positive social relative performance has a significantly larger effect on innovative search than its effect on market search (*Hypothesis 3b* supported).

Our prediction about negative relative performance (*Hypothesis 4a*) is partially supported. The results suggest that as negative social relative performance decreases by 1 unit, the firm will significantly increase innovative search intensity by 2.5 percentage units. We do not find a significant effect of negative social relative performance on market search. The insignificant effect may be because market search brings a less persistent return, which adds little help to solve the persistent poor performance. This is actually consistent with our theoretical framework. Moreover, F-test rejects the equality of estimated coefficients of negative social relative performance on innovative and market search. Thus, negative social relative performance has a larger effect on innovative search than on market search (*Hypothesis 4b* supported).

With respect to the estimated coefficients of the control variables, lagged search intensity, slack, and industry search intensity take significant signs and are consistent with our expectation. First, the positive significant coefficients on lagged innovative and market search suggest that search behaviors are past dependent. Second, the significant positive coefficients on absorbed slack suggest that innovative and market search intensity are both sensitive to an excess of administrative resources. As the results are obtained in an analysis that includes controls for the slack resource, thus the effect of relative performances on search intensity cannot be attributed to high slacks. Last, the coefficients on the inversed mills ratio are significant and suggest that it is reasonable to use the selection model.

Insert Table 2.4 here

Industry performance persistence

In order to estimate the industry-level persistence, we add the interaction of two-digit industry dummy variables with lagged dependent variables in our persistence model. We measure the industry performance persistence as the coefficients on the interaction. After that, we rank industry from high persistence to low persistence, as shown in Appendix A.1. From

Appendix A.1, Tobacco products industry (SIC 21) has the highest performance persistence and Forestry (SIC 08) has the lowest performance persistence, which is quite comparable to those obtained through other studies. We then put the top half of industries into the high-persistence group and the bottom half of industries into low persistence group and re-run our baseline search intensity model in the two subsamples. We do not include historical relative performance in this model because there are no theories to support whether the industry level performance persistence will affect the persistence of historical relative performance or not. We check the correlation between industry-level performance persistence and historical relative performance, and find they indeed exhibit low correlation. If our hypotheses hold, we expect to see the effects of relative performances on innovative search intensity are more prolonged in the high-persistence industry group. From the results reported in Table 2.5, we observe that relative performances' effects on innovative search intensity are stronger in the high-persistence group compared with their effects on low persistence group. As a comparison, we also report the results for market search intensity, and we observe that being in a high-persistence group does not intensify the effects of social relative performance on market search intensity. Also, we could see that the effects of social relative performance on innovative search intensity are much larger than those on market search intensity. Results from Table 2.5 support our predictions that innovative search intensity is more sensitive to high performance persistence (*Hypothesis 5*).

Insert Table 2.5 here

Robustness Check

Endogenous concern

Although the Heckman selection model could correct the endogeneity associated with sample selection bias, it doesn't correct endogeneity issue from other sources. We consider another possible endogeneity source, the reverse causality. It is possible that it is not the performance feedback triggers innovative/market search, but the search ends up with different performance feedback.

We deal with this endogeneity concern using Arellano-Bond system generalized method of moments (GMM) approach. In our application, the four relative performances and the lagged dependent variables could be endogenously decided. We used the $X_{i,t-3}$ and $X_{i,t-4}$ is used to instrument the first difference $(X_{i,t-1} - X_{i,t-2})$[6], where X represents the vector of endogenous variables (positive historical relative performance, negative historical relative performance, positive social relative performance, negative social relative performance, and lagged innovative/market search). The results are shown in Appendix A.2.1. Our Arellano-Bond serial correlation test statistics on the first and second order serial correlation reject the null hypothesis of serial correlation of the error term, which confirms the validity of using GMM in this specification. We use Hansen-Sargan overidentification test to check the joint validity of the instruments. The test statistics suggest that our results are not weaken by adding additional instruments and the results are consistent with our baseline results. As a result, we conclude that our baseline results are not driven by the endogeneity.

Other robustness checks

In order to test if our results are robust to different modeling approaches, we re-run the analysis using Tobit model, which is a typical technique to deal with censoring problem. In this

[5] The first difference on the right-hand variables is $X_{i,t-1} - X_{i,t-2}$ instead of $X_{i,t} - X_{i,t-1}$ because all the independent variables are lagged by one year compared with the dependent variable.

study, both innovative and market search intensity are left censored at zero. However, because the variables that predict censoring may not be the same variables that determine search intensity, the Heckman selection model works as our baseline model while the Tobit model works as a robustness check. The Tobit model yields similar results compared to our baseline results as shown in Appendix A.2.2. Also, because the effectiveness of Heckman selection depends on the effectiveness of selecting the right independent variables in the model, we run an OLS model without selection stage. As can be seen from Appendix A.2.3, the results are consistent with our baseline results.

Finally, in order to compare our results to the results in other BTOF studies, we restrict the sample to manufacturing firms and compare results of this study to Chen and Miller's (2007). Our replication of Chen and Miller (2007) show that the results in the manufacturing sample are consistent with their results on innovative search intensity, which implies that our sample creating and the variable building was correct. Our results from manufacturing subsample yield to similar results as the results in the whole sample.

DISCUSSION

Blending insights from the profit persistence literature with the BTOF, we find that the difference between social and historical relative performance lies in their level of persistence. We also explore how differences in their persistence lead to dissimilar innovative and market search. Our findings suggest that the social and historical relative performance will affect a firm's innovative and market search differently because of the difference in the level of persistence of relative performance and that of the persistence of return to innovative and market search.

Nature of Performance Feedbacks

This paper complements and extends previous research on differentiating effects between the two performance feedbacks, social and historical relative performance. Previous research points out important differences existing in the two performance feedbacks, such as its variability and reliability (Kim, et al., 2015) and forecasting ability (Greve, 2003c). Adding to their discussion, this paper examines an unexplored dimension of the comparison, which suggests the persistence of two performance feedbacks are not the same.

Performance Feedbacks and Organizational Search Activities

Our research also contributes to organizational search behaviors. Apart from Kim et al. (2015) and this paper, limited studies directly examine the differential effect on search activities triggered by the two performance feedbacks. Kim et al. (2015) examine how the differences in reliability and validity between the two performance feedbacks affect merger and acquisition activities of the firm. Adding to their discussion, this paper makes a unit contribution by positing that performance persistence drives the dissimilar effects of performance feedback on innovative and market search. Our findings suggest that there are more aspects to dig into the connection between the nature performance feedbacks and the nature of the organizational search.

In addition, our findings add an important dimension to prior work on performance feedbacks and organizational search. Prior literature suggests that being above or below aspiration level (Greve, 2003c) and distance to aspiration level (Baum, Rowley, Shipilov, & Chuang, 2005; Miller & Chen, 2004) play an important role in determining how performance feedbacks motivate organizational search. Our findings suggest a reinterpretation of good and bad performance, because social and historical relative performance have different implications in whether the good or bad performance is persistent or not. As a result, our finding suggests that future research should explicitly differentiate whether a firm is above/below historical or social aspiration level.

Another interesting question remains to be answered is how a firm will conduct a search if it has two conflicting relative performance. For example, our framework predicts that a positive social relative performance reduces search, while a negative historical relative performance motivates search. Then what will happen when a firm is above social relative performance but below historical relative performance? We argue that one possible way to solve this dilemma is to relax our assumption that a firm allocates equal attention towards social and historical aspiration. If we assume that a firm has different weights on different aspiration level, then we could know which relative performance exerts a greater influence on organizational search. For example, Greve (2003c) points out that the choice of social or historical relative performance is subject to the experience of decision makers, the availability and validity of the information. When a firm is in an industry with limited external information about other firms, it will have to place a heavier weight on historical aspiration than social aspiration. In that case, we expect that negative historical relative performance will trigger a firm to conduct a search even the firm has positive social relative performance. Similarly, if a firm is in an industry with standardized products, such as railroad industry, it is expected to rely less on historical aspiration level than social aspiration. In that case, we expect that negative social relative performance will thwart search even the firm has a positive historical relative performance at the same time. To sum up, this research calls for future research on the conflicting role of the social and historical relative performance. In order to enrich the theoretical framework on the performance feedback, we should not only know the difference in social and historical relative performance; but also, when the decision makers actually choose between them.

Need to Search and Ability to Search

Another implication of this study is to distinguish the need to conduct an organizational search from the ability to conduct a search. The action of organizational search could be triggered by both the need for search and ability of search. However, the need of search does not always get along with the ability to search. Then what happens if an organization has the need to search but does not have the ability to search? Also, what happens if an organization has the ability to search but lacks the need to search? Our findings offer partial answers to these questions. We propose that the need to search varies in persistent or non-persistent relative performances, and as a result, firm's search intensity changes accordingly. At the same time, previous literature points out that good performance enables an organization accumulates slack resources, which support its search activities (Chen & Miller, 2007; Iyer & Miller, 2008). Our estimation results find scenarios in which an organization reduces search even it possesses slack resources. Having positive social relative performance implies that an organization is likely to have accumulated slack resource through sustained good performance. If the ability to search is the dominant factor, an organization should increase search, which is contradictory to our findings. As persistence affects both the need and the ability to search, our results suggest that the need to search outweighs the ability of search in the scenario we describe. Our findings on negative social relative performance further confirm this implication. Negative social relative performance implies a situation with a limited number of resources to the firm. We find an organization still conducts an innovative search even in absence of resources. Future research can push forward in this direction by examining the relative strength of need and ability on organizational search.

CONCLUSION

By proposing a persistence-based framework of organizational search, we find that social relative performance is more persistent than historical relative performance. Combining this finding with the insight that the returns to innovative and market search differ in their temporality, we show how the two search activities react differently to social and historical relative performances, and how industry-level performance persistence impacts these reactions. These findings, when taken together, suggest that performance feedbacks from the social or historical reference group are different in nature, and that the resulting search response is influenced by the persistence of returns to that search response.

This paper also contributes to the profit persistence literature by explicitly argue how persistence in good and poor performance affects a firm's consequential search activities. Despite the previous research on profit persistence literature that has intensively discussed the patterns and causes of performance persistence, there is still no clear answer to how performance persistence will affect a firm's consequential actions. One reason is that the focus of performance persistence study is to investigate the factors that lead to performance persistence, instead of the consequences of performance persistence. Another stream of literature, the BTOF literature, focuses on the consequential actions triggered by a firm's performance feedbacks. This paper connects profit persistence study with BTOF study by differentiating the persistence of the two relative performances as well as showing how the difference in persistence affects organizational search activities.

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FIGURES AND TABLES FOR CHAPTER TWO

Table 2.1 Descriptive Statistics and Correlations

	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)	0.03	0.06	1																	
(2)	0.01	0.02	-0.25	1																
(3)	-0.04	0.24	-0.41	0.09	1															
(4)	0.04	0.08	0.23	-0.05	-0.26	1														
(5)	0.04	0.08	0.28	-0.04	-0.27	-0.26	1													
(6)	0.39	0.81	0.20	-0.12	-0.10	0.10	0.01	1												
(7)	0.03	0.10	0.21	-0.00	-0.33	0.05	0.47	-0.19	1											
(8)	0.03	0.06	0.77	-0.25	-0.51	0.23	0.23	0.22	0.15	1										
(9)	0.01	0.02	0.51	-0.64	-0.16	0.11	0.10	0.17	0.03	0.48	1									
(10)	4.32	2.14	-0.38	0.10	0.40	-0.25	-0.27	0.02	-0.31	-0.34	-0.14	1								
(11)	13.60	9.80	-0.19	-0.01	0.21	-0.13	-0.13	0.04	-0.14	-0.20	0.01	0.50	1							
(12)	0.28	0.27	0.35	0.00	-0.45	0.19	0.19	0.15	0.20	0.40	0.15	-0.31	-0.20	1						
(13)	0.83	1.28	0.36	-0.14	-0.11	0.11	0.11	0.18	0.02	0.32	0.21	-0.24	-0.15	0.19	1					
(14)	0.11	0.30	-0.06	-0.01	-0.00	-0.01	-0.02	0.07	-0.03	-0.07	-0.04	0.17	-0.01	-0.04	-0.08	1				
(15)	0.06	0.05	-0.12	0.07	0.08	-0.13	-0.01	-0.16	-0.00	-0.12	-0.12	0.07	-0.07	-0.10	-0.11	-0.00	1			
(16)	16.19	17.21	-0.03	0.01	-0.02	0.01	-0.01	0.17	-0.02	-0.03	-0.08	0.34	0.20	-0.04	-0.00	0.17	-0.05	1		
(17)	0.00	0.00	0.58	-0.25	-0.31	0.20	0.18	0.36	0.03	0.58	0.42	-0.29	-0.21	0.29	0.39	-0.01	-0.16	-0.02	1	
(18)	0.00	0.00	-0.13	0.41	0.03	-0.02	-0.01	-0.02	0.00	-0.13	-0.39	0.01	-0.11	0.04	-0.06	-0.02	0.04	0.05	-0.06	1

* Any absolute value, which is larger than 0.01 is significant at $p<0.05$; any absolute value, which is larger than 0.04 is significant at $p<0.01$

[a] N=179,078

[b] (1) Innovative search intensity$_t$; (2) Market search intensity$_t$; (3) ROA$_{t-1}$; (4) Positive historical relative performance$_{t-1}$; (5) Negative historical relative performance$_{t-1}$; (6) Positive social relative performance$_{t-1}$; (7) Negative social relative performance$_{t-1}$; (8) Innovative search intensity$_{t-1}$; (9) Market search intensity$_{t-1}$; (10) Firm size$_{t-1}$; (11) Firm age$_{t-1}$; (12) Absorbed slack$_{t-1}$; (13) Unabsorbed slack$_{t-1}$; (14) Potential slack$_{t-1}$; (15) Growth opportunity$_{t-1}$; (16) Industry profitability$_{t-1}$; (17) Industry Innovative search intensity$_{t-1}$; (18) Industry market search intensity$_{t-1}$.

Table 2.2 Results for Performance Persistence

	Social relative performance		Historical relative performance	
	Coefficient	t statistics	Coefficient	t statistics
Social relative performance$_{t-1}$	0.13**	(27.84)		
Historical relative performance$_{t-1}$			-0.05**	(13.96)
Firm size$_{t-1}$	0.03**	(26.81)	0.00**	(6.75)
Firm age$_{t-1}$	-0.01**	(41.29)	-0.00	(0.51)
Growth opportunity$_{t-1}$	-0.02	(0.60)	0.01	(1.41)
Industry profitability$_{t-1}$	-0.00	(1.83)	0.00	(1.22)
Constant		(3.28)	-0.04*	(2.03)
	0.77**			
Adjusted R^2	0.25		0.01	
N	165,518		146,518	

* $p < 0.05$; ** $p < 0.01$

[a] Models include three-digit industry-year fixed effect

[b] Standard errors are cluster by firm

[c] The number of observations differs among the models because of the taking of first differences or the serial correlation adjustment.

Table 2.3 Results for Search Activity Selection

	Innovative search selection		Market search selection	
	Coefficient	Z statistics	Coefficient	Z statistics
ROA$_{t-1}$	0.34**	(5.58)	1.00**	(19.02)
Absorbed slack$_{t-1}$	1.07**	(14.38)	1.33**	(24.49)
Unabsorbed slack$_{t-1}$	0.12**	(8.22)	-0.06**	(5.56)
Potential slack$_{t-1}$	-0.06	(1.73)	0.04	(1.25)
Industry profitability$_{t-1}$	-0.00	(1.62)	0.00	(1.41)
Constant	-3.08**	(8.45)	-19.51	.
Pseudo R^2	0.41		0.20	
N	175,343		178,243	

* $p < 0.05$; ** $p < 0.01$

[a] Models include three-digit industry-year fixed effect

[b] Standard errors are cluster by firm

[c] The number of observations differs among the models because of the availability of R&D expense and advertising expense.

Table 2.4 Results for Search Intensity Model

	Innovative search intensity		Market search intensity	
	Coefficient	t statistics	Coefficient	t statistics
Positive historical relative performance$_{t-1}$	3.00**	(14.93)	0.20**	(3.58)
Negative historical relative performance$_{t-1}$	4.00**	(17.44)	0.20**	(3.09)
Positive social relative performance$_{t-1}$	-0.10**	(5.20)	-0.00**	(4.12)
Negative social relative performance$_{t-1}$	2.50**	(10.19)	-0.10	(1.21)
Innovative search intensity$_{t-1}$	57.90**	(90.19)		
Firm size$_{t-1}$	-0.10**	(5.02)	0.10**	(15.14)
Firm age$_{t-1}$	0.00	(0.74)	0.00	(0.46)
Absorbed slack$_{t-1}$	0.01**	(4.17)	0.80**	(17.95)
Unabsorbed slack$_{t-1}$	0.01**	(24.03)	-0.00	(0.96)
Potential slack$_{t-1}$	-0.00	(0.53)	0.00	(1.23)
Growth opportunity$_{t-1}$	1.90**	(7.49)	0.20	(1.62)
Industry profitability$_{t-1}$	-0.00**	(4.20)	0.00	(0.56)
Industry innovative search intensity$_{t-1}$	213.60**	(11.11)		
Inverse Mills Ratio of innovative selection	1.70**	(13.45)		
Market search intensity$_{t-1}$			51.30**	(76.87)
Industry market search intensity$_{t-1}$			-51.20	(1.47)
Inverse Mills Ratio of market selection			0.70**	(14.46)
Constant	- 5.90**	(12.46)	-1.80**	(6.12)
Adjusted R^2	0.67		0.48	
N	164, 875		167,104	

* p < 0.05; ** p < 0.01

[a] Models include three-digit industry-year fixed effects.

[b] Standard errors are cluster by firm.

[c] coefficients are multiplied by 100.

[d] The number of observations differs among the models because of the availability of R&D expense and advertising expense.

Table 2.5 Industry Persistence Results

	Innovative search intensity		Market search intensity	
	Low-persistence group	High-persistence group	Low-persistence group	High-persistence group
Positive social relative performance$_{t-1}$	-0.02	-0.07**	-0.05*	-0.02*
	(0.60)	(2.63)	(2.49)	(2.33)
Negative social relative performance$_{t-1}$	2.25**	4.31**	0.30*	0.18**
	(6.32)	(18.41)	(2.13)	(3.13)
Innovative search intensity$_{t-1}$	51.03**	58.84**		
	(14.49)	(90.83)		
Firm size$_{t-1}$	-0.02	-0.12**	0.09**	0.04**
	(1.65)	(8.35)	(7.55)	(9.65)
Firm age$_{t-1}$	0.00	0.00	0.00	-0.00
	(0.46)	(0.99)	(0.76)	(0.73)
Absorbed slack$_{t-1}$	0.27	-0.11	0.68**	0.29**
	(1.85)	(1.09)	(7.20)	(11.65)
Unabsorbed slack$_{t-1}$	0.08**	0.41**	0.02	0.01*
	(4.08)	(21.51)	(1.47)	(2.16)
Potential slack$_{t-1}$	0.06	0.05	-0.02	0.02
	(1.51)	(0.97)	(0.61)	(0.92)
Growth opportunity$_{t-1}$	0.23**	1.80**	0.48*	0.15
	(4.53)	(5.94)	(2.20)	(1.42)
Industry profitability$_{t-1}$	-0.00*	-0.01**	0.00	-0.00
	(2.01)	(2.75)	(0.91)	(0.71)
Industry innovative search intensity$_{t-1}$	-172.39	282.08**		
	(1.58)	(12.77)		
Market search intensity$_{t-1}$			52.10**	51.25**
			(42.46)	(65.55)
Industry market search intensity$_{t-1}$			-9.76	-69.64
			(0.16)	(1.47)
Constant	-0.29**	0.24	-1.17**	-0.83**
	(2.76)	(1.81)	(6.64)	(10.44)
Adjusted R^2	0.42	0.65	0.52	0.44

* $p < 0.05$; ** $p < 0.01$

[a] Models include three-digit industry-year fixed effects. Standard errors are cluster by firm. [b] coefficients are multiplied by 100. [c] Low persistence group contains 38,535 firm-year observations, while high persistence group contains 140,754 firm-year observation.

Appendix A.1 Industry-by-Industry Performance Persistence Coefficients

Low persistence group			High persistence group		
Rank	SIC 2-digit industry	Persistence	Rank	SIC 2-digit industry	Persistence
1	08 Forestry	-0.17	31	52 Building Materials & Gardening Supplies	-0.00
2	02 Agricultural Production - Livestock	-0.17	32	27 Printing & Publishing	0.00
3	24 Lumber & Wood Products	-0.15	33	13 Oil & Gas Extraction	0.00
4	16 Heavy Construction, Except Building	-0.15	34	56 Apparel & Accessory Stores	0.01
5	45 Transportation by Air	-0.13	35	81 Legal Services	0.01
6	41 Local & Interurban Passenger Transit	-0.13	36	88 Private Households	0.02
7	23 Apparel & Other Textile Products	-0.11	37	59 Miscellaneous Retail	0.02
8	15 General Building Contractors	-0.11	38	50 Wholesale Trade - Durable Goods	0.02
9	53 General Merchandise Stores	-0.11	39	44 Water Transportation	0.03
10	58 Eating & Drinking Places	-0.11	40	54 Food Stores	0.03
11	55 Automotive Dealers & Service Stations	-0.10	41	14 Nonmetallic Minerals, Except Fuels	0.03
12	82 Educational Services	-0.09	42	29 Petroleum & Coal Products	0.04
13	75 Auto Repair, Services, & Parking	-0.08	43	34 Fabricated Metal Products	0.04
14	12 Coal Mining	-0.08	44	38 Instruments & Related Products	0.04
15	83 Social Services	-0.07	45	36 Electronic & Other Electric Equipment	0.05
16	32 Stone, Clay, & Glass Products	-0.07	46	20 Food & Kindred Products	0.04
17	72 Personal Services	-0.06	47	37 Transportation Equipment	0.05
18	79 Amusement & Recreation Services	-0.05	48	46 Pipelines, Except Natural Gas	0.05
19	47 Transportation Services	-0.05	49	33 Primary Metal Industries	0.07
20	25 Furniture & Fixtures	-0.04	50	87 Engineering & Management Services	0.08
21	31 Leather & Leather Products	-0.04	51	35 Industrial Machinery & Equipment	0.08
22	70 Hotels & Other Lodging Places	-0.04	52	48 Communications	0.09
23	42 Trucking & Warehousing	-0.04	53	28 Chemical & Allied Products	0.10
24	39 Miscellaneous Manufacturing Industries	-0.03	54	26 Paper & Allied Products	0.12
25	22 Textile Mill Products	-0.03	55	10 Metal, Mining	0.15
26	30 Rubber & Miscellaneous Plastics Products	-0.03	56	51 Wholesale Trade - Nondurable Goods	0.21
27	57 Furniture & Homefurnishings Stores	-0.03	57	78 Motion Pictures	0.22
28	76 Miscellaneous Repair Services	-0.02	58	73 Business Services	0.24
29	17 Special Trade Contractors	-0.01	59	07 Agricultural Services	0.25
30	80 Health Services	-0.01	60	40 Railroad Transportation	0.25
			61	21 Tobacco Products	0.26

[a] Persistence is obtained from the coefficient of interaction of two-digit SIC industry code and lagged relative performance.

[b] According to the magnitude of persistence, we put half of the industries in the sample into low persistence group and put the rest of industries into high persistence group.

Appendix A.2 Robustness Check

Appendix A.2.1 Arellano-Bond Estimators for System GMM

	Innovative search intensity		Market search intensity	
	Coefficient	Z statistics	Coefficient	Z statistics
Positive historical relative performance$_{t-1}$	3.79**	(3.76)	0.49*	(2.13)
Negative historical relative performance$_{t-1}$	28.50**	(16.50)	1.01**	(2.77)
Positive social relative performance$_{t-1}$	-0.28**	(2.82)	-0.03	(1.62)
Negative social relative performance$_{t-1}$	13.14**	(11.78)	0.24	(0.99)
Innovative search intensity$_{t-1}$	64.68**	(17.01)	0.12**	(3.88)
Firm size$_{t-1}$	0.81**	(7.39)	-0.00	(0.92)
Firm age$_{t-1}$	0.03	(1.52)	0.20	(1.09)
Absorbed slack$_{t-1}$	-1.48	(1.75)	0.08*	(2.20)
Unabsorbed slack$_{t-1}$	0.90**	(4.87)	0.43*	(2.19)
Potential slack$_{t-1}$	-1.14	(1.24)	0.14	(0.22)
Growth opportunity$_{t-1}$	8.69**	(3.49)	0.00	(0.46)
Industry profitability$_{t-1}$	-0.01	(1.67)		
Industry innovative search intensity$_{t-1}$	899.64**	(6.50)		
Market search intensity$_{t-1}$			49.17**	(12.71)
Industry market search intensity$_{t-1}$			1923.27**	(8.25)
Constant	-20.99	(0.69)	11.61	(1.27)
N	168, 298		168, 298	
Arellano-Bond test statistic for AR(1)	-29.19		-19.59	
Arellano-Bond test statistic for AR(2)	4.22		-1.88	
Sargan test statistic of over-identification	3880.07		1583.28	
Hansen test statistic of over-identification	1093.17		721.12	

* $p < 0.05$; ** $p < 0.01$

[a] First differences of the four relative performance are instrumented using lags of order 2 of the levels. Models include three-digit industry-year fixed effects.

[b] Standard errors are cluster by firm.

[c] coefficients are multiplied by 100.

Appendix A.2.2 Results from Tobit Model

	Innovative search intensity		Market search intensity	
	Coefficient	t statistics	Coefficient	t statistics
Positive historical relative performance$_{t-1}$	4.90**	(16.55)	0.30**	(14.43)
Negative historical relative performance$_{t-1}$	6.30**	(17.25)	0.20**	(5.53)
Positive social relative performance$_{t-1}$	-0.10**	(3.86)	-0.10**	(23.94)
Negative social relative performance$_{t-1}$	4.40**	(14.60)	-0.10*	(2.46)
Innovative search intensity$_{t-1}$	70.1**	(169.09)		
Firm size$_{t-1}$	0.20**	(12.16)	0.10**	(124.02)
Firm age$_{t-1}$	0.00**	(15.64)	-0.00**	(2.85)
Absorbed slack$_{t-1}$	0.80**	(6.99)	1.20**	(108.62)
Unabsorbed slack$_{t-1}$	0.60**	(32.51)	0.00**	(14.13)
Potential slack$_{t-1}$	0.10**	(0.99)	0.10**	(10.14)
Growth opportunity$_{t-1}$	2.60**	(5.86)	0.20**	(4.13)
Industry profitability$_{t-1}$	-0.00	(1.35)	0.00**	(6.63)
Industry innovative search intensity$_{t-1}$	275.2**	(11.66)		
Market search intensity$_{t-1}$			80.60**	(751.62)
Industry market search intensity$_{t-1}$			-121.10**	(11.11)
Constant	-10.60**	(17.54)	-0.26**	(3,984.07)
Sigma	0.06**	(230.60)	0.03**	(1,433.29)
	168,298		168,298	

* $p < 0.05$; ** $p < 0.01$

[a] Models include three-digit industry-year fixed effects.

[b] Standard errors are cluster by firm.

[c] coefficients are multiplied by 100.

Appendix A.2.3 Results for Search Activity Model without Selection

	Innovative search intensity		Market search intensity	
	Coefficient	t statistics	Coefficient	t statistics
Positive historical relative performance$_{t-1}$	3.10**	(15.37)	0.40**	(5.99)
Negative historical relative performance$_{t-1}$	4.30**	(17.63)	0.30**	(4.01)
Positive social relative performance$_{t-1}$	-0.10**	(4.92)	-0.03**	(4.32)
Negative social relative performance$_{t-1}$	2.50**	(10.51)	0.10	(1.40)
Innovative search intensity$_{t-1}$	58.50**	(91.96)		
Firm size$_{t-1}$	-0.10**	(5.00)	0.10**	(12.79)
Firm age$_{t-1}$	0.00	(0.33)	0.00	(0.17)
Absorbed slack$_{t-1}$	-0.20	(1.88)	0.30**	(12.58)
Unabsorbed slack$_{t-1}$	0.40**	(22.02)	0.01*	(2.59)
Potential slack$_{t-1}$	0.10	(1.11)	0.01	(0.49)
Growth opportunity$_{t-1}$	1.80**	(7.14)	0.18	(1.00)
Industry profitability$_{t-1}$	-0.00**	(2.73)	-0.00	(0.63)
Industry Innovative search intensity$_{t-1}$	303.90**	(12.17)		
Market search intensity$_{t-1}$			51.10**	(74.59)
Industry market search intensity$_{t-1}$			-37.38	(0.98)
Constant	-0.20	(0.84)	-0.93**	(12.18)
Adjusted R^2	0.67		0.48	
N	168,298		168,298	

* $p < 0.05$; ** $p < 0.01$

[a] Models include only three-digit industry-year fixed effects.

[b] Standard errors are cluster by firm.

[c] coefficients are multiplied by 100.

CHAPTER THREE:

FIRE SALE OR NEW START?

EFFECTS OF TECHNOLOGICAL ASSETS DIVESTITURE ON LARGE BANKRUPT FIRMS

INTRODUCTION

Corporate bankruptcy is a dire crisis for a firm, threatening its very survival. It also has significant economy-wide impacts: the American Bankruptcy Institute reports an average of 26,983 business filings every year the past three years. Bankruptcy is also a time of extensive resource reconfiguration, particularly on the divestiture of business assets, for the distressed firm. Indeed, according to the UCLA-LoPucki Bankruptcy Research Database, in 2015, 47% of large firms sold all or substantially all of their assets in bankruptcy. Given the widespread prevalence of bankruptcy cases and the large number of assets sales during bankruptcy, an interesting and important area of investigation is asset divestiture and its effects on bankrupt firms.

In this paper, we shift our attention to an increasingly important type of intangible assets: technological assets, particularly patents. As noted by the Ocean Tomo Annual Study of Intangible Assets, intangible assets made up of 84% of the S&P 500 market value in 2015, while in 1975, this ratio was just 17%. Consistent with this, Epstein and Pierantozzi (2009) observe that financially distressed companies are increasingly engaged in monetizing of technological assets and rely on their technological assets, especially patents, as a "last-ditch source of immediate cash (p.1)." For example, Nortel sold 6,000 wireless patents for $4.5 billion during its bankruptcy, and Kodak sold its digital photography patents for about $525 million. Furthermore, intangible assets in general and technological assets in particular, differ from physical assets in their harder to be imitated or substituted in the rapid expansion of goods and strategic factor markets, which make them more likely to be a source of competitive advantage (Teece, 1999).

We build a two-phase framework to examine the antecedents and consequences of selling technological assets. The first phase focuses on firms in bankruptcy and analyzes which kinds of technological assets are more likely to be sold during the bankruptcy phase. The second phase in the framework relates to the post-bankruptcy period and explores the performance changes and knowledge utilization associated with divestiture. A key feature of our framework is that it distinguishes between technological assets and the underlying knowledge associated with how to generate and utilize the assets. Though the two are closely related, the former may be divested in bankruptcy, the latter may not.

To test our predictions, we construct a new and comprehensive data set that identifies information on patent stock, patent assignment, and financial information of large public bankrupt firms in the United States. Our sample includes almost all large U.S. public firms with patent stocks or transactions that filed for bankruptcy since 1979. The sample enables us to track large bankrupt firms' profitability changes, technological performance changes, and knowledge utilization patterns changes associated with their divestiture activities.

Our findings confirm the predictions from our framework. First, we find that high-value technological assets are more likely to be divested than low-value ones during bankruptcy, while non-core technological assets are more likely to be divested than core ones. Second, selling high-value technological assets is associated with a sizable improvement in profitability compared with selling low-value ones. As expected, we find a general declining trend in technological performance in the post-bankruptcy phase for firms that sell technological assets. Rather counterintuitively but consistent with our framework, we find that the level of such a reduction in technological activity is lower when firms sell assets in their core technological areas than when they sell assets in non-core areas. We argue and provide evidence that this could be because the knowledge in a firm's core technological areas is more embedded than that in non-core areas, and thus the level of knowledge in the core area is less likely to decrease after the divestiture of corresponding technological assets. Further, our investigation of knowledge utilization patterns in the post-bankruptcy phase shows that the firms that sell core technological assets are associated with less reduction in knowledge retention and leverage.

Together, our results make three important contributions to the strategic management literature on resource reconfiguration (e.g., Karim & Mitchell, 2004; Karim & Kaul, 2015; Karim & Capron, 2016). Broadly defined, resource reconfiguration refers to "adding to their current stock (of resources, units, and business activities), removing from this stock, and recombining or redeploying what is within this stock" (Karim & Mitchell, 2004, p.3). As Karim and Capron (2016) observe, most reconfiguration studies focused on traditional resources such as acquired subunits (Capron, Mitchell, & Swaminathan, 2001; Xia & Li, 2013) and foreign subsidiaries (Mata & Portugal, 2000). We extend the analysis to the technological asset, an important type of intangible asset that has not been extensively studied in this literature. Further, the context of most prior studies is resource reconfiguration during mergers and acquisitions. Considering the resource reconfigurations during bankruptcy are likely to be significantly different from those during the post-acquisition period with its prolonged financial distress and an urgent need for survival, we extend the prior studies to a specific context, when a firm goes bankrupt.

Second, by theoretically separating two types of resources involved in the divestiture process---technological assets and the knowledge associated with generating and utilizing these assets---we shed new light on resource interrelatedness. As a firm's resource base incorporates various interconnected resources, reconfiguring one resource could potentially affect other resources. Previous research points out that a firm can reconfigure its knowledge base by proactively acquiring external knowledge (e.g. Makri, Hitt, & Lane, 2010; Zollo & Singh, 2004) or by developing knowledge in-house (e.g. Galunic & Rodan, 1998). Our paper suggests that divesting technological assets may also affect the knowledge resources within a firm. In particular, our findings suggest that whether divesting technological assets will affect the knowledge or not largely depends on the embeddedness of knowledge, which differs in its degree between a firm's core and non-core technological areas. By empirically testing the effect of divesting technological assets on knowledge utilization of the firm, we suggest that reconfiguring one type of resources could also affect the usage of another type of resource. Thus, we extend the previous research on the link between reconfiguration and the resource being reconfigured (e.g. Feldman, 2013; Kaul, 2012).

In addition to the aforementioned contributions, we also extend the bankruptcy research to technological assets along two new dimensions. To our knowledge, most prior bankruptcy studies examine the reallocation of physical assets (e.g. Maksimovic & Phillips, 1998; Pulvino, 1999). Although some research (Bernstein, Colonnelli, & Iverson, 2016; Ma, Tong, & Wang, 2017) have started investigating the reallocation of nontraditional assets among bankrupt firms, it is still not clear how divesting one type of asset affects other assets in an organization, and how asset divestiture affects different dimensions of firm performance. We contribute to this literature by exploring the connection between the divestiture decisions and performance impact of divesting one asset, technological assets, with the retention of another asset, organizational knowledge. In addition, by examining how changes in profitability, technological performance, and knowledge utilization are associated with the divestiture of technological assets among bankrupt firms, and how the attributes of the divested assets affect these relationships, we significantly extend our current understanding of the performance effects of asset divestiture during bankruptcy. Furthermore, the management literature on bankruptcy typically examines the role of corporate governance in determining post-bankruptcy performance (e.g., Arora, 2016;

Daily, 1994; Daily & Dalton, 1994; Donoher, 2004; Lee, Peng, & Barney, 2007). Our approach of connecting resource management research with bankruptcy context seeks to answer how post-bankruptcy performance will be affected by nature of assets divested, thus extending the domain of bankruptcy research in management beyond corporate governance.

THEORETICAL DEVELOPMENT AND HYPOTHESES

Model Overview

Figure 1 provides an overview of our theoretical framework. We divide the process of divesting technological assets among bankrupt firms into two broad stages: the bankruptcy phase, during which the bankrupt firm makes the decision to sell assets, and the post-bankruptcy phase, during which the bankrupt firm continues operation. We focus on three aspects of the entire process: (i) the asset-sale decision in the first phase, and the changes in (ii) financial, (iii) technological performance, and (iv) knowledge utilization from the first phase to the second phase. In developing our hypotheses, we argue that both the asset-sale decision and the resultant performance and knowledge utilization effects depend on the attributes of assets divested. Specifically, we examine two attributes of the technological assets: (i) whether the assets are of high value or not ('high/low-value technological assets'); and (ii) whether the assets represent the dominant technological fields of the firm or not ('core/non-core technological assets'). Broadly, we argue that high-value technological assets are more likely to be sold during bankruptcy than low-value ones (because of their ability to raise greater financial assets), while non-core technological assets are more likely to be sold than core ones (as they require extra investments to utilize the assets, and bankrupt firms are usually not willing to make such investments). In terms of the effect of these two divesting strategies on post-bankruptcy performance, we argue that selling high-value technological assets is likely to be associated with improved profitability because of the financial assets raised. Selling non-core technological assets is likely to result in a decline in technological performance (compared with selling core assets) because the related knowledge in non-core technological areas is less embedded in the firm and the less-embedded knowledge gets depreciates faster, which leaves the bankrupt firm less knowledge to utilize for the continuation of existing innovation activities as well as starting new ones.

Insert Figure 3.1 here

Asset Value and Asset Divestiture Decision

Unlike a financially healthy firm, a bankrupt firm is facing financial distress that puts a large burden on it to liquidate assets. Hotchkiss, John, Mooradian, and Thorburn (2008) point out that asset divestiture could be a relatively low-cost alternative to raise funds for the bankrupt firms. Considering the financial distress, during bankruptcy, the key reason for asset divestiture is the cash-flow need. However, a firm may not be able to realize the full value of an asset during a bankruptcy sale. The time pressure from both the bankruptcy procedure as well as the depreciation of assets can force bankrupt firms to sell the assets at a depressed price (Pulvino, 1998, 1999). In addition, the search costs associated with finding buyers are exacerbated due to the time constraints during bankruptcy.

Liquidating high-value assets is more likely to satisfy these constraints than selling low-value ones. First, compared with selling low-value technological assets, selling high-value ones requires fewer searches as each transaction is likely to generate more cash, which reduces the number of transactions needed to meet the cash flow requirement. Further, high-value technological assets are likely to attract more buyers (Gambardella, Giuri, & Luzzi, 2007; Gaviggioli & Ughetto, 2013), which reduces the search costs of finding a buyer and increases the chances of making a satisfactory deal. For instance, using patent auction data, Odasso, Scellato, and Ughetto (2015) find that highly valued patents have higher auction closing prices. Along the same lines, Gambardella *et al*. (2007) argue that low-value technological assets can hardly meet the demand in the market, and thus provide little economic profits via licensing. Together, these arguments suggest that high-value technological assets are more likely to be divested than the low-value ones because high-value technological assets are likely to be discounted less during liquidation compared to their low-value counterparts. This leads us to predict:

H1: Among bankrupt firms, a technological asset is more likely to be sold when it is of high value than low value.

As mentioned earlier, the divestiture strategy could relieve financial distress by raising financial assets. The sale of assets enables the firm to repay debt (Brown, James, & Mooradian, 1994), to take good investment opportunities with the funds generated (Hotchkiss *et al*., 2008), to signal good news to the stock market (Adams & Clarke, 1995), and to fund the remaining operations of the firm (Alderson & Betker, 1999). These benefits associated with divestiture enable the firms to function more effectively in the post-bankrupt phase. These benefits are larger for the firms that divest high-value assets than those that divest low-value assets, because divesting high-value technological assets is likely to raise more financial assets. Thus, we predict:

H2: Relative to the pre-bankruptcy profitability, divesting high-value technological assets will be associated with a larger improvement in profitability after emergence from bankruptcy, compared with divesting low-value technological assets.

Asset Types and Asset Divestiture

Apart from the value of technological assets, whether the assets are in the firms' core technological areas or not could also affect the divestiture decisions. Technological assets are likely to result from the previous knowledge utilization activities within an organization. The required conditions for being able to continue utilizing the knowledge in the core and non-core technological areas are different; thus, the firm's decisions to exit the two areas and divest the correspondent technological assets are different.

The first condition needed to continue utilizing the knowledge is investing in knowledge-generating activities until the firm embeds the knowledge within itself. Similar to Karim (2012)'s structural embeddedness concept, in this paper, knowledge embeddedness refers to that knowledge resides in an organization and has some level of dependence upon the firm. Knowledge depreciates over time, and without sufficient investment to embed the knowledge within the firm, it depreciates even more rapidly over time (Hall, Griliches, & Hausman, 1986, p. 265). The levels of organizational embeddedness of knowledge in core and non-core technological areas are different; as a result, the required investments in the two fields are different. The firm's knowledge in the non-core areas tends to be shallower and less embedded than its knowledge in the core areas, because of lack of previous investments in the non-core areas. Thus, if a firm wants to maintain its stock of knowledge in the non-core areas, it has to make higher-than-proportionate investments to compensate for the higher knowledge depreciation in the non-core areas. These investments are typically like fixed costs (that is, invariant to the volume of business), which then become sunk costs after a firm makes such investments. Given the financial constraints during a bankruptcy procedure, a firm is less likely to make these investments. Thus, a firm would be more likely to exit non-core technological areas and to divest the corresponding non-core technological assets.

The second condition for maintaining knowledge utilization is to invest in the complementary assets to support the knowledge utilization. Complementarity among resources implies that the value of each asset will increase with an increase in the relative magnitude of other complementary resources (Amit & Schoemaker, 1993; Dierickxx & Cool, 1989). Complementary resources for knowledge utilization include operational resources, innovation capabilities, marketing resources, equipment and plants, access to raw materials, R&D workers, advocating managers, and corresponding upstream and downstream assets. Technological assets in the non-core areas are less likely to be supported by a full array of complementary assets (unlike assets in the core areas). Lack of complementary assets reduces the level of potential short-term financial benefits that such assets may provide. Figueroa and Serrano (2013) find that small firms are more actively engaged in selling patents because they do not have complementary assets to utilize the patents. Similarly, Gambardella *et al*. (2007) and Kollmer and Dowling (2004) find that a lack of co-specialized assets for innovation leads to licensing out a firm's patents. Developing and accumulating those complementary assets need time and are thus less likely to generate short-term profits. The heightened emphasis on short-term survival during bankruptcy makes the bankrupt firms less likely invest in developing and acquiring those complementary assets for knowledge utilization. Thus, based on the different requirements in investing the core and non-core technological areas to exploit the correspondent knowledge fully, we predict:

H3: Among bankrupt firms, a technological asset is more likely to be sold when it is in the non-core technological areas than in the core areas.

The knowledge-based view of the firm suggests that the underlying knowledge stock and knowledge flow of a firm will influence the firm's technological performance (e.g., Dierickx &

Cool, 1989; Kogut & Zander, 1992). On average, the level of technological activities will decline after bankruptcy, consistent with a reduction in the stock of technological assets. However, considering the difference in the levels of embeddedness of knowledge in the non-core and core areas, we argue that the level of such a reduction in technological activities is lower when a firm sells assets in their core areas than when it sells assets in non-core areas.

As discussed before, the knowledge in the core technological areas is likely to be more embedded, which simultaneously allows the firms to forgo some short-term investments in sustaining the underlying knowledge and benefit from the underlying knowledge. The greater embeddedness of knowledge in the core areas can reduce the extent of knowledge depreciation in the short term. On the contrary, knowledge depreciates faster in the non-core areas due to its less-embeddedness. Divesting assets in the non-core areas and reducing investments in these areas make the firms even less likely to generate technological outputs. Thus, the loss of knowledge leads firms that sell non-core technological assets to experience worse technological performance in the post-bankruptcy period.

H4: Relative to their pre-bankruptcy technological performance, firms that divest non-core technological assets will be associated with a larger decline in technological performance after emergence from bankruptcy, compared with the ones that divest core technological assets.

Based on the same arguments, the following corollaries also hold:

Corollary 4a: Relative to their pre-bankruptcy technological performance, firms that divest low-value and non-core technological assets will have a greater decrease in technological performance after emergence from bankruptcy, compared with firms that sell high-value and core technological assets.

Corollary 4b: Relative to their pre-bankruptcy technological performance, firms that sell high-value and non-core technological assets will have a greater decrease in technological performance from bankruptcy, compared with firms that sell low-value and core technological assets.

Knowledge Utilization

The divestiture of the core or non-core technological assets may not only affect the technological performance of a bankrupt firm, but also affect the pattern of knowledge utilization within the firm. The knowledge management process consists of three steps from knowledge creation, knowledge retention, to knowledge transfer (Argote, McEvily, & Reagans, 2003). According to them, the three steps are interdependent: only after the knowledge retained in a firm, can it be transferred to another field and create new knowledge.

As the knowledge in the non-core technological areas is less embedded and depreciates faster, a firm needs to reinvest in creating knowledge in order to utilize knowledge in those areas. However, during bankruptcy, a firm is less likely to make such investments considering the financial constraint. The declining in the knowledge stock leaves the firm with less knowledge to continue its existing innovation activities in its current technological areas. As a result, the knowledge retention pattern in existing technological areas is likely to be negatively affected. Also, the knowledge utilization pattern in the new technological areas, which we refer to knowledge leverage, will differ between a firm that sells core technological assets and a firm that sells non-core ones. The greater embeddedness of knowledge in the core technological areas allows a firm to apply its knowledge to other areas, while the faster depreciation of knowledge in the non-core technological areas leaves the firm with less knowledge to leverage to other fields. Thus, we predict:

H5a: Relative to their pre-bankruptcy knowledge utilization, firms that divest non-core technological assets will be associated with a larger reduction in knowledge retention in existing technological areas after emergence from bankruptcy, compared with the ones that divest core technological assets.

H5b: Relative to their pre-bankruptcy knowledge utilization, firms that divest non-core technological assets will be associated with a larger reduction in knowledge leverage into new technological areas after emergence from bankruptcy, compared with the ones that divest core technological assets.

METHODOLOGY

Sample

We construct our sample based on four data sets: the UCLA-LoPucki Bankruptcy Research Database (BRD),[7] the Compustat Database, the U.S. Patent and Trademark Office (USPTO) Assignment Database, and the USPTO Patent Database.[8] Our sample includes financial data and patenting data from 1976 to 2014 and covers patenting large bankrupt firms that filed bankruptcy from 1979 to 2014. As patent assignments are regularly registered (Chesbrough, 2006; Dykeman & Kopko, 2004; Figueroa & Serrano, 2013) and BRD records all the large bankruptcy firms since 1979, linking those data sets via a name-matching procedure

[7] This database records information on all large public firms from 1979 to 2014. It defines "large" firms as those with more than $100 million in annual reported assets at the year of bankruptcy filing, measured in 1980 dollars.

[8] The two databases record patent-related information. The USPTO patent assignment database records all patent assignments from 1970 to 2014. The USPTO patent database records all patent applications from 1790 to the present.

enables us to identify the divestiture of technological assets, which are proxy by patents, among all U.S large bankrupt firms.

Following Maksimovic and Phillips (1998), we exclude firms that filed for Chapter 7 in our sample. We track the bankrupt firms' patenting and financial information for five years[9] before the bankruptcy filing as the pre-bankruptcy phase and five years after emergence from bankruptcy as the post-bankruptcy phase. Our final sample contains 283 patenting firms, in which 108 firms sold patents during bankruptcy and 175 firms had patent stocks but did not sell them during bankruptcy. In total, we have 3,317 firm-level observations and 70,889 patent-level observations.

Estimation

To test *H1* and *H3*, we use a logit model with firm and three-digit U.S. patent class fixed effects. We select the logit model because our dependent variable is a dichotomous variable. We also report the linear probability model results in Appendix B.1 as a robustness check for the model sensitivity. The firm fixed effect enables us to control for factors that are stable within a firm, and the patent class fixed effect enables us to control for unobserved factors that are stable within a patent class. The regression specification is:

$$p(dummy\_sale_{i,j,f} = 1) = \beta_0 + \beta_1 * X_i + controls_i + \sigma_j + \sigma_f + \varepsilon_{i,j,f} \quad (1)$$

$Dummy\_sale_{i,j,f}$ denotes the decision of divesting the *ith* patent in patent class *jth* of firm *fth* during [*F*, *E*], *F* is the year when the firm files for bankruptcy and *E* is the year when the firm emerges from bankruptcy. X_i is a set of covariates that identify whether the patent is of high

[9] Our selection of five years before bankruptcy filing and five years after emergence follows Hotchkiss (1995).

value (*high value*) or not and whether the patent belongs to the core technological areas of the firm or not (*core*). *High value* is equal to one if the number of forward citations received by the sold patent is more than three, and zero otherwise. We choose the value three because the average number of forward citations received by the patents applied in the USPTO is three. *Core* is equal to one if the patent belongs to a firm's core technological areas, and zero otherwise. Core technological areas are defined as the top two patent classes for which a firm receives patents.

$Controls_i$ includes a set of patent-level characteristics that may affect the likelihood of the patent being sold. These controls include patent age, backward citations, and claims. *Age* is the log transformation of one plus the difference between the year of the bankruptcy filing and the year of application for a patent. *Back* is the log transformation of one plus the number of backward citations of a patent. *Claims* is the log transformation of one plus the claims of a patent.

σ_j is the patent class fixed effect, σ_f is the firm fixed effect, and $\varepsilon_{i,j,f}$ is the error term that is clustered at the firm level. Because some patents are sold more than once, and some transactions involve multiple patents, we also verify the significance of coefficients using standard errors clustered at the patent level in regression (1) as the robustness check. The results for the robustness check are available upon request. The coefficient β captures the amount of increase in the predicted log odds associated with a one-unit increase in X_i (going from selling low-value to high-value patents, from selling non-core to core patents), holding other predictors constant.

Our second specification evaluates the sale of patents on a firm's profitability, technological performance, and knowledge utilization. Considering that firms make the divestiture decision endogenously, which causes the independent variable, *sale*, to correlate with the residual, we follow Waldinger (2010) and Shaver (2011) to use a difference-in-difference (DID) regression with firm fixed effects to address this potential endogeneity problem. Our model specification is:

$$Performance_{f,t} = \alpha_0 + \alpha_1 * Post_f + \alpha_2 * Sale_f * Post_f + \alpha_3 * Stock_{f,t} + \alpha_4 * Z_{f,t} + \sigma_f + \mu_{f,t} \quad (2)$$

Performance is a set of dependent variables that capture the *profitability*, *technological performance*, and *knowledge utilization* of the firm. *Profitability* is measured by EBIT divided by assets to control for firm size (Kalay, Singhal, & Tashjian, 2007). EBIT has been used extensively in the prior bankruptcy literature as a proxy for operating cash flows of a firm (Andrade & Kaplan, 1998; Kaplan, 1989). We measure two aspects of a firm's technological performance: its quantity of outputs and quality of outputs. *Patent* a*pplied* and *Patent class applied* capture the quantity of outputs. *Patent applied* is measured by log transformation of one plus the number of patents a firm applies for during year *t*. *Patent class applied* is measured by log transformation of one plus the number of distinct patent classes a firm applies during year *t*. We proxy the quality of technological performance by three variables. *Patent total value* reflects how valuable the technological outputs of the firm are, and we measure it by log transformation of one plus the mean of forward citations of all patent a firm applies during year *t*. *Patent self-value* reflects how valuable the technological outputs are to the bankrupt firm itself, and we measure it by log transformation of one plus the mean of self-citations of all patent a firm applies during year *t*. *Patent external value* reflects how valuable the technological outputs are to other firms, and we measure it by log transformation of one plus the mean of forward citations minus self-citations of all patent during year *t*.

We measure two dimensions of a firm's knowledge utilization. The first dimension is *knowledge retention*, which is measured by the log transformation of one plus the number of patents applied in the existing technological class. The second dimension is *knowledge leverage*, which is measured by the log transformation of one plus the number of patents applied in new technological class.

Sale is a categorical variable, which identifies the technological asset divestiture pattern of the firm during [F, E]. It takes a value of zero if the firm does not sell patents during [F, E]; a value of one if, among the sold patents, less than 50% are high-value patents and less than 50% are core patents; a value of two if, among the sold patents, at least 50% are high-value patents and less than 50% are core patents; a value of three if, among the sold patents, less than 50% are high-value and at least 50% are core patents; and a value of four if, among the sold patents, at least 50% are high-value and at least 50% are core patents.

Post is a dummy variable that equals one if year *t* is larger than *E*, and equals zero if year *t* is less than *F*.

Stock is the log transformation of one plus the total number of patents held by a firm. We include the patent stock of the bankrupt firms because the stock of technological assets is likely to affect the performance of the firm.

Z is measured by Altman's Z-score, which captures the financial distress level of a firm. A lower Z-score suggests a higher financial distress level of the firm. As severe financial distress tightens the budgets of the firm to invest in operation and innovation, we expect that Z-score is positively correlated with the profitability and technological performance of the firm.

We report heteroscedasticity-robust standard errors in all the model estimations. We use the standard errors clustered at the firm level for specification (2). In the specification (2),

$\alpha_1$estimates the expected mean change in *performance* from the pre-bankruptcy era to the post-bankruptcy era among the non-sale group, which is the bankrupt firms that have patent applications before bankruptcy but does not sell patents during bankruptcy. α_2 estimates the expected difference in the mean change in *performance* from the pre-bankruptcy era to the post-emergence era between the sale and non-sale groups. The estimated coefficient could be written as:

$$\hat{\alpha}_2 = \left(\hat{y}_{sale,post} - \hat{y}_{sale,pre}\right) - \left(\hat{y}_{nonsale,post} - \hat{y}_{nonsale,pre}\right)$$

RESULTS

Baseline Results

We provide the descriptive statistics of the sample in Table 3.1 and Table 3.2. Table 3.1 shows the patent-level summary statistics for regression (1). Table 3.2 presents the firm-level summary statistics for regression (2). From Table 3.1, we see that the mean age for each patent (*age*) is 10.47 ($e^{2.44} - 1$). Similarly, the patents in our sample have on average 7.92 backward citations and 10.56 claims. This patent-level information is comparable with attributes of traded patents noticed by previous literature (e.g. Fisher and Leidinger, 2014). The correlations between variables are reasonable. We do the same check for Table 3.2. Based on these checks, we conclude that the construction for the patent-level and firm-level sample is appropriate.

Insert Tables 3.1 and 3.2 here

The results of testing the relationship between patent attributes and firm's decision to divest patents during bankruptcy are shown in Table 3.3. Column (1) contains the patent-level control variables, which could influence the likelihood of the sale of a patent. The results suggest that younger patents, patents with more claims, and patents with more backward citations are significantly more likely to be sold during bankruptcy. Specifically, we see that *age* is significantly associated with patent sale, consistent with previous research (Serrano, 2010). The claims of a patent reflect the knowledge of that patent and could be a rough predictor of patent value (Harhoff, Scherer, & Vopel, 2003). Therefore, the positive coefficient on *claims* is expected. Column (4) is the overall model with control variables plus the measure of patent value (*high value*) and the core patents (*core*). From column (4), we can see that the odds that the sold patents are high-value patents are about 1.5 times (odds ratio = 1.453; standard error = 0.057) the odds that the sold patents are low-value patents. Also, the odds that the sold patents are core patents are less than half (odds ratio = 0.237; standard error = 0.232) the odds that the sold patents are non-core patents. Together, this suggests that a high-value patent or a non-core patent is more likely to be sold than their counterparts during bankruptcy. Our results support *H1* and *H3*.

Insert Table 3.3 here

Table 3.4.1 reports the results for the effect of the sale of patents on six dependent variables. Column (1) captures its effect on profitability, while columns (2) to (6) capture its effect on technological output, shedding light on the technological performance of the firm. Columns (1) to (6) are the difference-in-difference estimation with firm fixed effects. From the coefficients on *post*, we can see that compared with the pre-bankruptcy period, the post-bankruptcy period has significantly less profitability (coefficient = –0.020; standard error = 0.011), a lower number of patent applied (coefficient = –0.155; standard error = 0.071), a narrower range of patent classes (coefficient = –0.212; standard error = 0.057), and fewer forward citations received (coefficient = –0.163; standard error = 0.073).

Let us turn to the differential effect of divesting high-value and low-value technological assets on profitability. Compared to the firms that do not sell patents during bankruptcy, those that sell high-value patents are associated with a 0.061-unit-improvement (0.061 for the firms that sell high-value and non-core patents and 0.000 for the firms that sell high-value core patents) in profitability from the pre-bankruptcy phase to the post-bankruptcy phase. Similarly, compared to the firms that do not sell patents, those that sell low-value patents are associated with 0.046 (0.023 + 0.023) units of improvement in profitability from the pre-bankruptcy phase to the post-bankruptcy phase. Thus, the difference in selling high-value patents and low-value patents is 0.015 (0.061 – 0.046). This is a sizable difference, considering the average profitability of bankrupt firms in our sample is 0.042. However, the Wald tests in Table 3.4.2 suggest that the effect of selling high-value and low-value patents on profitability changes is not statistically different. Overall, *H2* is partially supported.

Insert Table 3.4 here

Columns (2) to (6) illustrate the effect of the sale of core/non-core patents on the technological performance of the bankrupt firms. The coefficients on *post* in columns (2), (5), and (6) are negative and significant, which suggest that compared to the pre-bankruptcy phase, the firms in the post-bankruptcy phase have a 16.3% reduction in the average value of their patents applied, have 15.5% fewer patent applied, and their patents applied belong to 21.2% fewer technological classes. Despite the general declining trend in post-bankruptcy technological performance compared to the pre-bankruptcy technological performance, the level of such reduction is different for the firms that sell patents from the core and non-core technological areas. Specifically, compared to the firms that sell core patents during bankruptcy, those sell non-core patents have fewer patent applied ($-0.24 - 0.52 + 0.16 + 0.25 < 0$; F-statistic 21.41; $p = 0.000$), fewer forward citations for the patents applied ($-0.25 - 0.55 + 0.21 + 0.20 < 0$; F-statistic 14.04; $p = 0.002$), and the firms apply patents in fewer technological classes (–0.74 – 1.24 + 0.28

+ 0.42<0; F-statistic 26; p = 0.000) from the pre-bankruptcy period to the post-bankruptcy period (*H4* is supported).

Similarly, we observe that compared to firms that sell high-value and core patents, firms that sell low-value and non-core patents have fewer patents applied (–0.24 – 0.25<0; F-statistic 12.22; p = 0.006), fewer forward citations received (–0.25 – 0.20<0; F-statistic 5.73; p = 0.017), and fewer technological classes (–0.74 – 0.42<0; F-statistic 12.85, p = 0.000) from the pre-bankruptcy period to the post-bankruptcy period (*Corollary 4b* is supported). Similarly, compared to firms that sell low-value and core patents, firms that sell high-value and non-core patents have fewer patent applied (–0.52 – 0.16<0; F-statistic 10.32; p = 0.000), fewer forward citations (–0.55 – 0.21<0; F-statistics 8.46; p = 0.004), and fewer technological classes (–1.24 – 0.28%<0; F-statistics 13.75; p = 0.000) from the pre-bankruptcy period to the post-bankruptcy period (*Corollary 4a* is supported).

Table 3.5.1 shows the effect of divesting technological assets on the knowledge utilization pattern of the firm. We find that compared to selling core patents, selling non-core patents is associated with a reduction (–0.47 – 0.316 – 0.096 – 0.237<0; F-statistic = 13.43; p = 0.000) in the number of patents applied in new technological areas, and a reduction (–1.05 – 0.463 – 0.286 – 0.115<0; F-statistic = 20.58; p = 0.00) in the number of patents applied in existing technological areas. Our results suggest that selling non-core technological assets indeed reduces both knowledge retention and knowledge leverage activities compared with selling core technological assets, as predicted in *H5a* and *H5b*.

Insert Table 3.5 here

Graphical Analysis

Our graphical analysis in Figures 3.2 offers a more intuitive explanation of our findings.

Figure 3.2.1 shows the profitability of the firms from five years before bankruptcy filing to five years after emergence from bankruptcy for two groups: the firms that sell high-value patents and the firms that sell low-value ones. Figure 3.2.2 to 3.2.4 illustrate the technological performances during the same periods for two other groups of firms: those that sell core patents and those that sell non-core patents.

As illustrated by Figure 3.2.1, compared to firms that sell low-value patents, those that sell high-value patents have better post-bankruptcy financial performance, especially from one year after emergence. Also, they do not differ much in the pre-bankruptcy profitability, which suggests that the difference in post-bankruptcy profitability may not come from the difference in pre-bankruptcy profitability.

As illustrated in Figures 3.2.2 and 3.2.4, we can see a clear, steep reduction of technological outputs of the group that sells non-core patents compared with the ones that sell core patents. Regarding the quality of technological output, Figure 3.2.4 shows that the firms that sell non-core patents during bankruptcy have a steeper reduction in the number of forward citations after emergence, compared with the firms that sell core patents. In Figure 3.2.3 and 3.2.4, we can observe a similar steeper declining trend in the mean number of patents applied and the mean number of patent class applied among the firms that sell non-core patents, compared with the ones that sell core patents. Together, these results suggest that compared to the divestiture of core technological assets, the divestiture of non-core technological assets is associated with a steeper reduction in the quantity and quality of technological outputs from pre-bankruptcy phase to the post-bankruptcy phase.

Insert Figure 3.2 here

Robustness Checks

A potential concern in our baseline model specification is that a firm's post-bankruptcy performance change could come from pre-bankruptcy financial and technological performance, instead of the divestiture of technological assets. To deal with that, we exploit the fact that U.S. bankruptcy courts use a "blind rotation system" to randomly assign bankruptcy cases to the judges in the district based on their availability. While a judge should obey the law, how the judge will interpret each case varies significantly based on the discretion of the individual judge (Chang & Schoar, 2006; Dobbie & Song, 2015). As a result, the randomly assigned judge will affect the patent sale and has an exogenous nature, which is useful to build good instrument variables for our study. Specifically, we include five instrument variables: the denominator for the four variables is the total number of bankruptcy cases of the assigned judge; and the numerators, respectively, are the number of approved asset sales, the number of approved patent sales, the number of cases involved in high-value patent sales, and the number of cases involved in core patent sales by each judge. Considering the endogenous variables interacted with *post*, we use the interaction of the instruments and *post* as instrument variables in the two-stage least squares estimation.

We report the second-stage results of using the judge-instrumented patent sale variables in Appendix B.4. We apply the "rule of thumb" proposed in Staiger and Stock (1997) to check the F-statistics of all the first-stage regressions. All the F-statistics are larger than 10, which implies the weak identification may not be a problem in the estimations. Also, we check the Hansen J-statistics for the overidentification tests, and we find that the null hypothesis, that the model is overidentified, is rejected. Appendix B.4.1 presents the effect of selling high-value patents against that of selling low-value patents, while Appendix B.4.2 presents the effect of selling core patents against that of selling non-core patents. From both tables, we can see that the sale of patents is associated with worse technological performance. However, the sale of core patents makes the post-bankruptcy technological function less bad, which is consistent with our baseline results. Although the effect of the sale of high-value patents on profitability is not significantly different from that of selling low-value patents, the direction on the coefficient is consistent with our prediction that selling high-value patents improves profitability.

As another robustness check, we use propensity score matching (PSM) to test our model sensitivity of specification (2), which is the effects of divesting technological assets. PSM allows us to build pairs of bankrupt firms that sell and do not sell patents based on their similarity of other factors such as firm size, age, and so on. Using these observable characteristics, PSM enables us to remove relevant differences and provide unbiased estimates of the treatment effect (Dehejia and Wahba, 2002). Our PSM matches a focal firm with its nearest neighbor on their pre-bankruptcy financial information such as assets, sales, equity, liability, and financial distress level. The PSM results are reported in Appendix B.2. The outcome variables we compare are the differences between the average five-year pre-bankruptcy performances and the average five-year post-bankruptcy performances. We use a five-year average performance because we expect the effect of divestiture on performance change could take time, especially to alter technological function. We find that firms that sell high-value patents during bankruptcy are associated with improved profitability compared with those that sell low-value patents, while the sale of core patents is associated with more patent applied and more patent classes applied compared with the firms that sell non-core patents. Our PSM results are broadly consistent with our baseline results.

We also check if our results are sensitive to the measures we selected. In the baseline regression, we measure the patent value using five-year forward citations. Our results are consistent if we change the measure of patent value to three-year or seven-year forward citations.

We also check if our definition of *high value* is sensitive to the criteria we select, by using the mean forward five-year citation of patents in the same technological class and at the same application year as the alternative threshold. All these results are available upon request. After these robustness checks, we confirm that our results are not sensitive to the measures in the baseline regressions.

DISCUSSION

Divestiture of Technological Assets versus Physical Assets

Compared to previous research on the divestiture of physical assets, our results suggest that the drivers of the divestiture of physical assets and technological assets are not the same even they have some overlaps. Considering many physical assets are specific to the industry, previous literature on physical asset divestiture during bankruptcy highlights the importance of the industry condition in influencing the divestiture decisions (Maksimovic & Phillips, 1998; Ramey & Shapiro, 2001). This stream of literature suggests that the changes in the industry conditions imply the changes in the demands for the assets; as a result, the industry conditions will affect whether a firm decides to sell assets and how many assets the firm can sell. Our results suggest that the divestiture of technological assets is associated with the attributes of those assets rather than the industry condition. Buyers for technological assets are less likely to be restricted to certain industries than buyers for physical assets. Industry conditions may be a less important factor in the divestiture decision when a firm is considering divesting a less industry-specific asset.

Apart from industry condition, divestiture of physical assets is found to be constrained by the demand in the local markets (Bernstein *et al*. 2016; Maksimovic & Phillips, 1998). Having many firms in the local market will reduce the search costs of bankrupt firms to find a buyer;

thus, it will be easier for bankrupt firms to sell assets, especially physical assets such as plants, buildings, and equipment. However, for intangible assets such as patents, local markets may exert little effect on divestiture. Buyers could come from any locations, and there are negligible, if any, associated transportation costs in purchasing technological assets.

Apart from drivers of asset divestiture, the performance impacts of divesting physical assets and technological assets are not the same. How the technological performance and knowledge utilization are affected by divestiture have not been discussed in the previous research on physical assets. This is because general physical assets are less likely to be linked to technological performance and knowledge utilization. Most of the previous empirical studies on the impact of divestiture examine two broad performances, accounting profitability and market profitability, as noticed by Lee and Madhavan (2010). Thus, we extend the discussion to see how divestiture could affect a firm's post-bankruptcy technological performance and knowledge utilization. Our results suggest that divestiture strategy and the attributes of the technological assets have a sizable effect on the bankrupt firms' technological performance and knowledge utilization.

Knowledge Embeddedness

The knowledge-based view suggests that knowledge is likely to be the source of competitive advantage (Grant, 1996). While this theory highlights the role of knowledge in sustaining competitive advantage, how the knowledge evolves over time receives relatively less discussion as noticed by Srivastava, Fahey, and Christensen (2001). Our perspective toward separating technological assets and knowledge enables us to offer tentative answers to the question: divesting which kinds of technological assets would be less likely to affect the knowledge of a firm? We argue that knowledge in the core areas is more embedded in the firms than the knowledge in the non-core areas. The greater embeddedness of assets enables the firms to continue innovation activities even after divesting the corresponding technological assets. Our results confirm this prediction and suggest that even in general, divesting technological assets leads bankrupt firms to apply for fewer patents and to apply for less valuable patents after bankruptcy; firms that sell core technological assets have a less reduction than bankrupt firms that sell non-core technological assets.

As the development and fade of knowledge are not directly observable, the previous research examines the knowledge changes by examining the turnover of a firm's employees, as the knowledge is likely to reside in the human capital of the firms (e.g. Coucke, Pennings, & Sleuwaegen, 2007). We perform an exploratory analysis of the knowledge changes associated with selling core/non-core patents using patent inventor data set by Lai, D'Amour, Yu. Sun and Fleming (2010). This dataset identifies individual inventors of U.S. utility patent from the 1975 and 2010. Merging the inventor data with our sample, we are able to identify 114,352 inventors for the bankrupt firms that sell patents during bankruptcy. We then examine how the inventor's decision to leave after bankruptcy are associated with the divestiture of non-core/core patents among the bankrupt firms. We control for the financial distress level of the firm. From Appendix B.3, we could see that core inventors are less likely to leave the firms. We also find that compared to firms that sell non-core patents, the ones that sell core patents are actually associated with less likelihood of inventor exit after bankruptcy. As knowledge is likely to reside in individuals, the results from inventor dataset support our arguments that the knowledge is likely to be more embedded in core technological fields and divesting assets in these fields is less likely to be associated with loss of knowledge.

Alternative Explanation

An alternative explanation for our finding is that the bankrupt firms sell non-core technological assets in order to resolve a past mis-expansion. Often, over-diversified firms try to tackle the mis-expansion problem by focusing on their core assets and activities (Kaul, 2012; Lang, Poulsen, & Stulz, 1995; Shleifer & Vishny, 1992) and reducing diversification (Hoskisson & Hitt, 1994; Markides, 1992). If that explanation holds, firms that sell non-core technological assets should show a decrease in patenting activities in the non-core areas and an increase of patenting activities in the core areas, while firms that sell core assets should keep the same trend in the technological activities. We first check the concentration ratio of technological outputs for the firms that sell non-core and core assets in our sample. We find that firms that sell core assets on average have a higher concentration ratio (*H* index = 0.25) than the ones that sell non-core assets (*H* index = 0.10). This suggests that mis-expansion could be a possible reason for selling non-core assets because firms that sell non-core assets have a more diversified technological portfolio.

We then restrict our sample to the firms with a lower concentration ratio (*H* index < 0.25), because firms with a higher concentration ratio may sell core technological assets simply because they possess only these assets. Our results in Appendix B.5 show that our prediction of the differential effect of selling core and non-core technological assets still holds. This finding suggests that although the concentration ratio of firms' technological portfolio could affect the divestiture decision, the impact of divestiture on subsequent technological performance may not be due to the resolution of mis-expansion, but is likely due to the knowledge explanation we offer in this paper.

Empirical Studies on Asset Divestiture

This paper also contributes to the empirical studies on asset divestiture. Considering the asset divestiture decision is endogenously decided by the firm, the impact of divesting assets could arise from existing differences among the firms, instead of the divestiture decision itself. As a result, we use a DID approach, which addresses many such potential problems. As Szucs (2014) points out, DID singles out the effect of being "treated", here the firms that sell certain technological assets during bankruptcy, on the outcome variables, here profitability, technological utilization, and knowledge utilization. While some previous bankruptcy research (e.g. Graham, Kim, Li, & Qiu, 2013) has utilized DID approach in the estimation, this method has been not used to study the divestiture of technological assets. In addition, some research (Ma, et al., 2017) investigates the reasons for divestiture of technological assets during bankruptcy utilizing methods such as ordinary least squares (OLS), which may lead to potential endogeneity problem. In addition, our results are robust to alternative approaches to deal with endogeneity, such as judge instrument estimation.

CONCLUSION

In this paper, we investigate how the attributes of technological assets will affect the divestiture decisions among bankrupt firms and their subsequent profitability, technological performance, and knowledge utilization patterns. Consistent with our predictions, we find that high-value technological assets are around 1.5 times more likely to be sold than low-value technological assets, while core technological assets are less than half as likely to be sold than the non-core technological assets. Furthermore, we find that compared to firms that do not sell high-value technological assets, those that sell high-value technological assets show economically significant improvement in profitability after bankruptcy. Moreover, compared to the post-bankruptcy performance of firms that divest core technological assets, those that divest non-core technological assets have a steeper decline in the quantity and the quality of technological outputs, as well as less knowledge utilization in both existing and new technological areas.

To conclude, our findings contribute to the resource reconfiguration literature by extending the current understanding of divestiture decisions to bankrupt firms and to technological assets. We believe investigation on the knowledge and assets divestiture among bankrupt firms will be a fruitful stream of research. Future research could advance in this field by examining the conditions when knowledge will be retained or abandoned after assets divestiture, and these conditions are especially important to bankrupt firms, who need to retain their fast-declining resource bases.

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FIGURES AND TABLES FOR CHAPTER THREE

Table 3.1 Patent-Level Summary Statistics

	N	Mean	SD	Min	Max
Dummy_sell	70889	0.262	0.439	0	1
High value	70889	0.460	0.498	0	1
Core	70889	0.334	0.472	0	1
Age	70889	2.440	0.724	0	3.497
Back	70889	2.189	0.722	0.693	4.025
Claims	70889	2.448	0.782	0.693	3.912

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Dummy_sell	1					
(2) High value	0.076^{***}	1				
(3) Core	0.014^{***}	-0.005	1			
(4) Age	-0.314^{***}	0.065^{***}	-0.103^{***}	1		
(5) Back	0.073^{***}	0.083^{***}	0.058^{***}	-0.201^{***}	1	
(6) Claims	0.157^{***}	0.125^{***}	0.093^{***}	-0.210^{***}	0.215^{***}	1

Table 3.2 Firm-Level Summary Statistics

	N	Mean	SD	Min	Max
Profitability	3317	0.042	0.115	-2.070	1.162
Patent total value	3317	0.727	0.851	0	4.043
Patent self-value	3317	0.133	0.281	0	2.251
Patent external value	3317	0.679	0.818	0	4.025
Patent applied	3317	1.138	1.366	0	5.056
Patent class applied	3317	0.918	1.043	0	3.784
Knowledge leverage	3317	0.449	0.655	0	4.575
Knowledge retention	3317	0.700	1.031	0	4.812
Sale	3271	0.974	1.300	0	4
Stock	3298	1.685	3.693	-4.605	7.927
Z	3314	1.777	1.859	-3.590	8.395

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Profitability	1										
(2) Patent total value	0.061^{***}	1									
(3) Patent self-value	0.088^{***}	0.536^{***}	1								
(4) Patent external value	0.048^{**}	0.991^{***}	0.433^{***}	1							
(5) Patent applied	0.127^{***}	0.579^{***}	0.538^{***}	0.537^{***}	1						
(6) Patent class applied	0.135^{***}	0.594^{***}	0.507^{***}	0.558^{***}	0.977^{***}	1					
(7) Knowledge retention	0.156^{***}	0.464^{***}	0.362^{***}	0.440^{***}	0.724^{***}	0.770^{***}	1				
(8) Knowledge leverage	0.089^{***}	0.493^{***}	0.497^{***}	0.455^{***}	0.920^{***}	0.919^{***}	0.528^{***}	1			
(9) Sale	0.052^{**}	0.166^{***}	0.155^{***}	0.149^{***}	0.213^{***}	0.214^{***}	0.283^{***}	0.389^{***}	1		
(10) Stock	0.070^{***}	0.388^{***}	0.350^{***}	0.359^{***}	0.622^{***}	0.616^{***}	0.362^{***}	0.609^{***}	0.137^{***}	1	
(11) Z	0.487^{***}	0.146^{***}	0.152^{***}	0.132^{***}	0.199^{***}	0.203^{***}	0.238^{***}	0.135^{***}	0.106^{***}	0.097^{***}	1

Table 3.3 Logit Regression: Drivers of Patent Sale during Bankruptcy

	(1)	**(2)**	**(3)**	**(4)**
age	-1.041	-1.100	-1.101	-1.162
	(0.264)***	(0.264)***	(0.257)***	(0.257)***
	[0.353]	[0.333]	[0.333]	[0.313]
back	0.178	0.165	0.180	0.167
	(0.068)***	(0.068)**	(0.072)**	(0.072)**
	[1.195]	[1.179]	[1.197]	[1.181]
claims	0.137	0.110	0.141	0.114
	(0.065)**	(0.067)	(0.065)**	(0.067)*
	[1.147]	[1.117]	[1.151]	[1.121]
high value		0.364		0.374
		(0.059)***		(0.057)***
		[1.439]		[1.453]
core			-1.430	-1.441
			(0.236)***	(0.232)***
			[0.239]	[0.237]
constant	4.762	4.908	5.299	5.473
	(1.135)***	(1.133)***	(1.093)***	(1.083)***
Observations	61,895	61,895	61,895	61,895

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

[a] The dependent variable is *dummy_sale* in (1), (2), (3) and (4).

[b] age, back, claims are log transferred.

[c] The model includes firm and patent class fixed effects.

[d] Standard errors are clustered by firm.

[e] Standard errors are shown in parentheses and odds ratio in square brackets.

Table 3.4.1 Sale of Patents on Technological Performance

	Profitability	Technological Performance				
	(1) Profitability	(2) Patent total value	(3) Patent self-value	(4) Patent external value	(5) Patent applied	(6) Patent class applied
post	-0.020	-0.163	-0.010	0.007	-0.155	-0.212
	(0.011)*	(0.073)**	(0.023)	(0.016)	(0.071)**	(0.057)***
Sale(=1)*post	0.023	-0.249	-0.034	0.123	-0.239	-0.736
	(0.015)	(0.187)	(0.046)	(0.113)	(0.182)	(0.334)**
Sale(=2)*post	0.061	-0.554	-0.178	-0.162	-0.520	-1.241
	(0.035)*	(0.180)***	(0.080)**	(0.136)	(0.176)***	(0.417)***
Sale(=3)*post	0.023	0.206	0.110	0.046	0.160	0.278
	(0.029)	(0.218)	(0.104)	(0.071)	(0.202)	(0.278)
Sale(=4)*post	-0.000	0.197	-0.113	0.268	0.253	0.420
	(0.014)	(0.098)**	(0.142)	(0.224)	(0.113)**	(0.059)***
stock	-0.001	0.076	0.008	0.009	0.072	0.094
	(0.002)	(0.015)***	(0.004)*	(0.004)**	(0.015)***	(0.019)***
Z	0.034	0.035	0.006	0.006	0.033	0.020
	(0.005)***	(0.015)**	(0.006)	(0.005)	(0.015)**	(0.014)
Constant	-0.016	0.458	0.065	0.112	0.436	0.735
	(0.007)**	(0.029)***	(0.010)***	(0.012)***	(0.029)***	(0.035)***
R^2	0.63	0.55	0.45	0.57	0.54	0.78
N	1,864	1,864	1,864	1,864	1,864	1,864

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

[a] The model includes firm fixed effects.

[b] Standard errors are clustered by firm.

[c] Standard errors are shown in parentheses

Table 3.4.2 Wald Test Results

	(1)	(2)	(3)	(4)	(5)	(6)
Test if 2=3 (high value non-core vs low-value	0.77	8.46	5.67	7.42	10.35	13.75
and core)	(0.382)	(0.004)	(0.017)	(0.007)	(0.002)	(0.000)
Test if 1=4 (low value non-core vs high-value	3.23	5.73	0.28	6.67	12.22	12.85
core)	(0.073)	(0.017)	(0.595)	(0.010)	(0.006)	(0.000)
Test if 2+4=1+3	0.10	0.97	3.61	0.36	0.40	0.83
(high value vs low value)	(0.753)	(0.326)	(0.058)	(0.551)	(0.528)	(0.363)
Test if 1+2=3+4	1.85	14.04	1.23	13.89	21.41	26.00
(noncore vs core)	(0.175)	(0.002)	(0.268)	(0.002)	(0.000)	(0.000)

p values associated with the F statistics are shown in parentheses.

Table 3.5.1 Sale of Patents on Knowledge Utilization

	Knowledge Utilization	
	(1)	(2)
	Knowledge leverage	Knowledge retention
Post	-0.177	-0.034
	(0.032)***	(0.043)
Sale(=1)*Post	-0.470	-0.463
	(0.143)***	(0.272)*
Sale(=2)*Post	-0.316	-1.050
	(0.132)**	(0.305)***
Sale(=3)*Post	0.237	0.115
	(0.186)	(0.141)
Sale(=4)*Post	0.096	0.286
	(0.162)	(0.120)**
Stock	0.042	0.049
	(0.009)***	(0.017)***
Z	0.025	0.004
	(0.009)***	(0.007)
Constant	0.264	0.443
	(0.017)***	(0.027)***
R^2	0.49	0.78
N	1,864	1,864

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

[a] The model includes firm fixed effects.

[b] Standard errors are clustered by firm.

[c] Standard errors are shown in parentheses

Table 3.5.2 Wald Test Results

	(1)	(2)
Test if 1+2=3+4	13.43	20.58
(noncore vs core)	(0.000)	(0.000)

p values associated with the F statistics are shown in parentheses.

Figure 3.1: Model Framework—Causes and Consequences of Divesting Technological Assets

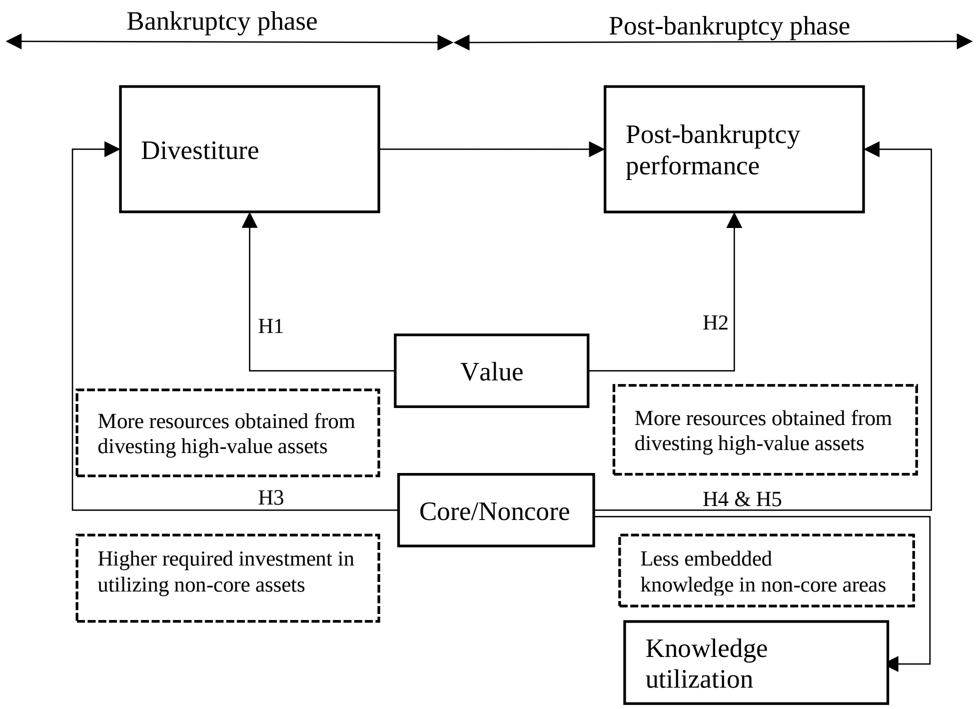


FIGURE 3.2: The Sale of Patents on Profitability and Technological Performance

Figure 3.2.1: The Sale of High-/Low-Value Patents on Profitability

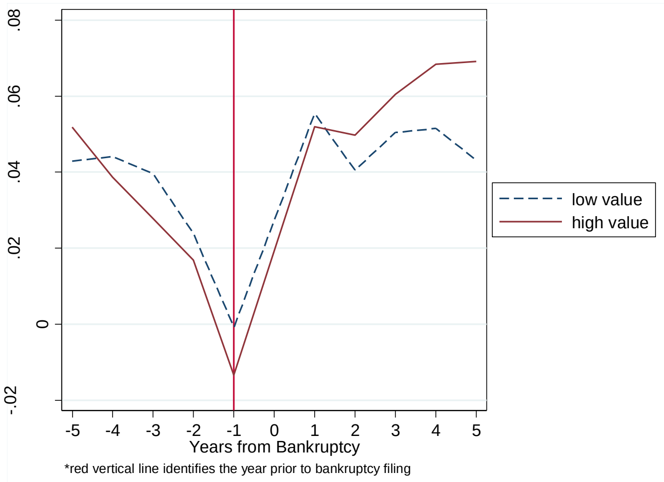


Figure 3.2.3: The Sale of Core/Non-Core Patents on Number of Patents Applied

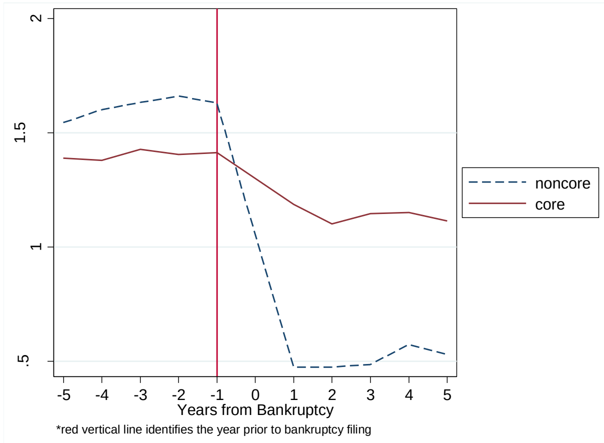


Figure 3.2.2: The Sale of Core/Non-Core Patents on Forward Citations Receive

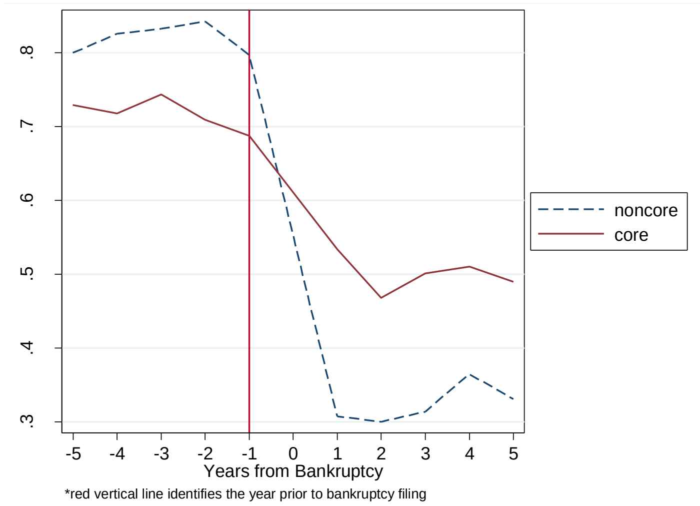
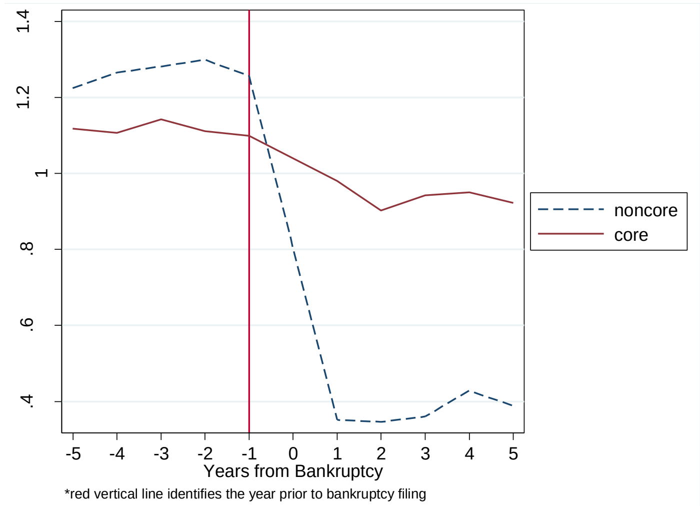


Figure 3.2.4: The Sale of Core/Non-Core Patents on Number of Patent Classes Applied



Appendix B.1 LPM Regression: Drivers of Patent Sale during Bankruptcy

	(1)	(2)	(3)	(4)
age	-0.070	-0.073	-0.072	-0.075
	(0.025)***	(0.025)***	(0.025)***	(0.025)***
back	0.013	0.012	0.013	0.012
	(0.006)**	(0.006)**	(0.006)**	(0.006)**
claims	-0.000	-0.002	0.000	-0.002
	(0.006)	(0.007)	(0.006)	(0.007)
high value		0.020		0.019
		(0.008)**		(0.008)**
core			-0.072	-0.071
			(0.015)***	(0.015)***
constant	0.668	0.672	0.687	0.691
	(0.147)***	(0.147)***	(0.146)***	(0.146)***
R^2	0.70	0.70	0.70	0.70
Observations	70,626	70,626	70,626	70,626

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

[a] The dependent variable is *dummy_sale* in (1), (2), (3), and (4).
[b] The model includes firm and patent fixed effects.
[c] Standard errors are clustered by firm.
[d] Standard errors are shown in parentheses.

Appendix B.2.1. Propensity Score Matching Results

Treatment group	Change in *profitability*	Change in *patent total value*	Change in *patent self-value*	Change in *patent external value*	Change in *patent applied*	Change in *patent class applied*
Firms that sold high-valued patents V.S. sold low-value ones	0.029**	-0.237*	-0.272***	-0.154	-0.410	-0.325
	(0.013)	(0.136)	(0.078)	(0.117)	(0.224)	(0.177)

* *p*<0.1; ** *p*<0.05; *** *p*<0.01. Standard errors are shown in parentheses.

Appendix B.2.2. Propensity Score Matching Results

Treatment group	Change in *profitability*	Change in *patent total value*	Change in *patent self-value*	Change in *patent external value*	Change in *patent applied*	Change in *patent class applied*
Firms that sold core patents V.S. sold non-core ones	-0.030***	-0.067	-0.045	-0.032	0.431**	0.382***
	(0.011)	(0.144)	(0.036)	(0.147)	(0.207)	(0.164)

* *p*<0.1; ** *p*<0.05; *** *p*<0.01, Standard errors are shown in parentheses.

Appendix B.2.3 Sale of Patents and Inventors Exit

	(1) Leave	(2) Leave
Z	-0.014	-0.014
	(0.005)**	(0.005)**
Post	0.049	0.042
	(0.049)	(0.072)
Core inventor	-0.434	-0.436
	(0.010)***	(0.010)***
Post*Core inventor		0.020
		(0.045)
Post*Core tech		-0.168
		(0.073)**
Core inventor*Core tech		0.036
		(0.036)
Constant	0.584	0.585
	(0.030)***	(0.030)***
R^2	0.23	0.23
N	114,352	114,352

Notes: This sample includes all the inventors of the firms which sell patents during bankruptcy in our sample. The dependent variable is a binary variable, which equals to one if an inventor leaves the firm after bankruptcy and equals to zero if the inventor remains in the firm. Core inventor equals one if the inventor has invented core patents for the firm and zero otherwise. Core tech is a firm-level variable which equals to 1 if among the sold patents, at least 50% are patents in core technological areas; and zero otherwise. Z is the Altman's Z score of the firm in the corresponding year. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Appendix B.4 Judge Instrument Results

Appendix B.4.1 Second Stage Results for Selling High-Value Patents

	Profitability	Technological Performance				
	(1) Profitability	(2) Patent total value	(3) Patent self-value	(4) Patent external value	(5) Patent applied	(6) Patent class applied
High value*Post	0.032	-0.415	-0.191	-0.356	-0.297	-0.417
	(0.033)	(0.256)	(0.089)**	(0.255)	(0.427)	(0.317)
Post	0.002	-0.240	0.022	-0.250	-0.635	-0.455
	(0.010)	(0.139)*	(0.040)	(0.134)*	(0.258)**	(0.184)**
Stock	-0.002	0.064	0.009	0.059	0.092	0.069
	(0.002)	(0.019)***	(0.005)**	(0.019)***	(0.025)***	(0.020)***
Z	0.030	0.038	-0.000	0.038	0.030	0.041
	(0.004)***	(0.021)*	(0.007)	(0.020)*	(0.026)	(0.021)*
R^2	0.34	0.16	0.06	0.15	0.24	0.25
N	698	698	698	698	698	698

Notes: The sample is restricted to the firms that sell patents during bankruptcy. High value equals one if the among the sold patents, at least 50% are high-value patents; and zero otherwise. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Appendix B.4.2 Second Stage Results for Selling Core Patents

	Profitability	Technological Performance				
	(1) Profitability	(2) Patent total value	(3) Patent self-value	(4) Patent external value	(5) Patent applied	(6) Patent class applied
Core tech*Post	0.001	0.648	0.125	0.634	1.084	0.955
	(0.017)	(0.222)***	(0.089)	(0.213)***	(0.366)***	(0.291)***
Post	0.012	-0.588	-0.089	-0.571	-1.097	-0.914
	(0.009)	(0.125)***	(0.045)**	(0.121)***	(0.245)***	(0.183)***
Stock	-0.002	0.066	0.012	0.061	0.107	0.081
	(0.002)	(0.017)***	(0.004)***	(0.017)***	(0.026)***	(0.021)***
Z	0.029	0.039	-0.001	0.039	0.020	0.035
	(0.005)***	(0.022)*	(0.007)	(0.022)*	(0.025)	(0.020)*
R^2	0.32	0.18	0.05	0.17	0.31	0.33
N	674	674	674	674	674	674

Notes: The sample is restricted to the firms that sell patents during bankruptcy. Core tech equals one if the among the sold patents, at least 50% are patents in core technological areas; and zero otherwise. * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Appendix B.5 Sale of Patents on the Post-Bankruptcy Performance (within High-Diversified Firms)

	Profitability	Technological Performance				
	(1) Profitability	(2) Patent total value	(3) Patent self-value	(4) Patent external value	(5) Patent applied	(6) Patent class applied
Post	-0.021	-0.089	0.047	-0.083	-0.375	-0.346
	(0.017)	(0.121)	(0.046)	(0.117)	(0.128)***	(0.105)***
Sale(=1)*Post	0.035	-0.408	-0.098	-0.393	-0.799	-0.594
	(0.018)*	(0.228)*	(0.067)	(0.219)*	(0.386)**	(0.289)**
Sale(=2)*Post	0.056	-0.684	-0.224	-0.654	-1.073	-0.853
	(0.034)	(0.214)***	(0.092)**	(0.207)***	(0.463)**	(0.307)***
Sale(=3)*Post	-0.022	0.250	0.219	0.156	0.596	0.566
	(0.060)	(0.374)	(0.225)	(0.337)	(0.493)	(0.383)
Sale(=4)*Post	-0.014	0.065	-0.585	0.315	0.679	0.420
	(0.018)	(0.130)	(0.048)***	(0.127)**	(0.169)***	(0.133)***
Stock	-0.003	0.064	0.016	0.057	0.121	0.087
	(0.003)	(0.023)***	(0.007)**	(0.022)**	(0.041)***	(0.032)***
Z	0.036	0.039	-0.001	0.039	0.011	0.026
	(0.007)***	(0.027)	(0.008)	(0.027)	(0.029)	(0.023)
Constant	-0.002	0.651	0.089	0.625	1.309	1.067
	(0.014)	(0.080)***	(0.029)***	(0.080)***	(0.141)***	(0.107)***
R2	0.56	0.55	0.44	0.54	0.72	0.71
N	713	713	713	713	713	713

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

[a] The model includes firm fixed effects.

[b] Standard errors are clustered by firm.

[c] Standard errors are shown in parentheses.

CHAPTER FOUR:

HUMAN CAPITAL CHURN DURING BANKRUPTCY

INTRODUCTION

Strategy research on human capital management highlights the role of firm-specific human capital as a source of sustainable competitive advantage (e.g. Coff & Kryscynski, 2011). The tacit and socially complex knowledge of the firm is likely to reside within the employees of an organization (Almeida & Kogut, 1999). The turnover of employees makes the otherwise immobile tacit knowledge transferrable across the organizational boundary. Acquiring human capital can lead to knowledge inflow to the focal firm (Song, Almeida, & Wu, 2003), while the departure of a firm's key talents can lead to knowledge spill over to another firm (e.g. Arrow, 1962; Agrawal, Ganco, & Ziedonis, 2009; Bernstein, 2015). As a result, investigating employee turnover patterns, especially the skilled employee turnover patterns, has implications for managing organizational knowledge and subsequent organizational performance.

According to previous literature, employee turnover stems from three sources: individual factors, organizational factors, and the interaction of the individual and organizational factors. Previous research suggests that individual factors such as employee education experience, work experience, and work performance will affect the likelihood of an employee enters or leaves an organization. Apart from individual factors, organizational factors such as firm size, patent enforcement litigiousness, patent transaction decisions, and Initial Public Offering (IPO) will affect an organization's ability to retain its valuable human capital (e.g. Agarwal, et al., 2009; Bernstein, 2015; Hoisl, 2007; Ma, Tong, Wong, 2017). In addition, the fitness between an employee and an organization is found to affect the employee turnover (e.g. Ganco, Ziedonis, & Agarwal, 2015; Hoisl, 2007; Palomeras & Melero, 2010).This stream of literature provides theoretical foundations for studying the employee turnover in organizations.

Another stream of literature points out unique resource reallocation problems in bankrupt firms (e.g. Maksimovic & Philips, 1998). It treats bankrupt firms as less efficient users of resources and examines whether certain bankruptcy law facilitates the resource reallocation to more efficient users and what types of resources and strategies matter for the turnaround of bankrupt firms. Broadly, there are three types of resources in bankrupt firms have been studied: physical resource (Pulvino, 1999), financial resource (Thornhill & Amit, 2003, Dawley, Hoffman, & Lamont, 2002), and human resource (e.g. Berk et al., 2010). Specifically, the stream of research on bankruptcy and human resource examines how specific human capital such as board structure (Daily & Dalton, 1994), managerial knowledge (Thornhill & Amit, 2003), external stakeholders (Xia, et al., 2016), vulture investors (Hotchkiss & Mooradian, 1997) affect the turnaround of the bankrupt firms. Some other research track the changes of a resource such as changes in employee wage (Berk et al., 2010) and change in plant-level productivity (Maksimovic & Phillps, 1998) alongside bankruptcy. Despite the rich investigation on how bankrupt firms reallocate resources and how specific human resource affects bankrupt firms' turnaround, studies examining the specific employee turnover patterns in bankrupt firms are still limited.

We add to both employee turnover literature and bankruptcy literature by examining the specific employee turnover patterns in bankrupt and non-bankrupt firms. While the previous literature on employee turnover largely focuses on the employee turnover patterns in non-bankrupt firms, comparing this phenomenon between bankrupt and non-bankrupt firms enables us to investigate the human capital reallocation process among the firms that face survival problems. Unlike non-bankrupt firms, bankrupt firms suffer from deteriorating performances and declining resources stock, which can restrict their ability in attracting and retaining key talents.

Considering the possible connection of human capital turnover and bankruptcy, we ask two questions in this study: How will bankruptcy affect the gain, loss, and retention of skilled human capital within a firm? What types of employees are more likely to be retained in the bankrupt firms—star employees or novice employees?

In order to answer our proposed research questions, we construct a novel data set that tracks the entire career path of patent inventors associated with U.S. public listed firms that filed bankruptcy from 1980 to 2010. In order to compare the employee turnover patterns between bankrupt and non-bankrupt firms, we use the principal score matching (PSM) to identify a group of non-bankrupt firms for the bankrupt firms based on a set of firms' ex-ante observable characteristics in both groups of firms. Using the difference-in-difference (DID) approach, we compare the inventors' entry and exit patterns in bankrupt firms before and after bankruptcy with the corresponding patterns in firms that do not file bankruptcy over the same time spans.

We intend to make three contributions. First, we speak to the micro-foundation research in strategic management. Foss (2011) strengthens the importance of the micro-level study because micro-level factors are likely to drive other aggregated level outcomes. Coff and Kryscynski (2011) call for the examination an important micro-foundation level factor, the human capital of a firm. Particularly, they point out that resolution of the dilemma of attraction and retention of human capital could create value for a firm. We respond to this call and compare the dilemma of attraction and retention of human capital within bankrupt and non-bankrupt firms. While previous research examines the different sources that lead to employee turnover among non-bankrupt firms, we add to this stream of research by examining another organizational source of human capital turnover—the bankruptcy. Our findings suggest that bankrupt and non-bankrupt firms differ in their human capital turnover patterns. We point out that bankrupt firms suffer from a loss of skilled human capital, especially the star employees, when they approach bankruptcy, and this declining trend lasts even after them emerging from bankruptcy.

Second, we also speak to resource reallocation research in bankrupt firms. Morrow et al. (2007) find that recombining a firm's existing stock of resources, as well as acquiring resources through mergers or acquisitions, have a positive effect on organizational recovery. As the human resource is an important resource of an organization, examining a firm's strategic actions in recombining human resources offers important implications to the bankrupt firms. While previous bankruptcy literature focuses on macro-factors such as bankruptcy laws in affecting resource reallocation, a firm's human capital change patterns are also worthy of investigation. Apart from this paper, as far as we know, Graham, Kim, Li, and Qiu (2013) is the only one that examines bankruptcy and human capital (employee wages) change patterns during bankruptcy. We extend previous literature by demonstrating the skilled labor turnover patterns in bankrupt firms.

Last but not least, we add to the discussion about corporate failure. As Thornhill and Amit (2003, P.506) point out, "Just as medical science would be unlikely to progress by studying only healthy individuals, organization science may be limited in the knowledge attainable only from the study of successful firms". The fitness of a firm's resources and capabilities with the requirements of the external environment could matter for the survival or death of a firm (Amit & Schoemaker, 1993; Thornhill & Amit, 2003). Thornhill and Amit (2003) find that inability to adapt to environmental change largely explains the bankruptcy of established firms. Adding to them, we investigate how inventors turnover happens and how bankrupt firms search and sort their related talents proportions alongside bankruptcy. We find that bankrupt firms have fewer new inventors enter the organization even before the bankruptcy filing. These changes in employees turnover could be an early signal that predicts the bankruptcy.

HYPOTHESES

Hiring and retaining its skilled employees such as scientists and engineers are an important part of a firm's innovation activities. As a result, a firm's intention and ability to conduct innovation will naturally affect its skilled personnel turnover. A bankrupt firm is likely to suffer from faster inventor turnover compared with a comparable non-bankrupt firm due to its reduced motivation to involve in innovation and its limited number of uncommitted resources to support innovation.

Innovation Motivation

Bankrupt firms are less likely to be motivated to conduct innovation compared with non-bankrupt firms. Innovation involves a wide range of activities from research projects investment, novel product or service production process improvement, to new product and service announcement. Threat-rigidity research (e.g. Staw, Sandelands, & Dutton, 1981; Barker & Mone, 1998; Sutton & D'Aunno, 1989) suggests that when an organization faces external adversity, it is likely to restrict its information search. This leads an organization to rely on well-learned routines, such as administrative routines, and reduce innovation activities. Bankruptcy is a clear defined survival threat, which is found to inhibit innovation (Chen & Miller, 2007; McKinley, Latham, & Braun, 2014). Compared to other routinized activities, conducting innovation has great uncertainty and yields more variation in future return (Kanter, 1988). Similar to other innovation activities, hiring innovation-related personnel is an investment of uncertainty because the capabilities of those skilled employees can hardly be known before their employment (Spence, 1973). The large uncertainty also suggests that investment in skilled employees requires commitments to long-term human resources management. These long-term human resource management activities include designing a long-term compensation plan of its skilled labor (Manso, 2011), and tolerating early projects failure (Holmstrom & Tirole, 1989).

However, bankrupt firms are less likely to commit to these long-term human resources development activities because they are more focused on short-term survival goals. Previous literature suggests that bankrupt firms focus more on survival goals as they proximity to bankruptcy increases (Chen & Miller, 2007; Iyer & Miller, 2008; Staw, et. al, 1981). This shift of focus to survival goals make a firm less likely to search for new technologies (Chen & Miller, 2007) and to initiate mergers and acquisitions (Iyer & Miller, 2008), as it approaches bankruptcy. An organization has limited resources and these resources need to be allocated among various goals and investment decisions that compete for the scarce resources (March, 1991). For non-bankrupt firms, they could support their innovation activities without sacrificing the resource needs of other activities as they have relatively abundant resources, compared to bankrupt firms. However, bankrupt firms face more intense competition for resources between their innovative activities and their activities to support their daily functions, compared to non-bankrupt firms. The server resource competition in bankrupt firms will lead them to conduct less human capital investments, as these investments are long-term oriented. Consistent with this argument, previous research finds a reduction in employee wages in bankrupt firms (Berk, Stanton, & Zechner, 2010; Graham, Kim, Li, & Qiu, 2013). Apart from employee wages, bankrupt firms also suffer from loss of key human capital such as its CEOs. Gilson and Vetsuypens (1993) find that almost one-third of all CEOs are replaced by bankrupt firms and the remaining CEO experience about 35% reduction in their compensation. Considering the adversity caused by bankruptcy on human capital management and the firm's focus on short-term survivals, we predict that bankrupt firms are less motivated to conduct human capital management.

Innovation Ability

Mone et al. (1998) point out that the level of uncommitted resources will affect how a firm could respond to performance deterioration by innovation. They define uncommitted resources as those which "immediately available in the short run to fund organizational initiatives" (p.123). With adequate uncommitted resources, an organization could initiate experimentation (Singh, 1986), initiate acquisition (Wan & Yiu, 2009), introduce a new product (Barker & Duhaime, 1997), and make continuous investments in research and development (R&D) (O'Brien, 2003). Without enough uncommitted resources, managers are less likely to engage in innovation as an organization searches to deal with performance shortfalls (Greve, 2011; Wiseman & Bromiley, 1991).

Bankrupt firms are less likely to have sufficient uncommitted resources. Bankrupt firms often have inadequate financial resources such as cash, which is a common uncommitted resource. Even if they could generate some financial resources from retrenchment strategies such as liquidating other assets or cutting cost, the generated financial resources are more likely to pay debt instead of supporting the continuation of innovation. As a result, the effects of such retrenchment attempts are not guaranteed. With limited uncommitted resources, a bankrupt firm is less likely to commit itself to, retain existing skilled personnel and attract new ones. Graham, Kim, Li, and Qiu (2013) find that on average bankrupt firm lose nearly half of its employees leave the firm just within five years after a bankruptcy filing.

Considering bankrupt firms have less motivation and ability to conduct human capital development, we predict:

H1: Compared to non-bankrupt firms, bankrupt firms are likely to have fewer new employees after the bankruptcy filing.

H2: Compared to non-bankrupt firms, bankrupt firms are likely to have more employees leave after the bankruptcy filing.

H3: Compared to non-bankrupt firms, bankrupt firms are more likely to have fewer employees remain after the bankruptcy filing.

Change of Human Capital Stock

Apart from general entry and exit patterns, we would like to investigate the changes of human capital stock within the firm from the pre-bankruptcy period to the post-bankruptcy period. Previous literature highlights two types of skilled labor of a firm: novice and star employees. These two types of skilled labor differ in their degree of general practical knowledge. Star employees are the ones, who do not only have accumulated innovative knowledge in previous experience, but their innovation outputs also have wide applications (Strumsky & Fleming, 2007). Compared to star talents, novice scientists and engineers have less experience in innovative activities. As individual employees possess knowledge and experience from multiple domains, their impact on firm's tacit knowledge depends on the degree of their previous experience (Dimov & Shepherd, 2005).

As we discussed before, bankrupt firms have resource constraints and less motivation in retaining their skilled labor. What kind of skilled labor departs is affected by the nature of the human capital. With more past experience, a star employee has larger chances to develop their network and know different technological domains (Fleming, Mingo, & Chen, 2007). The wider network and richer experience in different domains enable the star employees to find more external job opportunities. At the same time, star scientists are attractive to external firms, as possessing key scientists could affect the firm's entry into correspondent technological areas (Zucker & Darby, 2007) and increase the firm's capability of inventing more valuable and radical technologies (Strumsky & Fleming, 2007). As a result, hiring star employees from another firm could positively affect a firm performance. For example, Parrotta and Pozzoli (2012) find that recruitment of skilled workers with industry-specific knowledge enhances the productivity of recipient firms. The high value of star employees makes such individuals more easily to leave an organization when their working condition deteriorates, compared to novice employees. Bernstein (2015) points out that the productive patent inventors are more likely to leave their employers than less productive ones. Palomeras and Melero (2010) also find that the higher an inventor's quality, the more likely he/she will move to another firm. Ganco et al. (2015) find that although patent enforcement deters human capital movement, the star inventors still leave a firm. Compared to non-bankrupt firms, star employees in bankrupt firms are even more likely to exit the focal firms, as the job opportunities in external markets are more attractive. As a result, we predict that bankrupt firms will have a sharper reduction in their star employees after the bankruptcy filing. On the other hand, as novice employees are less attractive to the labor market, we predict that bankrupt firms will retain more novice employees after bankruptcy.

H4a: Compared to non-bankrupt firms, bankrupt firms are more likely to retain novice employees after the bankruptcy filing.

H4b: Compared with non-bankrupt firms, bankrupt firms are less likely to retain star employees after the bankruptcy filing.

METHODS

Sample Construction

The sample constructed in this study is drawn from the UCLA-LoPucki Bankruptcy Research Database (BRD), the Compustat Database, the Patent Network Dataverse, and the U.S. Patent and Trademark Office (USPTO) Patent Database. The four datasets enable us to track the patent application and associated patent inventor turnover among bankrupt firms as well as non-bankrupt firms from 1976 to 2010. We use inventor data to proxy the skilled personal turnover, as it is a widely used proxy in previous research. As noticed in Bernstein (2015, P.23), "inventor method identifies the reallocation of the more creative inventors who patent frequently and presumably matter the most". Following previous literature, we use the first patent year as the year of entering in an organization (e.g. Zucker & Darby, 2006) and we consider an inventor exits a focal firm if that inventor has a subsequent patent in another firm (e.g. Aggarwal & Hsu, 2014). By tracking the inventor turnover, we are able to identify the skilled human capital retention and reallocation patterns within bankrupt and non-bankrupt firms.

We first identify the bankrupt and non-bankrupt firms with patent applications using the name-matching algorithm developed by Bessen (2009). We then identify the inventors associated with all utility patents in the above sample using Patent Network Dataverse. For each bankrupt firm, we use one-to-one PSM with replacement to match it with a non-bankrupt firm based on sales, total assets, total debt, current ratio, number of patent application, R&D intensity, profit ratio measured by ROA, and leverage. These covariates are widely used as matching covariates in previous studies (e.g. DeFond, Erkens, & Zhang, 2016; Szucs, 2014). All the variables are calculated at five-year pre-bankruptcy filing. Detailed information about the measures and summary statistics of these matching covariates can be found in *Table 2.1*. A non-bankrupt firm is considered a match to a bankrupt firm if they have the closest distance in those observed characteristics around the same period. We have 55,838 potential firm-year level controls with 294 firms in treatment groups; our potential controls are more than 190 times larger than the set of bankrupt firms. As a result, we conclude that our data is suitable for propensity score matching, which requires a large sample size (Szucs, 2014, Bettis et al., 2014). Our large treatment to potential control observation ratio suggests a sufficiently close match can be found for each treated firm. After PSM, we identify 266 unique bankrupt-healthy-firm pairs. In each pair, there is one bankrupt firm and one non-bankrupt firm. Our final sample includes a total of 270 bankrupt firms and 249 non-bankrupt firms. Among the 270 bankrupt firms, 158 of them belong to manufacturing sectors and 112 of them belong to non-manufacturing sectors. In the non-bankrupt firm group, we identify 172 firms belonging to manufacturing sectors and 77 firms belonging to non-manufacturing sectors.

Based on the PSM results, we build a pseudo window for the non-bankrupt firms to capture its inventor's mobility over the same periods with respect to that of the bankrupt firms in the same pair. Our specification is similar to other bankruptcy pre- and post- examinations such as Graham et al. (2013). Our estimation specification follows:

$$Inventor\ Movement_{f,j,t} = \sum_{k=-m}^{m} Bankruptcy_f \ * Post_{f,t}\delta_f + Control_{f,t}\beta + \mu_{f,j,t}$$

(1)

This specification captures the inventor movement of firm *f* at time *t* in the pair *j*. We are interested in the estimated δ_f. It captures the change in inventor mobility of bankrupt firms during each year between ten years pre-bankruptcy and ten years post-bankruptcy relative to the non-bankrupt firms in the control group.

$Inventor\ Movement_{f,j,t}$ represents five variables: *total_new*, *total_exit*, *total_retention*, *share_novice*, and *share_star*. *Total_new* is measured by the log transformation of one plus the number of inventor entries in the firm at year t. *Total_exit* is measured by the log transformation of one plus the number of inventor exits in the firm at year t. *Total_retention* is measured by the log transformation of one plus the number of existing inventors at the firm at year t. *Share_novice* is measured by the ratio of the number of existing novice inventors divided by the total number of existing inventors. *Share_star* is measured by the ratio of existing star inventors divided by the total number of inventor exits.

We consider the measure of novice and star inventors based on both quality and quantity of their invention. By considering both the quantitative and qualitative nature of human capital, we have the opportunity to better understand which aspects of human capital are associated with their retention patterns. Forward citations are widely used to evaluate the quality of inventors' outputs (e.g. Aggarwal, et al., 2014; Bernstein, 2015). We first calculate the total five-year forward citations of all patents of an inventor has before a focal year. In our inventor sample, 25% of inventors have less than one total forward citations, 50% of them have less than three total forward citations, and 75% of them have less than seven total forward citations. Based on that, we define an inventor as a novice if his/her previous patents' total forward citations are less than one. Similarly, star inventor equals one if he/she has more than seven total forward citations.

$Bankruptcy_f$ is a dummy variable that equals one if the firm files bankruptcy, and zero if it does not. $Post_{f,t}$ is a dummy variable equals to one if year t is after the firm emerges from bankruptcy and equals to zero if year t is before bankruptcy. We keep a relatively long period, which is nine years before bankruptcy and nine years after emergence, because we would like to investigate how the skilled employees' turnover patterns happen when a firm approaches bankruptcy and move away from bankruptcy. The control variables $Control_{f,t}$ include the two firm-level characteristics: first, we control for the R&D intensity of the firm, as a large portion of R&D expenditure is in form of wages for highly educated scientists and engineers and so it is likely to affect the inventor movements (Bernstein, 2015). Second, we control for patent stock using the log transformation of one plus number of patent applications applied for by the firm up to and including the firm-year (Aggarwal & Hsu, 2014). We also include the year, pair-firm, window, and industry fixed effects in the estimation. We do not include the dummy variable of bankruptcy individually in the specification because this variable is absorbed by the pair-firm fixed effect. In robustness check, we also test whether our results are sensitive to control variables selected. We add several additional financial performance variables, such as ROA and cash and marketable securities to liability ratio, and find that adding these control variables would not affect our results.

RESULTS

Summary statistics of our key variables are listed in Table 4.1. Table 4.2 illustrates the detailed information about the matching quality of our sample. As the results of PSM depend largely on whether the PSM identifies close enough control group and treatment group, following Manson (2016), we check the quality of our match using two-sided t-tests after the matching; this can be seen in Table 4.2.1. The results show that there are no significant differences at 95% confidence level for the means of each matching covariates used in the match. This suggests that our matching generates comparable control groups for the treatment groups. Following Szucs (2014), we also check whether the matched sample eliminates the biases between the treated and non-treated firms, as seen in Table 4.2.2. From the second column of

Table 4.2.2, we can see that the initial biases across all covariates between bankrupt and non-bankrupt firms are substantial. From the fourth column of Table 4.2.2, we can see that our approach largely reduces the biases with respect to the nine covariates employed in the estimation of the propensity score. Our standardized biases for all covariates after matching meet the 25% criterion suggested by Rubin (2001). In addition, most of our standardized biases after matching are reduced to below 10%. This leads us to conclude that our treatment and control group do not differ significantly with respect to the nine covariates employed in the estimation of the propensity score.

Table 4.3 reports our baseline estimation results. Columns (1) to (4) capture the four different inventor movement variables. Columns (1) and (2) reveal the effect of bankruptcy on the number of inventor entries and exits, while column (3) illustrates inventor retention patterns. From column (1) we can see that compared with non-bankrupt firms, a bankrupt firm is likely to be associated with a 30.7% reduction in the number of new inventors after bankruptcy compared with the pre-bankruptcy period. Our *H1* is supported. Surprisingly, in column (2) we find that bankrupt firms are associated with a 28.6% reduction in the number of inventor exits following bankruptcy in contrast to that of the pre-bankruptcy period, which is contradictory to our H2. The results suggest that bankrupt firms may be more capable of retaining inventors even when compared with healthy firms. We argue that this could be because even bankrupt firms have limited resources to retain their inventors; being associated with bankrupt firms limit the inventors' opportunities to seek other employment opportunities.

Column (3) illustrates the changes in the number of existing inventors. From column (3) we can see that bankrupt firms have a 23.1% reduction in the number of existing inventors after bankruptcy compared with non-bankrupt firms in the control group over the two periods. This supports our *H3*. Combining these findings together, our results suggest that despite the bankrupt firms have a smaller change in inventor exit compared with non-bankrupt firms, they are still experiencing a loss of total inventors as well as star inventors.

Insert Table 4.3 here

In order to compare the trend of employee turnover during bankruptcy, we also estimate the change of inventor's entry, exit, and retention by each window. Based on that estimation, we construct the change in the number of inventors in Figures 4.1.1 to 4.1.3. The three figures show that bankrupt firms and non-bankrupt firms in our control groups have a similar entry, exit, and retention patterns before one year prior to bankruptcy filing. After that, the two groups diverge in all four figures. Overall, non-bankrupt firms experience smoother inventor entry and exit patterns in the sample period, while bankrupt firms start to experience a declining inventor entry two years before bankruptcy and have sharper declining trends after the bankruptcy filing. Figure 4.1.2 shows that the number of inventor exits increases at two years after bankruptcy, but it starts to decline after four-year post-bankruptcy. In Figure 4.1.3, we can see the changes in the existing total inventors existing star inventors. Figure 4.1.3 further confirm our H3.

Insert Figures 4.1.1 to 4.1.3 here

To test our predictions about the inventor retention pattern, we break down the inventors into two categories and examine the change of relative inventor rates before and after bankruptcy. Our results in Table 4.4 suggest that compared with before bankruptcy period, we observe a 0.129 deduction in the rate of star inventors to total existing inventors, while we observe a 0.108 increase in the rate of novice inventors to total inventors. Combining these findings together, our results suggest that bankrupt firms are likely to hold less experienced inventors than the more experienced ones.

Insert Table 4.4 here

Figures 4.2.1 to 4.2.2 visually present the estimated rate of existing star and novice inventor to total inventor changes among bankrupt and non-bankrupt firms from nine years prior to bankruptcy filing to nine years after the bankruptcy filing. The two figures show that bankrupt firms and non-bankrupt firms in our control groups have very similar star inventor rate before two years prior bankruptcy filing. Figure 4.1.1 shows that while non-bankrupt firms have smoother adjust in their rate of novice inventors, bankrupt firms have a surge in their novice inventors from two years prior to bankruptcy and an overall increasing pattern after that. As we can see from Figure 4.2.2, while non-bankrupt firms have an overall increase pattern in star inventor rate, bankrupt firms have a steep decline in the rate of star inventors. This suggests that bankrupt firms turn to retain more novice inventors compared with star inventors after bankruptcy, and this increasing trend lasts for a prolonged period. Together, Figures 4.2.1 and 4.2.2 further confirm our *H4a* and *H4b*.

Insert Figures 4.2.1 and 4.2.2 here

We also consider estimating whether a star inventor is more likely to leave a firm after bankruptcy or not using inventor-level analysis. In our inventor-level data, we identify 2,026 inventors that enter the bankrupt firms from bankruptcy filing to five years post-bankruptcy, and identify 1,789 inventors that exist in the firm before bankruptcy but leave the firms after bankruptcy. In our inventor sample, inventors that left the firms make about 27.79% of the total inventors. Our sample is comparable to Hoisl (2007) in that they report 33% inventors who change their employers at least once. Table 4.5 illustrates our inventor-level results. Similar to Berstern (2015) we identify three types of inventors. Newcomers are the ones that have their first patents in the focal firms only after bankruptcy. Stayers are the ones that have patents in the firm before bankruptcy and patent again in the same firm in year [0, 5]. Leavers are the inventors that have patents in the firms before bankruptcy and patents in another firm in year [0, 5]. *Productivity* is the log transformation of the five-year forward citations of all patents of an inventor have before a focal year. From Table 4.5.2, we find that an inventor with more patent forward citations are more likely to leave the firms. Also, our inventor level results confirm that inventors associated with a bankrupt firms are more likely to leave the firm. Furthermore, we find that bankrupt firms are less likely to attract new inventors.

Insert Tables 4.5 here

Robustness Check

In our first robustness check, we first check whether our results are sensitive to our assumption of inventor exit year. As the inventor data cannot identify the exact date when an inventor leaves a firm nor the date an inventor begins working in the firm, using the inventor data to examine inventor mobility relies on some assumptions of mobility. The first patent application year is widely used as the year when an inventor joins a firm (e.g. Aggarwal & Hsu, 2014). However, the year an inventor exits an organization may differ based on two assumptions. In the measure of the year of exit in our baseline estimation, we assume that an inventor leaves the firm at the year when he/she applies for the last patent in the focal firm. This assumption may lead us to calculate the exit before the real exit year. On the other hand, some other studies assume the exit date is the date of an inventor's first patent in another firm (e.g. Aggarwal & Hsu, 2014; Bernstein, 2015; Hoisl, 2007). This assumption may cause the identified exit date to lag behind the real exit date. Considering the exact exit data are likely to be between the last patent application year in the focal firm and the first patent application year in another firm, we check whether our results are still held under the second assumption. As a result, we replicate the two baseline regressions regarding exit patterns and illustrate the results in Appendix C.1. The results suggest that our findings are not sensitive to the year of exit assumptions.

Insert Appendix C.1 here

In our baseline estimation, we use a one-to-one matching approach with replacement. Considering that PSM may be sensitive to design choices, we check several alternative PSM specifications: different caliper width and different matching replacement choices. These specifications reflect trade-offs between bias and variance. First, following Austin (2007), we set the closeness of the match, which is captured by the caliper width, to the 2% of the standard deviation of the predicted value of the propensity score. Second, instead of matching with replacement, we use matching without replacement in the robustness check. Our results from the two alternative designs are reported in Appendix C.2. The results are consistent with our baseline results. We also check whether our results are sensitive to the treatment to control ratio as well as different covariate choices.

Insert Appendix C.2 here

Also, we check whether our results are sensitive to the sampling methods. PSM can give us unbiased estimators of the treatment effect; there is a debate on whether the analysis needs to account for the matching (Austin, 2007). However, PSM doesn't guarantee that individual pairs will be well-matched on the full set of covariates. On average, the groups will be comparable, but any two matched individuals may not be (Schafer & Kang, 2008; Stuart, 2008). Thus, they suggest it is more common to estimate by pooled OLS instead of using the individual matched pair. As a result, we also display the Pooled OLS results in Appendix C.3. The results are comparable to our baseline results.

Insert Appendix C.3 here

In the baseline matching attempts, we match the bankrupt and non-bankrupt firms based on their attributes at the five-year pre-bankruptcy filing. However, these attributes could change dramatically as the firm approaches bankruptcy. For example, Hambrick and D'Aveni (1988) point out that assets depletion occurred "along the road to ruin". To ensure the robustness of the results, we also check whether our results are sensitive to the window we use to identify the bankrupt and non-bankrupt pairs. We reexamine different matching periods (ten years before bankruptcy). The results suggest that our results are robust to different selections of matching covariates snapshots and these results are available upon request.

Insert Appendix C.2.3 here

DISCUSSION

In this paper, we investigate the skilled labor turnover patterns among U.S. large bankrupt and non-bankrupt firms. We find that bankrupt firms are likely to have fewer inventors enter as well as retain after bankruptcy, compared to non-bankrupt firms. In terms of specific inventor retention patterns, we find that bankrupt firms are likely to retain more novice inventors than the star inventors. These findings imply that bankrupt firms may lack the capability to attract new skilled labor and retain star skilled labor. Together, our findings suggest that bankruptcy does not only affect the number of entering and exiting skilled labor, it also shifts the relative amount of talents within the firm. The findings shed light on bankruptcy research as well as human capital management research.

Learning about Failure

Comparing the employee turnover pattern between bankrupt and non-bankrupt firms enables us to add to the discussion of learning from failure. Previous literature offers a rich discussion of lessons from corporate failure. Adding to the major reason—the inability to solve financial distress—management literature has examined how lack of key human capital such as managerial knowledge and financial management ability could lead to corporate bankruptcy (Thornhill &and Amit, 2003). Adding to them, our study has implications for the effect of a firm's skilled personnel turnover on its innovative capability, and the subsequent bankruptcy. This study also speaks to the literature on how knowledge matters for organizational failure. As knowledge is one key source of the competitive advantage, lack of sufficient knowledge inflows and retention could lead to the eventual deaths of organizations. Apart from the stock of knowledge, some research finds lack of complementary assets to support exploiting knowledge stock matters for organizations' deaths (Golder & Tellis, 1993; Katz & Shapiro, 1985). Extending the previous research, our findings offer a third explanation of how knowledge links to the deaths of organizations. Our findings suggest that although the bankrupt firms are not short of human capital prior to bankruptcy, compared to the non-bankrupt firms, as they get closer to bankruptcy, they lose their important human capital. Furthermore, as more novice inventors instead of the star inventors stay in the bankrupt firm, the novice inventors still need time to adapt to existing organizational code; this slows the knowledge development speed at bankrupt firms. With fewer star inventors remained in the firm, the bankrupt firms may be less likely to develop new organizational knowledge. The results suggest that although bankrupt firms have fewer inventors exit compared with non-bankrupt firms, they may still be at a disadvantage in knowledge generation and development as they retain fewer star inventors and more novice inventors after bankruptcy compared with non-bankrupt firms. The findings suggest that the inability to maintain key human capital could lead to bankruptcy, and the human capital keeps deteriorating along the bankruptcy time spans.

Apart from the human capital management problem, the findings in this study also add to the early signals of corporate failure that managers of a firm should watch out. Hotchkiss (1997) finds that a bankrupt firm has a lower financial performance, compared to industry peers even four-years before bankruptcy, and this gap becomes even larger as the firm approaches the bankruptcy filing. Graham et al. (2013) find that the employee wage of bankrupt firms starts to decrease one-year before the bankruptcy filing. Although managers may wish to postpone the decline and eventual demise of their organization (Amihud & Lev, 1981), these researchers find that there are some early signals of corporate failure. Consistent with them, the results of this study suggest that the deteriorating in human resources happens even before the bankruptcy filing. The results in Figure 4.1.1 shows that the number of inventors' entry among bankrupt firms starts to decline even before the bankruptcy. In addition, Figure 4.2.2 shows that bankrupt firms start to experience a sharp drop in their rate of star inventors two years before bankruptcy. The findings suggest that the loss of important human capital could be an early signal of bankruptcy that an organization should watch out.

Skilled Employees Turnover

This paper speaks to the research on the antecedences of the skilled employee turnover. Bernstein (2015) finds that IPO reduces the inventor entry and increases the inventor exit. Ma et al. (2017) find that firms sell patents will retain more inventors. Some other factors such as firm's litigiousness (Agarwal et al., 2009), firm size (Breitzman, Hicks, & Albert, 2004; Hoisl, 2007), and inventor quality (Granco et al., 2015; Hoisl, 2007; Palomeras & Melero, 2010) are also found to affect inventor mobility. Extending this stream of research, we find that bankrupt firms are less likely to have inventor entry and inventor exit after bankruptcy.

Despite the general declining trend of skilled human capital in bankrupt firms. Some research suggests that there are situations that bankrupt firms can hold inventors instead of losing them (Ma, Tong, & Wang, 2017). Comparing findings in this essay to theirs bring interesting future research opportunities. While we examine the general skilled employee turnover patterns, they examine bankrupt firms with retrenchment strategies. While we find that in general, bankrupt firms suffer from skilled human capital loss, their findings suggest that bankrupt firms with technological assets retrenchment strategies actually hold more skilled human capital than those who do not. Combining the two findings, there are promising topics to investigate: such as how specific resource management strategies affect the skilled human capital turnover among bankrupt firms and how the impacts of these strategies differ between bankrupt and non-bankrupt firms.

We acknowledge that there could be limitations with our matching approach as PSM is only based on several observed characteristics of the firm. Unobserved characteristics such as firm's risk tolerance could affect whether a firm goes bankrupt or not as well as employee movement. Although we control for several observable characteristics in the estimation, the model is not completely free of endogeneity problem. Therefore, we interpret the results as descriptive more than causal. We find that, on average, a bankrupt firm has a 30.7% reduction in inventors enter after the bankruptcy and a 28.6% reduction in inventors exit than their counterparts in the subsequent years after the bankruptcy filing.

IMPLICATION

Our results suggest that bankrupt firms face unique problems regarding their human capital management. Previous research suggests that designing proper ex-ante contract could mitigate the loss of human capital by reducing the knowledge spillover to a firm's competitors. Combining findings in this study with research on human capital management, we suggest that studying these ex-ante contracts and their effects on human capital retention could be especially important for bankrupt firms, which suffer from a loss of skilled human capital as well as have problems in retaining star inventors.

Although this study does not directly test the effects of inventors' turnover on bankrupt firms' economic and innovation performance, combining results in this essay with previous research brings up four future research avenues. First, results in this essay suggest that there are fewer inventors entering the bankrupt firms compared with non-bankrupt firms. This reduction in inventors' entry could be due to the cost retrenchment action of bankrupt firms as a firm usually uses retrenchment strategies in face of severe decline (Barker & Mone, 1994). However, cost-retrenchment strategies could bring severer problems to the firm. Barker and Mone (1994) suggest that retrenchment is more likely to lead to steeper performance decline because it creates greater internal resources scarcity and pressure to reduce assets and costs. Lim et al. (2013) connect firms' retrenchment actions to rent generation mechanism. They find that cost retrenchment may have detrimental effects on firms with a relatively high Schumpeterian rent focus, which requires exploitation of firms' current resource bases. Future research could examine whether the skilled labor turnover is a retrenchment strategy or other strategies and how the skilled labor turnover affects economic performance among bankrupt firms.

Furthermore, previous studies suggest that inventor turnover could be beneficial to organizational turnaround as it brings new interactions among the individuals in an organization (e.g. Boyne & Meier, 2009). March (1991) elaborates how personnel turnover affects individual and organizational knowledge development. As a source of new knowledge, employees' entry provides possible knowledge inflow to the firm and expands knowledge utilization opportunities for the firm. With the mobility of inventor, a firm's existing innovation-related knowledge base could be renewed via new interactions among inventors (Hoisl, 2007; Song, Almeida, & Wu, 2003). Although our results suggest a general reduction in human capital stock in bankrupt firms, the new interaction of employees could bring changes in knowledge stock of a firm, which could improve innovation outcomes among bankrupt firms. Considering the possible new knowledge generation, future research could examine how employee turnover affects the innovation outcomes in bankrupt firms.

In addition, future research could examine how other human capital characteristics in affect human resource turnover in bankrupt firms. This paper focuses on the general skilled human capital. General human capital refers to the overall education and practical experience (Becker, 1975; Dimov & Shepherd, 2005). Apart from general human capital, there are opportunities to investigate the specific human capital, which refers to the experience related to a particular activity or context, as inventors may possess knowledge in different specific domains. For example, Gruber, Harhoff, and Hoisl (2013) examine the inventors with engineering degrees and scientific degrees. They find that inventors with scientific education are more likely to generate patents that have wider technological areas span. Their findings suggest that the difference in individual-level characteristics of inventors will affect the subsequent innovation performance. A firm's decision to attract, retain or dismiss skilled labor could be driven out of the consideration of expanding or contracting their business activities. As bankrupt firms may differ in those decisions compared with non-bankrupt firms, we plan to investigate these links in future research. Apart from the general and specific nature of human capital, other natures, such as human capital specificity to an organization, are worthy of investigation. Past literature suggests that asset specificity to sector increases the cost for firms redeploying their capital (Kim & Kung, 2016; Ramey & Shapiro, 2001). Kim and Kung (2016) point out that assets in industries such as manufacturing, oil rigs, and aircraft are more specific to these industries while assets in the service industry are less (Kim & Kung, 2016). Some human capital could be specific to one industry while other human capital could have more general uses. For example, employees who have expertise in general sciences could more likely find a career in another firm, while employees with firm-specific knowledge are more likely to stay in the bankrupt firms. The difference in human capital specificity could affect the employee turnover patterns. Combining these findings, this paper call for a future investigation into how different human capital natures, such as specificity, affect the human resource turnover patterns in bankrupt firms.

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FIGURES AND TABLES FOR CHAPTER FOUR

Table 4.1 Summary Statistics

	count	mean	std. dev.	min	max	Measures
total_new	5340	0.705	1.115	0	4.111	Natural logarithm of one plus the number of new inventors at year t
total_exit	5340	0.721	1.122	0	4.078	Natural logarithm of one plus the number of exiting inventors at year t
total_exist	5340	0.715	1.223	0	4.771	Natural logarithm of one plus the number of existing inventors at year t
share_star	1828	0.684	0.322	0	1	The rate of star inventor divided by the total inventors of a firm at year t
share_novice	1828	0.096	0.181	0	1	The rate of novice inventor divided by the total inventors of a firm at year t
patent application	5340	0.197	0.588	0	2.890	Natural logarithm of one plus the number of patents applied at year t
bankruptcy	5340	0.459	0.498	0	1	Equals to 1 if the firm is a bankrupt firm or 0 if it is not
rd_intensity	5340	0.030	0.062	0	0.376	R&D expenditure divided by total assets at year t

	total_new	total_exit	total_exist	share_star	share_novice	patent application	bankruptcy	rd_intensity
total_new	1							
total_exit	0.946***	1						
total exist	0.794***	0.748***	1					
share_star	-0.028	-0.048*	-0.057*	1				
share_novice	0.064**	0.071**	0.091***	-0.497***	1			
patent application	0.366***	0.372***	0.308***	0.055*	0.011	1		
bankruptcy	0.037**	0.043**	0.021	-0.124***	0.108***	0.065***	1	
rd_intensity	0.113***	0.111***	0.109***	0.148***	-0.106***	-0.012	-0.154***	1

Notes: all the outliers have been winsorized to 2% and 98%.

The high correlation between total_new and total_exit is due to the large many of inventors who only patent once. In order to test whether our results are sensitive to that sampling method, we restrict our sample to the inventors who apply for more than one patents in the robustness check. The results are consistent.

Table 4.2 Matching Quality

Table 4.2.1 Matching Covariates Mean

Matching variables	Details	Bankrupt firms (before the match)		Non-bankrupt firms (before the match)		Bankrupt firms (after the match)		Non-bankrupt firms (after the match)	
		Mean	STD	Mean	STD	Mean	STD	Mean	STD
assets	Natural logarithm of total assets (DeFond, Erkens, and Zhang, 2016)	6.53	1.67	5.44	2.62	6.50	1.56	6.53	2.32
sales	Natural logarithm of total sales (DeFond, Erkens, and Zhang, 2016)	6.34	1.89	5.31	2.71	6.32	1.90	6.35	2.35
debt	Natural logarithm of total debt (Szucs, 2014)	2.74	2.06	2.14	2.35	2.65	1.91	2.80	2.23
current ratio	Current assets scaled by current liabilities (DeFond, Erkens, and Zhang, 2016)	2.05	1.71	3.01	2.74	2.06	1.73	2.08	1.30
patents application	Natural logarithm of one plus number of patents applied	0.15	0.35	0.03	0.17	0.16	0.36	0.19	0.40
rd_intensity	R&D expenditure scaled by total sales (Szucs, 2014)	0.12	0.70	0.28	0.92	0.13	0.73	0.15	0.71
roa	Net income scaled by total assets (DeFond, Erkens, and Zhang, 2016)	-0.04	0.23	-0.07	0.33	-0.05	0.24	-0.04	0.29
leverage	Long-term debt scaled by total assets (DeFond, Erkens, and Zhang, 2016)	0.31	0.21	0.16	0.17	0.31	0.21	0.31	0.21

Notes: The table reports mean value of the treatment and control observable characteristics used in the matching procedure. Two-side t-tests on the difference between mean values between the treatment and control group indicate no significant differences at the 95% confidence level for each variable after the match.

Table 4.2.2 Standardized Biases of Covariates Before and After Matching

Matching variables	Initial bias (%)	Bias (%) after matching	Bias reduction (%)
assets	51.7	5	90.4
sales	46.6	4	91.5
debt	26.4	-0.2	99.4
current ratio	-39.8	6	85
patents application	46.9	7.6	83.7
rd_intensity	-18.1	0	100
ROA	4.2	14.8	253.1
leverage	82.5	-4.6	94.5

Table 4.3 Baseline Results: Pre- and Post-Bankruptcy Comparison

	(1)	(2)	(3)
	total_new	total_exit	total_exist
post	0.077	0.002	0.044
	(0.066)	(0.064)	(0.084)
bankruptcy*post	-0.307	-0.286	-0.231
	(0.104)***	(0.103)***	(0.124)*
patent application	0.791	0.794	0.491
	(0.049)***	(0.049)***	(0.049)***
rd_intensity	0.180	-0.058	0.100
	(0.396)	(0.398)	(0.471)
constant	0.593	0.277	0.370
	(0.189)***	(0.158)*	(0.201)*
R^2	0.21	0.21	0.21
N	5,340	5,340	5,340

Notes: 1) Year, pair-firm, and industry fixed effects are included in all specification.

2) Standard errors are clustered within each bankrupt and healthy firm pair.

3) Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

Figures 4 Changes in Entry and Exit Patterns of Bankrupt and Non-Bankrupt Firms

Figure 4.1 Changes in log(1+Number of New Inventors)

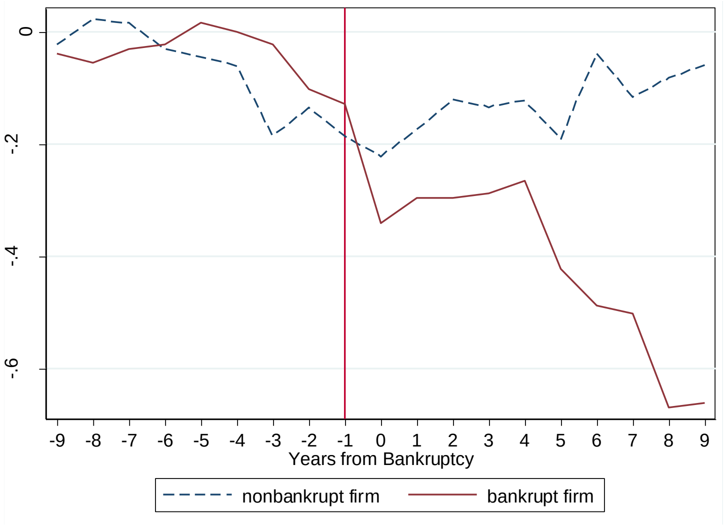


Figure 4.2 Changes in log(1+Number of Exiting Inventors)

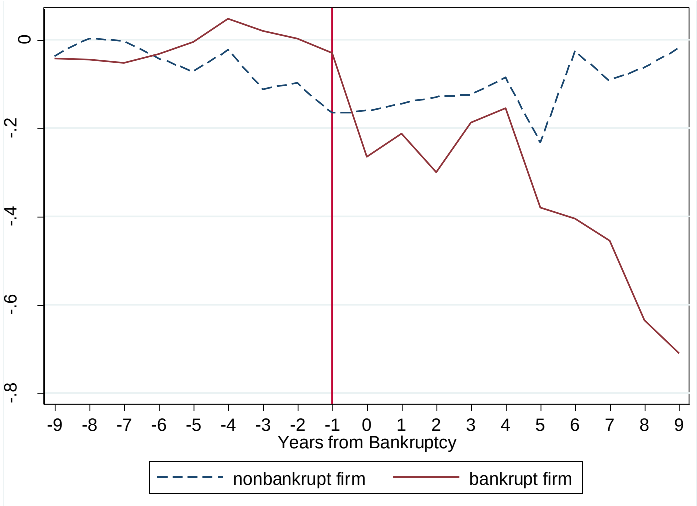
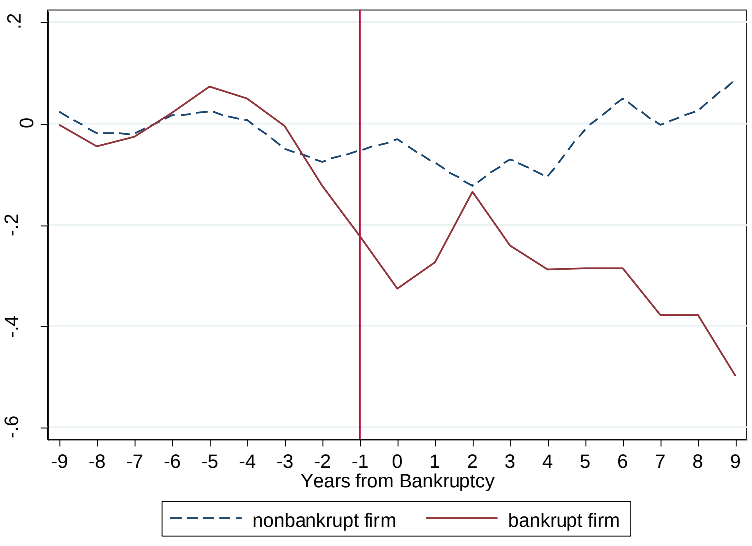


Figure 4.3 Changes in log(1+Existing Inventors)



Notes: In the figures, 0 is the year of the bankruptcy filing.

Table 4.4 Novice and Star Inventors Retention Pattern

	(1)	(2)
	share_star	share_novice
post	0.055	-0.013
	(0.042)	(0.022)
bankruptcy*post	-0.129	0.108
	(0.065)**	(0.034)***
patent application	-0.005	-0.011
	(0.022)	(0.015)
rd_intensity	-0.016	0.064
	(0.197)	(0.112)
constant	0.622	0.129
	(0.098)***	(0.035)***
R^2	0.07	0.04
N	1,828	1,828

Notes: 1) Year, pair-firm, and industry fixed effects are included in all specification.
2) Standard errors are clustered within each bankrupt and healthy firm pair.
3) Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

Figures 4.2 Changes in Rate of Novice/Star inventors of Bankrupt and Non-Bankrupt Firms

Figure 4.2.1 Predicted Changes in Existing Novice Inventors/Total Existing Inventors

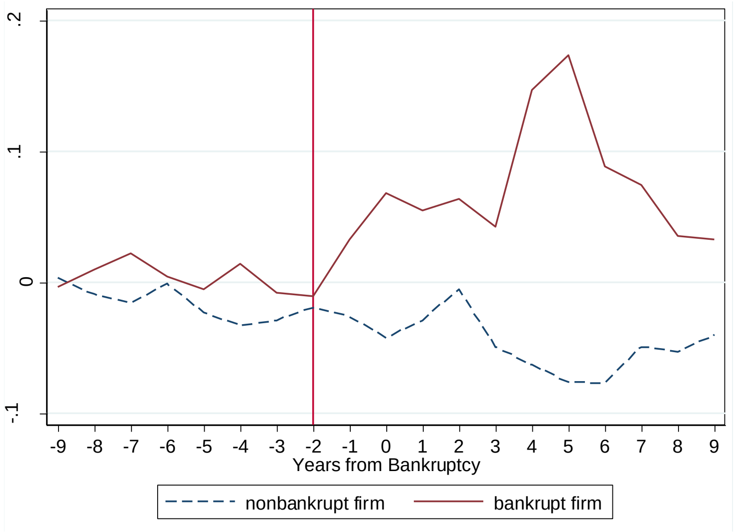


Figure 4.2.2 Predicted Changes in Existing Star Inventors/Total Existing Inventors

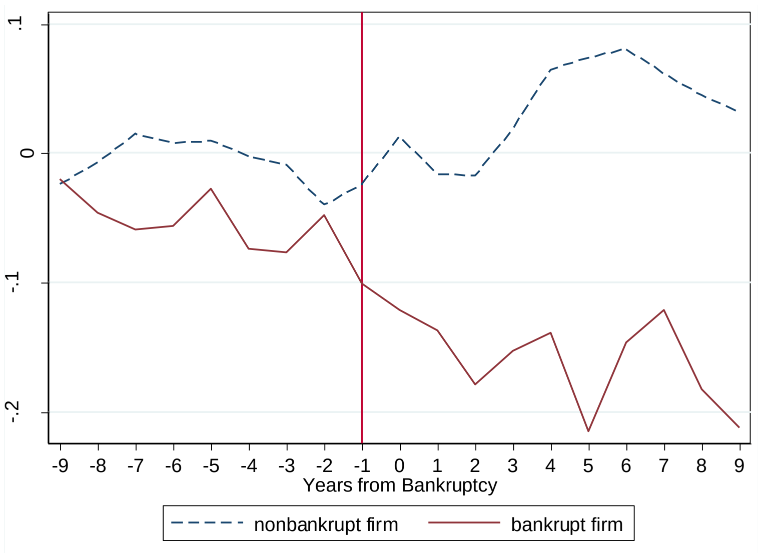


Table 4.5.1 Inventor Summary Statistics

	Bankrupt firms					Non-bankrupt firms				
	stayer		leaver			stayer		leaver		
	obs	mean	obs	mean	t statistics	obs	mean	obs	mean	t statistics
Productivity	1,276	1.879	1,789	1.729	4.189	5,991	2.035	3,515	2.088	-2.212**
	newcomer		incumbent			newcomer		incumbent		
	obs	mean	obs	mean	t statistics	obs	mean	obs	mean	t statistics
Productivity	2.026	1.750	10,772	1.887	5.390	7,040	2.105	12,000	2.053	-3.064**

The table provides the summary statistics of the identified inventors who have patent application in the focal firm before bankruptcy or before the same pseudo-bankruptcy filing year in the matched non-bankrupt sample. Stayers are the ones that patents in the firm before bankruptcy and patents again in (0, 5). Leavers are the inventors that patents in the firms before bankruptcy and patents in another from within (0, 5). Newcomer is the one who joins the firm after bankruptcy, and incumbent is the one who joins the firm before bankruptcy. Productivity is the log transferred total forward five-year citations of all patents of an inventor before a focal year.

Table 4.5.2 Inventor Level Analysis

	Model OLS			Model Logit		
	leaver	stayer	newcomer	leaver	stayer	newcomer
Productivity	0.013	-0.013	-0.020	0.081	-0.081	-0.115
	(0.004)***	(0.004)***	(0.002)***	(0.022)***	(0.022)***	(0.014)***
bankruptcy	-0.030	0.030	-0.165	-0.271	0.271	-1.196
	(0.014)**	(0.014)**	(0.006)***	(0.082)***	(0.082)***	(0.050)***
patent application	0.013	-0.013	-0.072	1.179	-1.179	-0.500
	(0.007)***	(0.007)***	(0.002)***	(0.064)***	(0.064)***	(0.021)***
rd_intensity	-0.289	0.289	0.975	-0.442	0.442	4.957
	(0.122)**	(0.122)**	(0.065)***	(0.730)	(0.730)	(0.392)***
constant	1.253	-0.253	0.070	17.107	-17.107	-21.553
	(0.118)***	(0.118)**	(0.101)	(1.200)***	(1.321)***	(704.903)
R^2	0.31	0.31	0.28	0.27	0.27	0.27
N	12,571	12,571	31,838	12,505	12,505	30,421

We include 2-digit sic industry fixed effect and bankruptcy filing year fixed effect. Robust standard errors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

Appendix C.1 Pre- and Post-Bankruptcy Comparison: Using the First Year of Patent in another firm as the Exit Year

	(1)	(2)	(3)	(4)	(5)
	total_new	total_exit	total_exist	share_star	share_novice
post	0.026	-0.125	0.239	0.161	-0.008
	(0.109)	(0.101)	(0.141)*	(0.089)*	(0.060)
bankruptcy*post	-0.303	-0.170	-0.383	-0.245	0.120
	(0.149)**	(0.133)	(0.192)**	(0.098)**	(0.072)*
patent application	0.808	0.683	0.513	-0.026	0.006
	(0.064)***	(0.062)***	(0.064)***	(0.019)	(0.012)
rd_intensity	-0.001	0.535	-0.150	0.158	0.000
	(0.522)	(0.396)	(0.626)	(0.319)	(0.130)
constant	0.595	0.019	0.382	0.500	0.162
	(0.279)**	(0.212)	(0.301)	(0.090)***	(0.048)***
R^2	0.24	0.24	0.20	0.08	0.05
N	3,164	3,164	3,164	1,107	1,107

Notes: 1) Year, pair-firm, industry and window fixed effects are included in all specification.

2) Standard errors are clustered within each bankrupt and healthy firm pair.

3) Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

Appendix C.2.1 Results on PSM without Replacement

	(1)	(2)	(3)	(4)	(5)
	total_new	total_exit	total_exist	share_star	share_novice
post	0.034	-0.041	0.236	0.162	-0.009
	(0.107)	(0.101)	(0.139)*	(0.088)*	(0.059)
bankruptcy*post	-0.303	-0.272	-0.382	-0.254	0.123
	(0.148)**	(0.137)**	(0.191)**	(0.098)**	(0.071)*
patent application	0.808	0.815	0.508	-0.026	0.007
	(0.064)***	(0.060)***	(0.064)***	(0.019)	(0.012)
rd_intensity	0.003	0.483	-0.158	0.166	0.000
	(0.524)	(0.491)	(0.628)	(0.318)	(0.130)
constant	0.600	0.186	0.381	0.497	0.159
	(0.279)**	(0.222)	(0.301)	(0.090)***	(0.047)***
R^2	0.24	0.25	0.19	0.08	0.05
N	3,207	3,207	3,207	1,131	1,131

Notes: 1) Year, pair-firm, industry and window fixed effects are included in all specification. 2) Standard errors are clustered within each bankrupt and healthy firm pair. 3) Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively

Appendix C.2.2 Results on Caliper Match with 0.2 Caliper Width

	(1)	(2)	(3)	(4)	(5)
	total_new	total_exit	total_exist	share_star	share_novice
post	0.026	-0.048	0.239	0.161	-0.008
	(0.109)	(0.103)	(0.141)*	(0.089)*	(0.060)
bankruptcy*post	-0.303	-0.274	-0.383	-0.245	0.120
	(0.149)**	(0.138)**	(0.192)**	(0.098)**	(0.072)*
patent application	0.808	0.815	0.513	-0.026	0.006
	(0.064)***	(0.061)***	(0.064)***	(0.019)	(0.012)
rd_intensity	-0.001	0.486	-0.150	0.158	0.000
	(0.522)	(0.489)	(0.626)	(0.319)	(0.130)
constant	0.595	0.186	0.382	0.500	0.162
	(0.279)**	(0.222)	(0.301)	(0.090)***	(0.048)***
R^2	0.24	0.25	0.20	0.08	0.05
N	3,164	3,164	3,164	1,107	1,107

Notes: 1) Year, pair-firm, industry and window fixed effects are included in all specification. 2) Standard errors are clustered within each bankrupt and healthy firm pair. 3) Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

Appendix C.2.3 Results on PSM Based on Covariates at Ten Years Before Bankruptcy

	(1)	(2)	(3)	(4)	(5)
	total_new	total_exit	total_exist	share_star	share_novice
post	0.332	0.210	0.475	0.141	0.004
	(0.155)**	(0.173)	(0.240)**	(0.073)*	(0.039)
bankruptcy*post	-0.658	-0.572	-0.740	-0.062	0.066
	(0.184)***	(0.204)***	(0.291)**	(0.072)	(0.051)
patent application	0.741	0.763	0.451	-0.010	-0.002
	(0.077)***	(0.074)***	(0.073)***	(0.015)	(0.014)
rd_intensity	0.435	1.222	0.896	-0.220	-0.254
	(0.970)	(0.952)	(1.067)	(0.447)	(0.403)
constant	0.687	0.372	0.663	0.308	-0.154
	(0.293)**	(0.247)	(0.331)**	(0.126)**	(0.072)**
R^2	0.24	0.24	0.19	0.08	0.06
N	2,067	2,067	2,067	734	734

Notes: 1) Year, pair-firm, industry and window fixed effects are included in all specification. 2) Standard errors are clustered within each bankrupt and healthy firm pair. 3) Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

Appendix C.2.4 Results on Matching with Three Nearest Neighbors

	(1)	(2)	(3)	(4)	(5)
	total_new	total_exit	total_exist	share_star	share_novice
post	0.044	-0.008	0.173	0.208	-0.070
	(0.133)	(0.132)	(0.152)	(0.080)**	(0.054)
bankruptcy*post	-0.272	-0.211	-0.380	-0.274	0.121
	(0.156)*	(0.158)	(0.170)**	(0.092)***	(0.056)**
patent application	0.774	0.768	0.540	-0.019	-0.001
	(0.069)***	(0.069)***	(0.057)***	(0.016)	(0.013)
rd_intensity	0.527	0.829	0.985	-0.121	0.154
	(0.439)	(0.443)*	(0.507)*	(0.261)	(0.157)
constant	0.559	0.387	0.425	0.551	0.117
	(0.066)***	(0.054)***	(0.061)***	(0.041)***	(0.021)***
R^2	0.23	0.24	0.19	0.10	0.04
N	6,207	6,207	6,207	2,109	2,109

Notes: 1) Year, pair-firm, industry and window fixed effects are included in all specification. 2) Standard errors are clustered within each bankrupt and healthy firm pair. 3) Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

Appendix C.3 Pre- and Post-Bankruptcy Comparison: Pooled OLS

	(1)	(2)	(3)	(4)	(5)
	total_new	total_exit	total_exist	share_star	share_novice
post	0.062	0.018	0.064	0.049	-0.011
	(0.060)	(0.057)	(0.079)	(0.044)	(0.022)
bankruptcy*post	-0.311	-0.288	-0.237	-0.127	0.107
	(0.109)***	(0.108)***	(0.130)*	(0.070)*	(0.037)***
patent application	0.790	0.795	0.494	-0.006	-0.011
	(0.051)***	(0.051)***	(0.051)***	(0.024)	(0.016)
rd_intensity	0.162	-0.085	0.057	-0.011	0.062
	(0.414)	(0.417)	(0.497)	(0.214)	(0.122)
constant	0.565	0.298	0.384	0.618	0.131
	(0.186)***	(0.151)*	(0.198)*	(0.106)***	(0.038)***
R^2	0.68	0.69	0.74	0.74	0.65
N	5,340	5,340	5,340	1,828	1,828

Notes: 1) Year, firm, industry and window fixed effects are included in all specification.

2) Standard errors are clustered within the firm.

3) Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

Appendix C.4 Inventor Level Regression: Alternative Models

	Tobit model			Negative binomial model		
	total_new	total_exit	total_exist	total_new	total_exit	total_exist
post	0.201	0.070	0.318	0.404	0.435	0.154
	(0.012)***	(0.012)***	(0.015)***	(0.078)***	(0.077)***	(0.077)**
bankruptcy*post	-0.795	-0.774	-0.781	-0.655	-0.437	-0.618
	(0.018)***	(0.017)***	(0.023)***	(0.107)***	(0.105)***	(0.103)***
patent application	1.497	1.495	0.791	1.062	1.000	0.699
	(0.002)***	(0.002)***	(0.002)***	(0.037)***	(0.036)***	(0.037)***
rd_intensity	1.023	0.237	0.380	1.850	1.331	0.458
	(0.020)***	(0.019)***	(0.012)***	(0.464)***	(0.476)***	(0.490)
constant	0.376	0.038	5.530	-0.348	-0.736	-0.483
	(0.003)***	(0.002)***	(0.003)***	(0.238)	(0.260)***	(0.317)
Pseudo R^2	0.349	0.349	0.492	.	.	.
N	5,340	5,340	5,340	4,844	4,862	3,329

Notes: 1) Year, pair-firm, and industry fixed effects are included in all specification.
2) Standard errors are clustered within each bankrupt and healthy firm pair.
3) Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

Appendix C.5 Results with Whether the Firms Applied for Patents as a Control

	(1)	(2)	(3)	(4)	(5)
	total_new	total_exit	total_exist	share_star	share_novice
post	0.077	0.002	0.042	0.054	-0.013
	(0.066)	(0.064)	(0.084)	(0.042)	(0.021)
bankruptcy*post	-0.307	-0.285	-0.234	-0.129	0.108
	(0.104)***	(0.103)***	(0.123)*	(0.065)**	(0.034)***
patent application	0.775	0.770	0.705	-0.007	-0.011
	(0.076)***	(0.076)***	(0.071)***	(0.036)	(0.023)
rd_intensity	0.177	-0.062	0.130	-0.016	0.064
	(0.396)	(0.398)	(0.468)	(0.196)	(0.112)
dummy_patent	0.030	0.045	-0.411	0.003	-0.001
	(0.091)	(0.094)	(0.093)***	(0.046)	(0.029)
constant	0.593	0.277	0.363	0.622	0.129
	(0.189)***	(0.158)*	(0.199)*	(0.098)***	(0.035)***
R^2	0.21	0.21	0.21	0.07	0.04
N	5,340	5,340	5,340	1,828	1,828

Notes: 1) dummy_patent is a dummy variable that controls for whether the firm applies for patents in year t.
2) Year, pair-firm, industry and window fixed effects are included in all specification.
3) Standard errors are clustered within each bankrupt and healthy firm pair.
4) Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and *** respectively.

VITA

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