Three Essays on Finance and Product Market Competition

by

Chang Suk Bae

B.S. in Mathematical Sciences, Korea Advanced Institute of Science and Technology, 2012

M.S. in Management Engineering, Korea Advanced Institute of Science and Technology, 2014

Submitted to the Graduate Faculty of the

Joseph M. Katz Graduate School of Business in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

University of Pittsburgh

2021

UNIVERSITY OF PITTSBURGH

JOSEPH M. KATZ GRADUATE SCHOOL OF BUSINESS

This dissertation was presented

by

Chang Suk Bae

It was defended on

May 21, 2021

and approved by

Dr. Shawn Thomas, Professor of Finance, H.J. Heinz Faculty Fellow, Katz Graduate School of Business

Dr. Leonce Bargeron, Associate Professor of Finance, PNC Endowed Professorship, Gatton College of Business and Economics

Dr. David J. Denis, Roger S. Ahlbrandt, Sr. Chair and Professor of Finance, Katz Graduate School of Business

Dr. Kenneth Lehn, Samuel A. McCullough Professor of Finance, Katz Graduate School of Business

Dissertation Director: Dr. Shawn Thomas, Professor of Finance, H.J. Heinz Faculty Fellow, Katz Graduate School of Business

Three Essays on Finance and Product Market Competition

Chang Suk Bae, PhD

University of Pittsburgh, 2021

This dissertation consists of three essays on finance and product market competition. In the first essay, I investigate corporate agility, the importance of which is emphasized in both field and academic research but understudied empirically. Using the business descriptions provided in firms' 10-K filings with the SEC as the main input, I construct a novel measure of corporate agility and confirm its validity. Next, I identify various firm flexibility measures as the determinants of corporate agility. I next find that product market performance improves with agility in the short-run and firm survival likelihood increases with agility in the long-run. I also document that the benefits of corporate agility are particularly realized when firms face industry-wide common shocks such as R&D or M&A waves, or trade barrier reductions and that firms increase agility at the expense of short-term profitability. Lastly, I find that agility is a negative predictor of future returns even after controlling for other firm risks and characteristics.

In the second essay, I investigate negative externalities of innovations along supply chains by analyzing the effects of customers' innovations on suppliers' trade credit provision. I find that suppliers extend more trade credit after customers innovate, and the effect is robust to controlling for various firm characteristics and industry-specific market conditions and to addressing potential endogeneity issues. The effect is mainly driven by the holdup channel as opposed to the demand channel or the financing channel. Next, I document that greater technological overlap between customers' innovation and suppliers' innovations attenuates the effect. Lastly, I find that suppliers

adopt more conservative financial policies and innovate more by learning from customer's innovation.

In the third essay, I investigate industry spillover effects of corporate fraud. Using a sample of securities class action lawsuits, I document that fraud mitigates financial constraints of product market rivals. This positive intra-industry spillover effect is stronger for firms in more concentrated industries or firms with less analyst coverage. In contrast, fraud worsens financial constraints for firms in the top-supplier and top-customer industries of the fraud firms. The negative spillover effect is dependent on trade credit provision.

Table of Contents

Preface xiv

1.0 First Essay: Corporate Agility, Product Market Performance, and Survival 1

1.1 Introduction 1

1.2 What is Agility? 9

1.2.1 Definition of Agility 9

1.2.2 Measuring Agility 12

1.3 Data Description 17

1.4 Empirical Results 23

1.4.1 Firm-level Agility 23

1.4.2 Industry-level Agility 25

1.4.3 Validation of Agility Measure: Investigation of Pharmaceutical Industry .. 28

1.4.4 Determinants of Agility 31

1.4.5 Agility and Performance 37

1.4.6 Agility and Survival 38

1.4.7 Endogeneity 40

1.4.8 Benefits of Agility 44

1.4.9 Seeking Agility 46

1.4.10 Costs of Agility 49

1.4.11 Stock Return Predictability 50

1.4.12 Robustness & Additional Tests 51

1.4.12.1 Robustness: Estimation Window of Agility 51

1.4.12.2 Robustness: Magnitude of Competitive Threats 52

1.4.12.3 Robustness: Falsification Tests... 53

1.4.12.4 Robustness: Reporting Quality of 10-K Filings 54

1.4.12.5 Product Differentiation vs. Assimilation 54

1.4.12.6 Quasi-agility 56

1.4.12.7 Residual Agility 56

1.4.12.8 Manufacturing Industry 57

1.4.12.9 Product Homogeneity... 58

1.5 Conclusion 59

2.0 Second Essay: Is Innovation Always Beneficial? Externalities of Innovation on Product Market Relationship 62

2.1 Introduction 62

2.2 Data Description 70

2.3 Empirical Results.. 72

2.3.1 Base Line Results: Customer Innovation and Supplier's Trade Credit 72

2.3.2 Mechanisms 73

2.3.2.1 Holdup Channel 73

2.3.2.2 Demand Channel 76

2.3.2.3 Financing Channel.. 77

2.3.3 Endogeneity 78

2.3.4 Technological Space of Customer Innovation 80

2.3.5 Financial and Investment Decision of Supplier...82

2.3.6 Robustness 84

2.3.6.1 Measurement of Trade Credit 84

2.4 Conclusion 85

3.0 Third Essay: Spillover Effect of Corporate Fraud: Evidence from Financial Constraints of Intra- and Inter-Industry Firms 87

3.1 Introduction 87

3.2 Data Description 93

3.2.1 Fraud Data 93

3.2.2 BEA IO Data 94

3.2.3 Compustat Firm Data 96

3.3 Empirical Results 98

3.3.1 Overall Spillover in Financial Constraints 98

3.3.2 Channels for Intra-industry Spillover 102

3.3.2.1 Competitive Effect 102

3.3.2.2 Attention Effect vs. Liquidity Effect 103

3.3.2.3 Comparison of Possible Channels for Intra-industry Spillover 105

3.3.3 Channels for Supplier and Customer Industry Spillover 107

3.4 Robustness Test 109

3.4.1 Placebo Test: Matched Sample Analysis 109

3.4.2 IV Estimation 111

3.4.3 Potential Issue about Industries Closely Related to Frauds 112

3.5 Conclusion 113

Appendix A : First Essay 156

Appendix B : Second Essay 174

Appendix C : Third Essay **176**

Bibliography **178**

List of Tables

Table 1: Summary statistics 115

Table 2: Summary statistics of text-based variables 116

Table 3: Product assimilation vs. Product deviation 117

Table 4: Persistence test 118

Table 5: Firm-level agility 119

Table 6: Industry-level agility 120

Table 7: Investigation of pharmaceutical industry 121

Table 8: Agility and product market performance 122

Table 9: Agility and firm survival 123

Table 10: Endogeneity 124

Table 11: Benefits of agility 125

Table 12: Agility and acquisition 126

Table 13: Costs of agility 127

Table 14: Stock return predictability 128

Table 15: Summary statistics 129

Table 16: Baseline regression 130

Table 17: Multiple fixed effects 131

Table 18: Holdup channel 132

Table 19: Demand channel 133

Table 20: Financing channel 134

Table 21: 2SLS regression 135

Table 22: Diff-in-diff regression 136

Table 23: Overlapping of technology space between customer and supplier........ 137

Table 24: Overlapping of technology space between customer and itself in the past........ 138

Table 25: Financial and investment decision of supplier 139

Table 26: Summary statistics........ 140

Table 27: Overall spillover in financial constraints........ 141

Table 28: Competitive effect as a channel for intra-industry spillover 142

Table 29: Attention effect vs. liquidity effect as a channel for intra-industry spillover........ 143

Table 30: Comparison of possible channels for intra-industry spillover........ 144

Table 31: Matched sample analysis........ 145

Table 32: IV estimation 146

Table 33: Potential issue about industries closely related to frauds 147

Appendix Table A1: Variable definition........ 156

Appendix Table A2: Persistence test with "fictitious" $Agility$ 157

Appendix Table A3: Pairwise correlation matrix........ 158

Appendix Table A4: Extended estimation window 159

Appendix Table A5: Magnitude of competitive threats 160

Appendix Table A6: Reporting quality 161

Appendix Table A7: Product Differentiation vs. Assimilation........ 162

Appendix Table A8: Quasi-agility........ 163

Appendix Table A9: Residual agility 164

Appendix Table A10: Manufacturing industry 165

Appendix Table A11: Reasons for delisting 166

Appendix Table A12: Homogeneous goods industry.. 167

Appendix Table B1: Robustness.. 174

Appendix Table C1: Variable descriptions 176

Appendix Table C2: Numerical transformation of bond rating 177

List of Figures

Figure 1: Industry-wise agility **149**

Figure 2: Investigatin of pharmaceutical industry **150**

Figure 3: Local linear regression of agility (in year t) on firm variables (in year t-1) **151**

Figure 4: Agility dynamics after acquisitions **155**

Appendix Figure A1: Word cloud of PEPSICO INC, COCA-COLA CO, and competitors **168**

Appendix Figure A2: Local linear regression of firm variables (in year t+1) on agility (in year t) **169**

Appendix Figure A3: Falsification test **173**

Preface

I thank my dissertation committee members Professor Leonce Bargeron, Professor David Denis, Professor Kenneth Lehn, and Professor Shawn Thomas for their guidance. I especially thank my dissertation chair Professor Shawn Thomas for his continued support and encouragement. I am also grateful to other professors at the University of Pittsburgh who I had the opportunities to learn from. I thank fellow doctoral students in the finance department as well as in other disciplines for their friendship.

I thank Carrie Woods and her team at the doctoral office for their care and support.

Finally, I am grateful to my family for their love and support.

1.0 First Essay: Corporate Agility, Product Market Performance, and Survival

1.1 Introduction

Alchian (1950), a seminal paper, introduces the notion of natural selection into economics and concludes that profit maximization is meaningless for firm survival in a world of uncertainty. The paper articulates that the natural selection process is the "survival of the fittest." Building on Alchian (1950) and anecdotal evidence from the business world, Lehn (2018) hypothesizes that greater corporate agility, defined as a firm's ability to adapt to environmental changes, is likely to increase firms' survival rates. Further, Lehn (2018) proposes that governance structures that expedite the decision-making process (e.g., decentralized governance structures) increase firms' agility. However, the notion of corporate agility and its effect on firm survival or performance have been empirically understudied in the literature, presumably due to the lack of a useful measure of corporate agility. This paper creates a novel measure of corporate agility using the dynamics of business descriptions provided by firms in their annual 10-K filings with the U.S. Securities and Exchange Commission (SEC). More specifically, this paper characterizes and quantifies corporate agility in the product market space using the 10-K business descriptions and defines it as a firm's responsiveness to the product encroachment of its rivals. Thereby, this paper investigates how variation in agility measured in the product market space affects firms' product market performance and survival rates.

The importance of corporate agility is apparent in the results of surveys of field experts. According to a survey from the Economist Intelligence Unit, an overwhelming majority of executives (88%) cite agility as a key to global success. However, more than one-quarter (27%) of respondents say that their organizations are at a competitive disadvantage because they are not agile enough to anticipate fundamental marketplace shifts. In addition, a report from the MIT Center for Information Systems Research claims that agile firms grow revenue 37% faster and generate 30% higher profits than non-agile companies.

An empirical challenge in studying corporate agility is that it is hard to accurately quantify agility, and thus, only a few papers empirically investigate its importance. These studies try to quantify corporate agility (e.g., Dove, 1995; Dove, 2002; Metes, Gundry, and Bradish, 1998; Goranson and Goranson, 1999); however, their metrics are score-based agility indices evaluated with subjective attributes regarding the notion of agility. As Lin, Chiu, and Chu (2006) points out, the scoring approach is subject to ambiguity and multi-possibility when mapping evaluators' judgements to a number. In contrast, this paper's measure has the advantage of being completely and objectively replicable by researchers using SEC 10-K business descriptions and the procedure outlined below. Also, the integrity of the measure is ensured in that firms' business descriptions are required to be representative and accurate by Item 101 in Regulation S-K. It is also dynamic in the sense that the inputs to the measure are updated annually and applicable to every firm that posts 10-K filings.

Previous literature (Sharifi and Zhang, 1999; Yusuf, Sarhardi, and Gunasekaran, 1999; Christopher and Towill, 2000; Lin, Chiu, and Chu, 2006) describes several dimensions of business environmental changes: consumer demand change, competition change, technological change, and change in social factors. More specifically, legal environment changes (i.e., regulation changes), cross-border environment changes (e.g., trade barriers), technological environment changes (i.e., innovation shocks), market demand changes, or social factor changes (e.g., changes in social norms) may be cited as factors promoting firm agility. However, it is challenging to implement tests using these types of environmental changes due to the lack of observability and definability. For example, when there is a change in social norms (e.g., campaign for minorities), an agile firm may alter or newly provide its own norm or policy (e.g., hire more minorities), which is hard to observe or define for researchers. This paper exploits the product market as the laboratory for corporate agility research, where agility and performance can be measured in a straightforward, observable, and intuitive way.

Using business descriptions in 10-Ks that are mandated to be representative and significant by item 101 of Regulation S-K of SEC, I first define a firm-year level measure of corporate agility in the product market through further developing the framework of Hoberg, Phillips, and Prabhala (2014). [1] Hoberg, Phillips, and Prabhala (2014) introduces a measure for competitive threats ("product market fluidity") by gauging the convergence of rival firms' products to a firm's current products and studies how product market fluidity influences financial policies such as payout and cash holdings. To quantify a firm's ability to adapt to business environment changes following the definition of corporate agility (Lehn, 2018), this paper computes a firm's (bidirectional) responsiveness to rival firms' competitive threats in the product market space using 10-K information as in Hoberg, Phillips, and Prabhala (2014).[2] In particular, I estimate a firm's product

[1] In addition to item 101 of Regulation S-K, the Sarbanes-Oxley Act of 2002 requires the company's CEO (and CFO) to certify that the 10-K is both accurate and complete. Thus, I presume business information given in 10-K is a reliable and accurate source for a firm's business. However, I acknowledge the possibility of bias in the corporate agility measure to the extent that firms can omit information at their discretion even though they are required to submit a complete business description.

[2] Hoberg, Phillips, and Prabhala (2014) investigates how competitive threats (in the product market space) leads to firm responses (in the financial space). Whereas, this paper observes firm responses (in the product market space) to

convergence to or divergence from rival firms' products (i.e., product responsiveness) when the rivals' products approach its current product space (i.e., competitive threats increases).[3] In other words, a firm's corporate agility is estimated as the sensitivity of its product similarity or dissimilarity (to its rivals' products) to the rivals' product similarity (to the firm's products). For example, an agile firm will develop newer products (relative to the rivals' products) when its rivals assimilate its current products so as to "escape" the increased competitive threats. Or alternatively, an agile firm can also strengthen its current products in order to "resist" rivals' competitive threats. On the contrary, a rigid firm will be irresponsive (i.e., neither converge nor diverge) to its rivals' threats and maintain the status quo.[4] If the rigid firm's agility value is estimated to be zero (as the opposite extreme of positive), then high agility scores reflect agile counterparts.

---

competitive threats (in the product market space) and exploits the responses themselves to construct the agility measure.

[3] Business description in 10-Ks narrates not only current products but also various dimensions of business such as business strategy (e.g., joint ventures and strategic alliances), investment status (e.g., mergers and acquisitions), environment, and risk factors. That is, a product description is a part of the entire business description. However, throughout this paper, I proceed with the product description as being identical to the business description to simplify the explanation of constructing a new measure of agility.

[4] This paper does not claim that responsiveness (i.e., "escape" or "resist" strategy) is optimal or irresponsiveness (i.e., maintaining the status quo) is suboptimal when threats arise. Following the definition of agility (i.e., responsiveness to rivals' threats), a high level of agility is not necessarily ex-ante optimal. Moreover, irresponsiveness (or being rigid) may be a firm's strategy to resist the external threats, but this paper defines "resist" strategy as consolidation of current production, differentiating it from irresponsiveness. Section 4.12.5 contrasts outcomes from "escape" and "resist" strategies.

I find that the choice between the “escape” and “resist” strategies depends on firms’ current status (i.e., cash holdings, profitability, R&D investment, industry concentration) in intuitive ways. The results show that firms on average choose the “escape” strategy (rather than “resist” strategy or the status quo) under competitive threats in line with the past studies which show a positive relationship between product market competition and innovation (Nickell, 1996; Blundell, Griffith, and Van Reenen, 1999; Carlin, Schaffer, and Seabright, 2004; Schmitz, 2005; Bloom, Draca, and Van Reenan, 2011) to the extent that innovation enables firms to “escape” the competition. In particular, firms with higher cash holdings, lower profitability, higher R&D expenditures, in more concentrated industries, or that are younger appear to develop new products (i.e., choose “escape” strategy) rather than strengthen current production (i.e., choose “resist” strategy) or maintain the status quo when facing rivals’ threats. This suggests that a firm’s agility, measured as the sensitivity of its responsive strategies (i.e., either “escape” or “resist” strategy) to rivals’ threats, represents actual firm behaviors.

A critical part of this study is to confirm the validity of the newly introduced measure of corporate agility. First, if my $Agility$ measure truly represents a dimension of abilities, one might expect stability and persistence of the measure. I find that a firm’s $Agility$ value is immune to different permutation of parameters used in its construction and shows some persistence within the same firm over time. Second, industry-level $Agility$ is examined to see whether firms in industries that are expected to be agile have higher values of $Agility$ than those in rigid industries. I specifically focus on pharmaceutical firms to exploit two industrywide variations that are likely to influence the agility of those firms: the FDA’s new drug approval time and rates. To wit, the pharmaceutical firms, which observe a faster drug approval speed and higher approval rates on average in their industry, will anticipate the expected time of drug approvals to decrease and the expected approval likelihood to increase, respectively. Hence, a faster drug approval process and higher approval rates should increase the introduction of new drug products for a given level of the rivals' threats, and, consequently, increasing firms' agility measures. Using subsample regressions of pharmaceutical firms, I find that drug approval rates (drug approval times) are positively (inversely) associated with the agility of pharmaceutical firms.

Next, I also examine whether and how firm flexibility variables are related to firm agility. To the extent that agility measures the ability to respond to business environment changes, "flexible" firms are likely to be endowed with agility. In addition to the conjecture in Lehn (2018) that governance or organizational flexibility or characteristics can be relevant for agility, I examine whether financial flexibility promotes agility. Using local linear regression (with Gaussian kernel functions), I observe that firm flexibility (i.e., financial flexibility, governance flexibility, organizational flexibility, operating flexibility) promotes firm agility. However, the results show that agility does not necessarily lead to an improvement in financial, governance, organizational, or operating flexibility, suggesting that agility is a unique firm characteristic distinct from other firm flexibility variables.

I find evidence that corporate agility influences product market performance and survival likelihood. Even though it is a stylized fact that greater firm agility improves performance, it is an empirical question as to the magnitudes and whether or not performance improvements are transitory or eventually lead to increased survival rates. For example, even if agility can enhance firm performance in the short term, the enhancements may fade away over time. Also, agility can increase firm survival likelihood with the improved performance in the short run, but it might also take time for the performance improvement leads to higher survival likelihood ultimately. Also, it is plausible that agile firms are targeted more frequently by acquirers that seek agility or the strong product market performance of agile firms. I find that agility significantly increases market share growth after 1 and 3 years, but the positive effect is not significant after 5 years. Meanwhile, agility is not significantly related to survival likelihood (i.e., probability of delisting) for the next year, but survival likelihood significantly increases with agility after 3 years. These effects are both statistically and economically significant. However, the results could also be driven by possible endogeneity of $Agility$ due to reverse causality or omitted variables problems. To address these concerns, I instrument for $Agility$ in a two-stage regression framework within the pharmaceutical industry, using the FDA's new drug approval time and rates as instruments. While the instruments correlate with $Agility$, there is little reason to believe that they have a direct influence on the product market performance or survival likelihood other than through their association with a firm's introduction of new drug products, and hence, its agility. On the other hand, lobbying activities of the pharmaceutical firms might influence the FDA's drug approval process, and at the same time, correlate with their performance. To further mitigate the confounding effect, the firm-level lobbying expenditures are controlled for the IV regressions. The IV tests provide evidence that the observed results are robust to addressing potential endogeneity concerns.

Next, I investigate possible channels through which firms attain competitive benefits from agility. Agile firms may be able to respond more proactively when facing industry-wide common shocks than their rigid counterparts. The results show that agile firms ramp up R&D investments (acquisition investments) following industry-wide R&D (M&A) waves more intensively than rigid firms. The results also suggest that agile firms have better product market performance than rigid firms when facing industry-level tariff reductions. In addition, acquirers' agility and targets' agility are negatively correlated implying that firms potentially seek agility through acquisitions. Next, I explore costs of attaining agility and find that firms increase agility at the expense of concurrent profitability.

Lastly, I examine stock return predictability of agility. If failure to build up agility leads to loss in market share, and eventually, likelihood of firm discontinuation, then agility should be negatively associated with priced distress risk. Specifically, agile firms are expected to earn lower stock returns than rigid firms. Besides, firms that cannot maintain agility will find it difficult to deal with uncertainty which arrives randomly, such as competition or technology shocks, and hence, investors raise the required rate of return. Meanwhile, to the extent that agility carries firm innovativeness, agile firms bear innovation risk which is priced and earn higher returns. Fama-MacBeth (1973) cross-sectional regression results suggest that agility is a negative predictor of future returns even after controlling for firm risk and characteristics.

This paper introduces a novel measure of corporate agility, which has been understudied in the previous literature. I believe this new measure can be a meaningful proxy for a hard to measure firm characteristic. In addition, this paper contributes to the literature on the determinants of product market performance and firm survival. My empirical results are consistent with the previous literature, which show a positive relationship between product market competition and innovation (Nickell, 1996; Blundell, Griffith, and Van Reenen, 1999; Carlin, Schaffer, and Seabright, 2004; Schmitz, 2005; Bloom, Draca, and Van Reenan, 2011) to the extent that product differentiation is achieved from innovation. However, there are also studies in the literature that finds a negative relationship between those (Aghion and Howitt, 1992; Hashmi, 2013). The mixed results in this literature potentially stem from the differences among the past studies in terms of data source, period, and definition of competition and innovation (Hashmi, 2013). However, my findings suggest that the relation between competitive threats and firm strategies depends on their current status (e.g., cash holdings, age, market share growth, R&D expenditures, industry concentration) which might be a reason why the sensitivity of innovation to product market competition varies in the literature.

My results are also consistent with the literature of cash holdings (e.g., Bolton and Scharfstein, 1990; MacKay and Phillips, 2005; Haushalter, Klasa, and Maxwell, 2007) by showing that firms with higher cash holdings appear to develop new products when facing rivals' threats. Specifically, the long-purse theory explains that predatory threats from rivals induce firms to increase financial flexibility. This paper's results add to the literature by suggesting that the enhanced financial flexibility is indeed useful in escaping the rivals' threats by enabling firms to develop new products.

This paper is also related to the literature on product life cycles, which concludes that firms need to adjust their product strategies (i.e., introduce new products or withdraw old ones) as firm growth critically relies upon either introducing fresh product lines or developing current ones (Levitt, 1965; Argente, Lee, and Moreira, 2020). This paper also contributes to this literature by documenting that the benefits, in terms of firm value or sales growth attendant to current product development or new product introduction, are larger when threats from rivals are present.

1.2 What is Agility?

1.2.1 Definition of Agility

Alchian (1950) develops the notion of natural selection in the economics context and explains that the selection process is the survival of the fittest rather than profit-maximized ones.

Along with Alchian (1950)'s view and anecdotal evidence in the business world, Lehn (2018) defines corporate agility as a firm's ability to adapt to environment changes.

This paper especially exploits the product market as the laboratory, and, computes a firm's (bidirectional) responsiveness to rival firms' competitive threats in the product market space using 10-K information as in Hoberg, Phillips, and Prabhala (2014). In particular, I estimate a firm's product convergence to or divergence from rival firm's products (i.e., product responsiveness) when the rivals' products approach its current product space (i.e., competitive threats increases). Put differently, a firm's corporate agility is estimated as the sensitivity of its product similarity or dissimilarity (to its rivals' products) to the rivals' product similarity (to the firm's products).

An agile firm will develop newer products (relative to rivals' products) when its rivals assimilate its current products so as to "escape" the increased competitive threats. Or alternatively, an agile firm can also strengthen its current production and focus more on the current set of products in order to "resist" rivals' competitive threat. On the contrary, a rigid firm will be insensitive (i.e., neither converge nor divergence) to its rivals' threats and maintain the status quo. If then, the rigid firm's agility is estimated to be zero as the opposite extreme of positive, high agility values of agile counterparts. Thereby, this paper suggests a dynamic and objective measure of agility in the sense that it is updated annually and is applicable to every firm which posts 10-K filings relative to score-based measures suggested in the previous literature (e.g., Dove, 1995; Dove, 2001; Metes, Gundry, and Bradish, 1998; Goranson and Goranson, 1999).

The notion of agility as a dimension of firm abilities should be closely related to existing firm abilities or characteristics but is an irreplaceable one to the best of my knowledge. More specifically, agility is likely to be in close connection with firm flexibility in that agility measures ability to respond to business environment changes. For instance, financial flexibility or slack can be related to agility because it is an ability to use internal cash or access the capital market immediately when an unexpected financial shortfall occurs (e.g., when unexpected investment opportunities arise). Financially flexible firms may be able to cope with other environment changes as well as the change in their financial position in a more agile way. For example, a financially flexible firm, with its financial strength, can modify its product market strategy quickly when there are competitive threats from rivals. Financial flexibility can promote agility in such a way. While this may be true, agility is a broader concept than financial flexibility in the sense that it is an ability to respond to various environment changes, including a firm's own cash shortfall or investment opportunities set change. Besides, the responses to the environmental changes are not limited to the use of internally hoarded cash or additional capital raising.

Likewise, flexibility in governance (e.g., rapid adjustment of executive compensation or turnover of executive members as a response to the firm performance declines or wrongdoings) or organizational flexibility (e.g., ability to reshape the structure of organization) may be related to agility following Lehn (2018)'s proposition that decentralized firms can promote agility with their low knowledge transfer costs, but is a narrower concept compared to agility. Also, operating flexibility (e.g., ability to shift from the current production or operation structure to new ones) may be related to agility.

Alternatively, financial flexibility, governance flexibility, organizational flexibility, or operating flexibility may be a substitute rather than a complement of agility. For example, financially flexible firms might be able to move agilely under competitive threats with their financial strength, or, they might not pursue agility since they can recover the future losses from the rivals' threats with their ease of financing. In any case, agility is a distinct (and probably more extensive) firm ability measure even if it should be closely related to existing ones. Section 4.3. explores these possibilities in more detail with empirical results.

1.2.2 Measuring Agility

I first start with decomposing the change in the similarity of business description between the firm and all the other firms. Following the framework of Hoberg, Phillips, and Prabhala (2014) (but with different notation), J_t is the number of all unique words used in the business descriptions of all firms (i.e., firms in Compustat-CRSP universe) in year t. W_{it} is the firm-level word vector in J_t-dimension where j-th component equals the number of times that j-th word (when ordered) is used in firm i's description. D_t is the J_t-dimension dictionary vector whose j-th component equals the number of times that j-th word is used in the business descriptions of all firms. W_{it} and D_t for any firm i and year t are normalized by their sum so that each vector forms the sum of 1 in order to keep each word's importance (or weight) relative to the other words. Then,

$$W_{it} \cdot D_t - W_{it-1} \cdot D_{t-1} = W_{it} \cdot D_t - W_{it} \cdot D_{t-1} + W_{it} \cdot D_{t-1} - W_{it-1} \cdot D_{t-1}$$

$$= W_{it} \cdot (D_t - D_{t-1}) + (W_{it} - W_{it-1}) \cdot D_{t-1} \quad (1)$$

$$= \underbrace{W_{it-1} \cdot (D_t - D_{t-1})}_{External\ Fluidity} + \underbrace{(W_{it} - W_{it-1}) \cdot (D_t - D_{t-1})}_{Trend\ Sensitivity} + \underbrace{(W_{it} - W_{it-1}) \cdot D_{t-1}}_{Internal\ Fluidity} \quad (2)$$

The first line of the equation, $W_{it} \cdot D_t - W_{it-1} \cdot D_{t-1}$, represents the total change in the similarity between firm i's description and overall firm's description from t-1 to t (when assuming that both terms are scaled through normalizing each vector before the inner products). After decomposition, the total change in similarity can be represented as (1) where the first term, $W_{it} \cdot$

$(D_t - D_{t-1})$, corresponds to the Hoberg, Phillips, and Prabhala (2014) product market fluidity measure and the second term, $(W_{it} - W_{it-1}) \cdot D_{t-1}$, represents the similarity between the word change of firm i and current word set of overall firms. [5] With additional decomposition, the product market fluidity term can be further split into two inner product terms as (2) shows. In sum, the last line of the equation shows that the first line can be decomposed into three inner products of vectors. The following explains the three terms.

$\boldsymbol{W_{it-1} \cdot (D_t - D_{t-1})}$**:** This first term is defined as "External Fluidity", which measures firm i's exposure to rivals' word set change. In firm i's perspective, this exposure comes from the rivals' movements, not its own movement. This differs from the original product market fluidity measure in Hoberg, Phillips, and Prabhala (2014). In this paper's notation, the original Hoberg, Phillips, and Prabhala (2014) fluidity can be represented as $W_{it} \cdot |D_t - D_{t-1}|$ (before vector normalization). In this paper, I use the external fluidity as a revised version of the original fluidity measure to serve the purpose of measuring agility of this paper. There are four reasons for revising the original fluidity measure. First, the absolute value function on $D_t - D_{t-1}$ doesn't allow the measure to distinguish between the decrease and increase in word usage of rivals.[6] Second, aside

---

[5] Technically speaking, the first term, $W_{it} \cdot (D_t - D_{t-1})$, is slightly different from the Hoberg, Phillips, and Prabhala (2014)'s measure in that there is no absolute function on the second vector, $D_t - D_{t-1}$, and the vectors are not normalized before the inner product. However, both commonly compute an inner product with the same ingredient vectors, W_{it} and $D_t - D_{t-1}$ in the purpose of gauging a firm's word exposure to that of surrounding firms. The difference is explained in the next paragraph.

[6] It is arguable that word decrease of a firm's rivals (i.e., a negative component of $D_t - D_{t-1}$) may imply an increase in threats on that word if the rivals move to newer or different products than the firm's products. However, both D_t and D_{t-1} are normalized in a way that a negative component of $D_t - D_{t-1}$ is necessarily compromised by some other

from the absolute value function, not only does the measure gauge the product market threat from rivals, but it might also contain contemporaneous change in the economic environment; more specifically, it could be the case that firm i have changed its word set from W_{it-1} to W_{it} where the change $W_{it} - W_{it-1}$ comes from the economy-wide change (e.g., technology or innovation shock to industries) which also shapes the rivals' change, $D_t - D_{t-1}$, contemporaneously. However, $W_{it} \cdot (D_t - D_{t-1})$ only represents the similarity between firm i's word choice at t (which is potentially an outcome of the economy-wide change as explained) and the change in rivals' words from t-1 to t. To the extent that the similarity between $W_{it} - W_{it-1}$ and $D_t - D_{t-1}$ is created by the economy-wide change that is unrelated to the product market threat motive of firm i and its rivals, the original fluidity measure plausibly over- or underestimates the actual product market threat. This paper, thus, filters out this coincidental similarity (i.e., $(W_{it} - W_{it-1}) \cdot (D_t - D_{t-1})$ in (2)) from the original fluidity measure (i.e., $W_{it} \cdot (D_t - D_{t-1})$ in (1)) to isolate the actual product market threat (i.e., $W_{it-1} \cdot (D_t - D_{t-1})$ in (2)). Third, when competing rivals choose their word set at t, the firm i's word information that is available and observable to rivals is W_{it-1}, not W_{it}. Therefore, it can be deemed that $W_{it-1} \cdot (D_t - D_{t-1})$ is a more realistic measure of product market threat measure than $W_{it} \cdot (D_t - D_{t-1})$. Finally, $W_{it-1} \cdot (D_t - D_{t-1})$ measures the similarity coming from rivals' move with holding the word set of firm i chosen at t-1 fixed, and thus, this new fluidity is, relative to the original fluidity measure, more free from endogeneity issue when

positive component of $D_t - D_{t-1}$, and which represents the increased threat on that new product. If then, the absolute value function can magnify the actual size of threats (without changing the direction of threats). Given that the actual size is important in measuring agility which is constructed in a way that how much magnitude of $W_{it} \cdot (D_t - D_{t-1})$ is comparable to the magnitude of $(W_{it} - W_{it-1}) \cdot D_{t-1}$, I use raw difference between D_t and D_{t-1}.

being used in corporate finance research. The endogeneity issue arises from the fact that an individual firm endogenously chooses its word description, and at the same time, corporate policies.[7]

$(\boldsymbol{W_{it}} - \boldsymbol{W_{it-1}}) \cdot (\boldsymbol{D_t} - \boldsymbol{D_{t-1}})$: This second term represents the covariance between firm i's word change and that of rivals (before normalizing vectors). Hence, this term can proxy for the degree that firm i synchronizes its word set from W_{it-1} to W_{it} as rival firms change their word from D_{t-1} to D_t. As explained above, this covariance can measure contemporaneous similarity in word set of firm i and rivals resulting from the economy-wide change, which is commonly faced by firm i and rivals but not related to threat motive of either side. At t, rivals can only observe firm i's words disclosed at t-1 (W_{it-1}) but not its words disclosed at t (W_{it}), and vice versa. Hence, it is likely that rivals and firm i "coincidentally" synchronize their words following the trend which reflects the current economic environment, rather than that firm i or rivals threat or imitate each other. Therefore, I define this term as "Trend Sensitivity" (of firm i).

$(\boldsymbol{W_{it}} - \boldsymbol{W_{it-1}}) \cdot \boldsymbol{D_{t-1}}$: The last term represents the similarity between firm i's word change and the current word set of rivals. Unlike the external fluidity, $W_{it-1} \cdot (D_t - D_{t-1})$, measures the threat on firm i created from rivals, this last term measures the pressure on rivals created from firm i. At the same time, this can be interpreted as firm i's attempt at t to imitate or assimilate the rivals' products disclosed at t-1. Hence, I call this term "Internal Fluidity" (of firm

[7] In order to ensure that the ingredient vectors and revised fluidity measure are correctly computed in this paper, I check correlations with the original fluidity measure provided in the Hoberg-Phillips Data Library (http://hobergphillips.tuck.dartmouth.edu/). To wit, both $W_{it-1} \cdot |D_t - D_{t-1}|$ and $|W_{it-1} \cdot (D_t - D_{t-1})|$ are significantly correlated with the original fluidity measure with positive correlations of 13.4% and 13.5%, respectively. I am grateful to Professors Gerard Hoberg and Gordon Phillips for making this data available.

i) since it comes from firm i's movement, not rivals' movements. Note that this measures the voluntary action of firm i to imitate the current product of rivals, D_{t-1}, not to react to the economy-wide change or trend which is captured by $D_t - D_{t-1}$.

In this framework, I construct agility measure by calculating the absolute value of sensitivity of internal fluidity (at year t+1) to external fluidity (at year t). More specifically, I run firm-by-firm regression

$$Internal\ Fluidity_{i,t+1} = \beta_0 + \beta_{i,t+1} \cdot External\ Fluidity_{i,t} + \epsilon_{i,t} \qquad (3)$$

with 5-year consecutive observations of each firm i where[8]

$$Internal\ Fluidity_{i,t+1} \equiv (W_{it+1} - W_{it}) \cdot D_t$$

$$External\ Fluidity_{i,t} \equiv W_{it-1} \cdot (D_t - D_{t-1})$$

Hence, $|\beta_{i,t+1}|$ estimates how an increase in rivals' threat (i.e., increase in external fluidity) translates into firm i's product assimilation (i.e., increase in internal fluidity) or product deviation (i.e., decrease in internal fluidity) relative to rivals' products. Thus, the larger the $|\beta_{i,t+1}|$ is, the

[8] The 5-year requirement only applies to the observations used in the regressions of (3). For instance, the β of a firm that has observations only for the period of 2006-2010 can be estimated only for the year 2010, not the rest of the period. Next, those with available β values are only included in the sample used throughout this paper.

more agilely firm i reacts to the competitive threats. Finally, I define $Agility_{i,t+1}$ as the logarithm of $|\beta_{i,t+1}|$ since the distribution of raw $|\beta_{i,t+1}|$'s is highly right-skewed with skewness of 5.66.[9]

1.3 Data Description

The paper's data collection process and sample screening are based on that of Hoberg and Phillips (2016) and Hoberg, Phillips, and Prabhala (2014). The two papers use a web-crawling algorithm to extract business descriptions in 10-Ks of Compustat-CRSP firms. Most 10-Ks provide a business description in their Item 1 or Item 1A.

Firms are excluded from the initial Compustat-CRSP sample if (i) they are financials (SIC code 6000-6999) or utilities (SIC code 4900-4949), (ii) they have a book value of equity less than \$250,000, or (iii) they have asset value less than \$500,000. After the screening procedure, firm-year observations with the fiscal year in 1997-2018 are included because the electronic filing on Edgar has been required since 1997. The final sample period is from 2003-2018 since the agility measure construction (i.e., the estimation model in (3)) requires 5 years of consecutive

---

[9] The main results remain qualitatively similar (or become more statistically significant in some specifications) when raw $|\beta_{i,t+1}|$'s are used as $Agility_{i,t+1}$ values. Alternatively, the results are robust when extreme values (i.e., top 1% and bottom 1%) of $|\beta_{i,t+1}|$ are censored from the sample, or, $|\beta_{i,t+1}|$'s are winsorized at the 1% level before the logarithm transformation. On the other hand, the empirical distribution of t-statistics for $\beta_{i,t+1}$ has a kurtosis of 4.031 and skewness of 0.018 even when extreme values (i.e., top 1% and bottom 1%) are censored from the distribution, indicating that the t-statistics have fat-tailed distribution on both sides and $\beta_{i,t+1}$'s are significant sufficiently often.

observations of both D_t and W_t. As a result, the final sample contains Compustat-CRSP firms that satisfy the above screening condition and whose agility can be estimated.

[Insert Table 1 here]

Panel A of Table 1 reports the summary statistics for sample firms and Compustat-CRSP firms in the same period as the sample. The Compustat-CRSP firm-year observations meet the same screening condition as the sample firms but whose agility cannot be measured through the model (3) estimation due to the insufficiency of 10-K information. The sample characteristics suggest that firms whose 10-K information is available and hence agility can be estimated are larger, more profitable, and more established than other Compust-CRSP firms. Panel B of Table 1 compares the summary statistics between different quintile groups of $Agility$. The last column shows the differences in firm variables between Q1 (i.e., lowest $Agility$) firms and Q5 (i.e., highest $Agility$) firms. The difference between Q1 and Q5 is statistically significant but is smaller in magnitude than the difference between the sample and Compustat-CRSP reported in the last column of Panel A. This implies that firms in the sample are quite homogeneous in those firm characteristics even if they have distinct $Agility$ values. In addition, there is a weak monotonic relation with $Agility$ quintile rank of $Cash/AT$, $Log(Asset)$, ROA, $Tangibility$, and $R\&D/AT$. All those variables are controlled in this paper's tests to isolate the effect of $Agility$.

To define an entire dictionary (D_t) each year, I follow Hoberg and Phillips (2010) where two versions of dictionaries (i.e., main dictionary vs. local dictionary) are defined. A main dictionary discards words that appear in more than a certain threshold of all business descriptions in the same year.[10] A local dictionary is constructed based on the size of a local clustering coefficient of each word in main dictionary. More specifically, Hoberg and Phillips (2010) requires a word in the main dictionary to have a sufficiently high local clustering coefficient in order to be included in the local dictionary. The higher a word's local clustering coefficient is, the more likely that the word is used in the "language" among firms that report similar business descriptions (i.e., firms which are likely to be rivals to each other).

[Insert Table 2 here]

Table 2 Panel A shows that $Agility$ varies quite much between observations with a mean and standard deviation of -1.191198 and 1.281941, respectively, even if $Internal\ Fluidity$ and $External\ Fluidity$ are comparable to each other in terms of mean, standard deviation, minimum, and maximum. The measures in Table 2 Panel A are computed using a 5% threshold and local dictionary, which will be used throughout this paper. In Table 2 Panel B, permutations on the threshold level and dictionary version are allowed (e.g., 25% local clustering threshold with the main dictionary), and $Agility$ measure does not vary much across permutations (even if the relative magnitude of $Internal\ Fluidity$ and $External\ Fluidity$ varies). Thereby, the results strengthen the reliability of $Agility$ as a firm characteristic.

Even though it is intuitive that agile firms choose either product assimilation or product deviation as compared to rigid firms which are irresponsive (i.e., neither product assimilation nor

[10] Hoberg and Phillips (2010) uses a 5% threshold, and Hoberg and Phillips (2016) uses 10%, 25%, and 100% thresholds.

deviation) to its rivals' threats and maintain the status quo, it is worth investigating how firms on average choose between product assimilation and product deviation. Also, the choice between product assimilation and product deviation may depend on firms' current status (e.g., cash holdings, profitability, R&D investment, industry concentration, age). Therefore, I run pooled OLS regression of $Internal\ Fluidity$ on $External\ Fluidity$, and interactions between $External\ Fluidity$ and firm status variables.

[Insert Table 3 here]

Table 3 shows that firms on average choose product deviation, as shown by the negative coefficient of $External\ Fluidity$, which is consistent with the negative mean values of $\beta_{i,t+1}$ in Table 2. These results are in line with the previous evidence of a positive relationship between product market competition and innovation (Nickell, 1996; Blundell, Griffith, and Van Reenen, 1999; Carlin, Schaffer, and Seabright, 2004; Schmitz, 2005; Bloom, Draca, and Van Reenan, 2011) to the extent that product deviation can be achieved from innovation. In addition, the coefficients of interaction variables indicate that the degree of product deviation is even greater for firms with higher cash holdings, lower profitability, higher R&D expenditures, in higher industry concentration, or that are younger when facing rivals' threats.[11] These findings suggest

[11] It is worth pointing out that I do not argue that the observed firms' behaviors under rivals' threats are ex-ante optimal. However, the observed behaviors seem consistent with what can be expected intuitively. For example, cash-rich firms have more capacities to develop new products than cash-poor firms when facing rivals' threats. They could – rather than should – choose to develop new products as compared to their cash-poor counterparts. Also, firms that have invested more in R&D are able to introduce new products, whereas those who have invested less in R&D cannot.

that $Agility$, measured as the sensitivity of $Internal\ Fluidity$ to $External\ Fluidity$, potentially represents firm behaviors which are expected intuitively, and, $Internal\ Fluidity$ and $External\ Fluidity$ are fine ingredients of $Agility$.

If $Agility$ measure truly represents a dimension of abilities, one might expect that there is some level of persistence in the measure within a firm over time. If, for example, a firm's $Agility$ level shows that it is very agile in a year and become very rigid in the next year, and again become very agile in the following year, $Agility$ measure has a limitation in capturing an ability of a firm. For this diagnostic, I follow the persistence test of Cohen, Diether, and Malloy (2013) where a firm's ability to translate its past R&D into future sales is measured. Specifically, I check how many firms in an $Agility$ quintile group remain in the same $Agility$ quantile group over time (i.e., 1, 2,.., 5 years after the quintile formation).

[Insert Table 4 here]

Table 4 Panel A shows that $Agility$ is quite persistent in each quintile, and the two extreme quintiles (i.e., quintiles 1 and 5) have higher persistence than the intermediate quintiles, especially in the early years. For example, "high" agility group (i.e., quintile 5) firms remain in the same quintile more than 50% of the time in the following year and 22.5% of the time after 5 years. I then check migration rates of quintiles to different quintiles 1 year after the quintile formation to see how easily and frequently firms move from an agility quintile to another in the following year. Table 4 Panel B reports the transition matrix where each row represents migration rates of each quintile to other quintiles. The results show that the migration rate monotonically decreases as firms move further away from the current level of agility (i.e., firms remain in the neighborhood quintiles). For example, high agility group (quintile 5) firms stay in the same quintile 55.8% of the time and move to low agility group (quintile 1) only 7.1% of the time.[12]

However, it is also plausible that the persistence rates of $Agility$ shown in Table 4 might be merely side effects of the structure of the sample panel or construction process of $Agility$ where the observations used in estimating $Agility$ in consecutive years overlap within a firm. To relieve the concern, I also simulate the sample using the same parameters (i.e., the same firms in the same sample period) but with different values of $Internal\ Fluidity$ and $External\ Fluidity$ to create a "fictitious" $Agility$ measure. More specifically, I run 1,000 times of simulations using "fictitious" $Internal\ Fluidity$ and $External\ Fluidity$, which are normal variables with mean and standard deviation being the same as those of "true" $Internal\ Fluidity$ and $External\ Fluidity$, respectively. I then check the persistence of the fictitious $Agility$ for each simulation using quintile groups in Appendix A Table A2. When comparing this simulated persistence to the persistence of actual data, most of the figures in Panel A of Table 4 are lower in magnitude than those in Panel A of Appendix A Table A2. In addition, the figures in the same cell position are significantly different between Panel A of Table 4 and Panel A of Appendix A Table A2 at the 99% confidence level. Also, Panel B of Appendix A Table A2 shows that the simulated firms migrate more often to other $Agility$ quintiles than the actual sample firms, and the migration

[12] Firm persistence of agility can be deliberately increased by lengthening the estimation window since a longer window uses more overlapping observations within a firm and thus leads to more constant estimates within a firm. At a glance, within-firm (i.e., within-GVKEY) variation decreases from 63.3% of the total variation to 45.5% of the total variation as the estimation window changes from 5 years to 10 years. The within-firm variation of $Agility$ (63.3%) is comparable to that of other firm variables; it falls between that of $Size$ (3.0%) and that of MTB (77.9%), which show the minimum and maximum variation among firm variables, respectively. Section 4.9.1 explores further details.

rates are significantly different between Panel B of Table 4 and Panel B of Appendix A Table A2 at the 99% confidence level. Overall, the results support that $Agility$ is persistent over time and the observed persistence is not the side effects of the sample structure or construction process of $Agility$.

1.4 Empirical Results

1.4.1 Firm-level Agility

Table 5 Column 1 and 2 report examples of top 30 agile firms for the 1st half sample period (the year 2003-2010) and 2nd half sample period (the year 2011-2018), respectively. For the first (second) 8-year period, each firm's $\overline{Agility}_{[2003,2010]}$ ($\overline{Agility}_{[2011,2018]}$) is computed as the average of $Agility$ only when the firm has at least 4 non-missing $Agility$ values in the period.

[Insert Table 5 here]

9 of 30 firms continuously show a high level of agility in both periods. For example, CELGENE CORP, a pharmaceutical firm, ranked 14th and 7th in the first and second periods, respectively. According to an article from McKinsey & Company, the firm has invested both in-house R&D and "search and development" (i.e., R&D partnerships and investment or acquisitions of firms in the earliest stages of development), and which led the firm as one of the most successful players in the pharmaceutical industry where innovation environment is increasingly varied and

fast-moving.[13] CELGENE CORP's recent acquisition of JUNO THERAPEUTICS in 2018 reflects its high agility; CELGENE CORP acquired the firm as a response to rivals seeking to sell generic versions of its major product ("Revlimid"), the patent of which was to be expired in a few years. JUNO THERAPEUTICS was one of a handful of U.S. firms developing CAR-T therapy that was unique in the blood cancer market, and field analysts expected that CELGENE CORP could add to its existing drug pipeline and diversify the product portfolio through the acquisition.[14]

Table 5 Column 3 demonstrates the top 30 firms with respect to the increase in agility from the 1st period to the 2nd period (i.e., $\overline{Agility}_{[2011,2018]}$ - $\overline{Agility}_{[2003,2010]}$). Among those, PEPSICO INC (ranked 21st of 251) is well known for its diversification strategies. The company started to produce a wide range of products in the consumer packaged goods industry as well as the beverage industry following the decline in consumption of carbonated soda drinks and increased pressure from competitors such as DR PEPPER SNAPPLE GROUP, RED BULL GMBH, and NESTLÉ in the beverage industry. On the other hand, the biggest competitor, COCA-COLA CO (ranked 100th of 251 firms), adopted a different strategy even though it had experienced

---

[13] "R&D in the 'age of agile'". https://www.mckinsey.com/industries/pharmaceuticals-and-medical-products/our-insights/r-and-d-in-the-age-of-agile#

[14] "Celgene in Talks to Buy Juno Therapeutics". https://www.wsj.com/articles/celgene-in-talks-to-buy-juno-therapeutics-1516140153

"Celgene diversifies portfolio with purchase of Juno Therapeutics".

https://www.bizjournals.com/newyork/news/2018/01/22/celgene-buys-juno-therapeutics.html the same pressure as PEPSICO INC; [15] COCA-COLA CO focused more on carbonated soda drink products, or, diversified product portfolio only within the beverage industry.[16] Consistent with the evidence, PEPSICO INC ranks higher than COCA-COLA CO with respect to the increase in agility in the sample used in Table 5.

1.4.2 Industry-level Agility

To provide a further diagnostic of $Agility$, I examine between-industry differences of $Agility$ with time series average values of $Agility$ within the sample period.

[Insert Table 6 here]

Table 6 shows that retail trade industries (SIC 2-digit code 53, 56, 57, 58) rank highest in the list, followed by business or management services industries (73, 87). On the other hand, manufacturing industries (20-39) show dispersion in agility; low-Q manufacturing industries (27, 30, 32, 33, 34, 35, 37, 38) rank low, but high-Q manufacturing industries (20, 23, 25, 28, 36) rank

---

[15] The values of $External\ Fluidity$ of Pepsico inc and Coca-cola co are significantly positively correlated with correlation of 60.6% and have similar mean (-6.15E-6 vs. -8.32E-6) over the sample period, implying that the two firms experience similar magnitude and direction of competitive threats.

[16] Appendix A Figure A1 presents the word cloud of PEPSICO INC, COCA-COLA CO, and their competitors as an illustration. As the competitors increase the usage of “beverage” and “drink” from year 2003 to 2010, PEPSICO INC increases the usage of “food” and “snack” from year 2011 to 2018. On the other hand, COCA-COLA CO’s usage of “beverage” stays similar from year 2011 to 2018.

high. Also, IT industries (36, 73) rank fairly high, but not in top, reflecting the difference between agility and innovativeness. In addition, asset heavy industries (13, 16) and public service industry (49) rank low, illustrating that firms that cannot operate agilely due to their asset structure or regulation have a low level of $Agility$.

Next, I delve into industry-level agility to see whether firms in industries that are expected to be agile have higher values of $Agility$ than those in rigid industries in time-series with a more granular level (SIC 3-digit). For this purpose, I first compare four industries that are expected to have substantial differences in product characteristics, operation, asset structure, and therefore, agility between each other: software (SIC 3-digit code 737), pharmaceutical (SIC 3-digit code 283), and oil and gas (SIC 2-digit code 29 and 3-digit code 131) industries. The average $Agility$ of firms in each of the industries is shown in Fig 1A. Average values are reported from 2007-2018 since there are only limited number of firms (less than 10 firms) before 2007 in the oil and gas industry.

[Insert Fig 1 here]

Fig 1A demonstrates that industry averages fluctuate over time, but there is some persistence within each industry in terms of agility. On average, the software and pharmaceutical firms have higher agility than the metal industry and oil and gas industry, which is presumably due to the fact that metal firms and oil and gas firms have asset-heavy business and difficulties in rapid product development (e.g., development of new oil well) and metal firms have lower growth opportunities. On the other hand, the software and pharmaceutical industries seem to have similar agility levels on average, but the pharmaceutical firms have more volatile agility than the software firms. It could be the case that the pharmaceutical firms are more regulated (by the FDA) than the software firms even though both firms strive for new products (as implied by their high R&D expenditures).

In the meantime, the oil and gas industry has a noticeable pattern in the 2008-2010 period. After the decline of agility in 2008, the agility level of oil and gas firms had soared for two years. My interpretation is that this pattern is related to the US shale gas and oil boom led by a new drilling technology called fracking, and, firms' response to the boom. The shale boom changed the competitiveness of the industry, and the firms reacted to the changed environment agilely. For example, Exxon Mobil Corp., one of the industry leaders, initiated an acquisition of XTO Energy Inc. to resist the increased competition of the industry. In fact, Exxon Mobil Corp. expressed its concern about the increased competitive threats as identified in its 2009 10-K filing when compared to the 2008 10-K filing. The business description of its 2009 filing expresses "… The energy and petrochemical industries are **highly competitive**. There is **competition** within the industries and also with other industries in supplying the energy, fuel and chemical needs of both industrial and individual consumers. The Corporation **competes** with other firms in the sale or purchase of needed goods and services in many national and international markets and employs all methods of **competition** which are lawful and appropriate for such purposes…"[17] Exxon Mobil Corp.'s acquisition of XTO Energy Inc. (which is specialized in the production of shale oil and gas) seems to be the breakthrough for the increased rivals' competition. In fact, a news article depicts,

---

[17] In fact, the firm used the words "competition", "competitive", or "compete" in Item 1 or Item 1A much more than before in 2009 (15 times vs. 6 times).

"…Exxon made its big move into the shale game in 2010, when it paid $36 billion for Fort Worth's XTO Energy, a leader in the Barnett Shale fracking boom…"[18]

Next, in Fig 1B, 1C, and 1D, I contrast the agility of industries in various dimensions apart from the usual SIC classifications: household items vs. non-household items; less regulated vs. more regulated; high-Q vs. low-Q industries. Fig 1B shows that the industries supplying households with items, such as food and clothes, are more agile than the industries producing non-household items, such as raw materials or industry equipment, which require standardized process. Fig 1C demonstrates lower average agility values of firms in more regulated industries, such as natural resources, public utilities, transportation, healthcare, and tobacco, than less regulated industry firms (i.e., firms producing nonessentials or under less safety precaution in the process of production or consumption). However, more regulated industries have more volatile agility, implying that corporate agility can be affected by industry regulations. Lastly, Fig 1D compares agility between high-Q industries (i.e., SIC-3 industries with market-to-book ratio above the median) and low-Q industries (i.e., SIC-3 industries with market-to-book ratio below the median). Firms in industries with more growth opportunities have higher agility than those not even though there is not a big gap.

1.4.3 Validation of Agility Measure: Investigation of Pharmaceutical Industry

A critical part of this study is to confirm the validity of the newly introduced measure of corporate agility. Although the results so far reflect that $Agility$ can truly measure the level of

[18] https://www.dmagazine.com/publications/d-ceo/2017/september/exxon-mobil-drilling/

firm agility, I provide further evidence to confirm the validity of the measure by specifically concentrating on the pharmaceutical industry that is highly regulated and governed by a federal agency, the FDA. Given that the FDA has an influential control over pharmaceutical firms in developing new products or expanding existing products as sole authority, their agility level is likely to be subject to and influenced by the FDA's decisions. Whereas, it is not clear which government agencies or entities potentially affect the agility level of firms in other industries.

There are two exploitable industrywide variations, which arguably are correlated with the agility of those firms: the FDA's new drug approval time and rates. To wit, the pharmaceutical firms, which observe a faster drug approval speed and higher approval rates on average in their industry, will anticipate the expected time of drug approvals to decrease and the expected approval likelihood to increase, respectively. Hence, faster drug approval speed and higher approval rates can increase the introduction of new drug products (i.e., $Internal\ Fluidity$) from pharmaceutical firms for a given level of the rivals' threats (i.e., $External\ Fluidity$), and consequently, improve their agility.[19]

As a proxy for approval times, I use New Drug Application (NDA) and Biologic License Application (BLA) approval times for the period from 1993-2015.[20] More specifically, the median total approval times of standard or priority drugs are used. As for the proxy of approval rates, I use approval rates for CDER NME NDA and BLA applications.[21]

---

[19] However, to the extent that the FDA's drug approval speed and rates affect the $External\ Fluidity$ as much as $Internal\ Fluidity$ in the same direction, we would expect a lower correlation between $Agility$ and drug approval speed (rates).

[20] https://www.fda.gov/media/102796/download

[21] https://www.fda.gov/media/101930/download

[Insert Fig 2 here]

Fig 2A (2B) shows the time trends of the industry average of agility and the approval rates (inverse of approval times).[22] Particularly, the industry agility and approval rates appear to have similar time trends in that both have an oscillating downward (upward) trend in the first (second) half of the period. On the other hand, both the industry agility and inverse of approval times, by and large, have an upward trend, but the industry agility seems to have a higher time-series variation. For more quantitative analysis, I also run firm-level OLS regressions using the pharmaceutical industry firms.

[Insert Table 7 here]

Table 7 shows that drug approval rates (drug approval time) is positively (inversely) associated with the agility supporting that higher approval rates (faster drug approval) can induce pharmaceutical firms to improve agility. Column 2 shows that the relation holds even after controlling for firm characteristics.[23] In addition, Column 3 demonstrates qualitatively similar

[22] Approval rates and times are separately plotted in Fig 2A and 2B, respectively, since they are on different scales and have differential time-series variations.

[23] The firm characteristics include cash, leverage, net leverage, board size, board independence, CEO duality, firm age, firm size, number of business segments, and firm HHI index that are more closely investigated as determinants of firm agility in the next section. However, long-term bond ratings (which is also examined in the next section) is not included as a firm control because most pharmaceutical firms (87%) of the sample do not have long-term bond ratings.

results when the median total approval times of standard drugs is used as the alternative proxy for drug approval time. Overall, the results support the validity of $Agility$ measure in the subsample of the pharmaceutical industry.

1.4.4 Determinants of Agility

Having established that industry characteristics can shape firm agility in the previous sections, I also examine what and how firm characteristics are related to firm agility in this section. To the extent that agility measures the ability to respond to business environment changes, “flexible” firms are likely to be endowed with agility. As an illustration, Lehn (2018) proposes that decentralized firms can promote agility with their low knowledge transfer costs (i.e., costs occurred when transferring knowledge from those with relevant knowledge to those with decision rights within a firm), which are especially valuable in the periods of rapid changes in the environment. In the same vein, organizationally flexible firms, such as firms with diverse business segments, are likely to be decentralized and thus agile. On the other hand, Lehn (2018) also points out that certain governance structures such as board independence and board size can be related to agility.

In addition to Lehn (2018)’s idea that organizational or governance characteristics can be relevant with agility, I conjecture that financial flexibility and operating flexibility can also promote agility by responding in a timely manner to changes in the environment. Once the surrounding environment changes, investment opportunities or cash flows are also influenced, and financial flexibility can protect firms from those unexpected changes. For instance, financially flexible firms can modify their product market strategies (i.e., choose either product assimilation or product deviation) with their financial strength in terms of speed and cost of external financing when the degree of competitive threats in the product market increases. Also, to the extent that product assimilation or differentiation requires shifts in operation, firms with high operating flexibility can react more easily to the increased competitive threats, and therefore, likely have high agility.

In the meantime, the countervailing effect can arise when firm flexibility is a substitute for agility. For example, financially flexible firms may not behave agilely under the consideration that they can maintain their firm values with their financial flexibility when their lack of agility comes into adverse effect (e.g., decline in cash flows). Alternatively, even though financial flexibility enhances agility overall, firms in some specific spectrum of financial flexibility might have different marginal benefits of agility. It is, therefore, an empirical question whether firm flexibility always promotes agility.

In accordance with the conjectures that firm flexibility can increase agility, I specifically categorize potentially relevant firm variables into three sets (i.e., financial flexibility, governance flexibility, organizational flexibility, and operating flexibility) and examine how they are related to agility. I use various proxies for each flexibility category since flexibility is usually measured in alternative ways in the past studies:

- Financial flexibility: cash-to-asset, leverage, net leverage, long-term bond ratings
- Governance flexibility: board size, board independence, CEO duality, short-term investors (%)
- Organizational flexibility: firm age, firm size, number of business segments, firm HHI index
- Operating flexibility: capital-to-labor (K/L), CAPEX-to-asset, asset redeployability, geographic dispersion

Note that net leverage is included to isolate the effect of debt from that of cash that is commonly regarded as "negative" debt. Short-term investors (%) is defined as the proportion of shares outstanding held by transient investors and serves as a governance flexibility measure considering that firms with short-term investors may have nimble decision-making process since they cater to the investors and are pressured by exit threats of the investors (Giannetti and Yu, 2020).[24] In addition, firm HHI index (i.e., sales concentration of business segments within a firm) is included as well as the number of business segments since more diversified firms (i.e., low firm HHI index) are likely to be organizationally flexible. Capital-to-labor (K/L) ratio is defined as the logarithm of fixed capital stock (net property, plant, and equipment) per employee, which is used in Mackay and Phillips (2005) and Haushalter, Klasa, and Maxwell (2007). Firms with capital-intensive technology (i.e., high K/L) are less likely to be flexible in their operation with their high fixed capital stock and high fixed cost. On the contrary, firms with labor-intensive technology (i.e., low K/L) can operate flexibly with their high labor cost that is more variable. Similarly, firms with high tangibility (i.e., high CAPEX-to-asset ratio) may find it hard to change their current production line due to the irreversibility of investments on physical assets. Thus, high CAPEX-to-asset can lead to low operating flexibility; in the meantime, high CAPEX-to-asset ratio also relates to high asset pledgeability or redeployability, which can promote financial flexibility (Almeida and Campello, 2007). In this sense, Kim and Kung (2017)'s asset redeployability measure is also used to isolate the effect of redeployability, which facilitates product transition by enabling firms

[24] I use Bushee's classification of 13F investors (Bushee 1998, 2001; Bushee and Noe 2000) available from Professor Brian Bushee's website (https://accounting-faculty.wharton.upenn.edu/bushee/). I am grateful to Professor Brian Bushee for making this data available.

to trade their assets in the secondary market.[25] Apart from these variables related to cost or asset structure, I next focus on geographic decentralization that likely leads to operational decentralization and flexibility; Garcia and Norli (2012) introduces geographic dispersion of a firm's business operations using state counts from 10-K filings, and I define geographic dispersion as one minus geographic concentration (HHI) of business operations.[26]

[Insert Fig 3 here]

Fig 3 demonstrates the relation between each firm variable (in year t-1) and agility (in year t) through estimating local linear regressions of $Agility$ on the variable. The local linear regression is estimated with the Gaussian kernel function and Silverman rule-of-thumb bandwidth selection. Given that there is no preexisting theory about what and how firm variables shape its agility, I take advantage of this non-parametric estimation in that it does not require a functional specification.[27]

---

[25] I use Asset Redeployability measure, which is constructed upon the Bureau of Economic Analysis (BEA) capital flow, available from Professor Hyunseob Kim's website (https://blogs.cornell.edu/hyunseobkim/asset-redeployability/). Industry-adjusted Asset Redeployability is used because it has substantial variation between industries in Kim and Kung (2017). I am grateful to Professor Hyunseob Kim for providing the dataset.

[26] I use Geographic Dispersion measure available from Professor Diego Garcia's website (https://sites.google.com/site/financieru/resources/software). I am grateful to Professor Diego Garcia for making this data available.

[27] The local linear regression approach has disadvantages that it requires computational intensity and large and densely sampled data. However, the current sample alleviates the concern for being fairly large and dense, as can be seen in the scatter plots. To alleviate the disadvantage, I also report the pair-wise correlation matrix in the Appendix A as Table A3.

Besides, the countervailing effect (i.e., substitute effect) deters from specifying the functional form uniformly across the spectrum of each variable.

Regression estimates on some of the variables (long-term bond ratings, board size, board independence, CEO duality, number of segments) look unstable as they have big confidence intervals at some points, presumably because they are constructed on discrete or categorical values. Except for those variables, each firm flexibility variable shows a relation with agility as conjectured. For example, in Panel A, cash holding is positively related to agility, and the relation is pronounced at the top 20%. Net leverage is inversely related to agility even though the raw leverage variable does not show a clear relation. In the meantime, the convex relation between agility and cash holdings (or net leverage) does not support the substitute effect between financial flexibility and agility. In Panel B, board size is negatively associated with agility, and the negative association is pronounced at the top 20%, implying that a substantially large (and thus inflexible) board deteriorates firm agility. Next, Panel C shows that organizationally flexible (i.e., younger, smaller, and diversified) firms appear to have a high level of agility. Lastly, in Panel D, K/L and Capex-to-asset are inversely associated with agility as predicted. However, positive association is observed in the right-end of K/L possibly because the number of employees is very low, and hence, labor costs can be quite fixed. Also, Capex-to-asset has some positive association with agility at its right-end, reflecting the effect of asset pledgeability or redeployability.[28] The pure effect of

[28] However, I cannot rule out the possibility that the positive association might result from AT (total assets) in the denominator of CAPEX/AT, which is inversely related to agility. Likewise, the observed relations between firm flexibility measures and agility may not be mutually exclusive, and which is also consistent with that the notions of different firm flexibility can be interrelated as shown in the previous literature. (e.g., Choi, Ju, Trigeorgis, and Zhang, 2021; Lambrecht, Pawlina, and Teixeira, 2016)

asset redeployability on agility appears to be positive. In the meantime, geographic dispersion has an inversed U-shaped relation with agility possibly because a firm's extremely high geographic dispersion and large geographic footprints may involve an excessive shipping cost increase when it changes its product set.

A related question might be whether agility increases firm flexibility. If agility increases firm flexibility, given the above results that firm flexibility promotes agility, then agility will serve as a necessary and sufficient condition of firm flexibility. If this is the case, then the measured agility will be no more or less than a measure of firm flexibility, and its impacts on product market performance or firm survival likelihood can be confounded. As an illustration, if an agile firm arranges its financial structure in a way that it is more financially flexible than before, then any observable impact of agility on product market performance or survival likelihood can result from the impact of increased financial flexibility.

To check the possibilities, I also estimate local linear regressions of each firm flexibility variable (in year t+1) on $Agility$ (in year t) in the Appendix A Fig A2. The results do not show clear relations between agility and firm flexibility variables as compared to Fig 3. The only noticeable pattern is that there seems to be an upward relation between agility and leverage or long-term bond ratings in the latter half range of agility, but there is also noisy relation in the first half range of agility similar to other firm flexibility variables. Overall, the results imply that firm flexibility promotes agility, and at the same time, agility is a unique firm characteristic as being differentiated from firm flexibility variables.

1.4.5 Agility and Performance

In this section, I investigate how agility influences product market performance. Although it is convincing that firms' agility can improve their performance, it is an empirical question whether the performance improvement can last in the long run or agility can eventually increase the survival rates. For example, even if agility can enhance firm performance in the short term, the enhancement may fade away over time.

[Insert Table 8 here]

In Table 8 Column 1, $Agility$ significantly increases the market share growth in the next year where firm, industry, and year fixed effects are controlled for. In Column 2, the effect of $Agility$ on the market share growth is still significantly positive even after including various firm characteristics. In terms of economic magnitude, a one standard deviation increase in $Agility$ is associated with an 8.97 percentage points higher market share growth, relative to mean percentage of market share growth of -0.01%. In addition, the positive effect is observed for the market share growth after 3 years in Column 3. The effect of $Agility$ on the market share growth after 5 years is positive but not statistically significant in Column 4.[29] Thus, the results support the role of agility in improving product market performance, especially in the short run.

[29] The number of observations drops down to almost half in Column 4 as compared to Column 2, and which could reduce the test's power.

1.4.6 Agility and Survival

The previous section finds that agility seems to improve the product market performance in the short run (up to 3 years) but not afterward. According to the findings, agility can increase firm survival likelihood with the improved performance in the short run, but it might also take time for the performance improvement leads to higher survival likelihood ultimately. Also, it is plausible that agile firms are targeted more frequently by acquirers that seek after agility or strong product market performance of agile firms.[30] Thus, it is an empirical question whether agility increases or decreases survival likelihood.

To identify a firm's survival status, I use CRSP delist codes (CRSP DLSTCD 200 and above) and delist dates. I run logistic and linear probability regressions of firm survival status (as of year t+1, t+3, and t+5) on $High\ Agility$ (i.e., firms with the top 20% $Agility$ in each industry and year) and $Low\ Agility$ (i.e., firms with the bottom 20% $Agility$ in each industry and year) measured at year t.[31]

[Insert Table 9 here]

---

[30] However, note that it is not clear whether an agile firm being acquired is always the value-decreasing to shareholders.

[31] The coefficients of $Agility$ are not statistically significant when survival likelihood is regressed by raw $Agility$ variable, possibly because (i) there is nonlinear relation between $Agility$ and survival likelihood, (ii) the effect of $Agility$ on survival likelihood is concentrated among high $Agility$ group, or, (iii) there is an endogeneity bias within the relation between $Agility$ and survival likelihood (which is addressed in Section 4.7.)

The coefficient of $High\ Agility$ in Table 9 Column 1 is negative but not statistically significant. The coefficients in Column 2 and 3 are significantly negative, implying that firm agility increases the survival likelihood, especially in the long run. On the other hand, the coefficient of $Low\ Agility$ is insignificant in Column 1, 2, and 3. In Column 4, 5, and 6, I opt for the linear probability models in order to accommodate high-dimensional firm fixed effects. In Column 4, the coefficient of $Low\ Agility$ is statistically insignificant. However, the coefficient of $Low\ Agility$ ($High\ Agility$) is significantly positive (negative) in Column 5 (6). In terms of economic magnitude, the odds of a $High\ Agility$ firm being delisted are about 11.31% lower than that of an average firm in Column 3. Therefore, it is concluded that firms benefit from a sufficiently high level of agility with respect to survival rates, especially in the long run.

Also, Table A11 in the Appendix A reports the unconditional probabilities of delisting of $High\ Agility$ and $Low\ Agility$ firms based on the reasons for delisting. I follow the classification of delisting codes in Fama and French (2004): voluntary delisting (CRSP DLSTCD 570 and 573), involuntary delisting or delisting for cause (CRSP DLSTCD 400 or above, excluding 570 and 573), and delisting for mergers (CRSP DLSTCD 200 – 399). Failure (i.e., either voluntary, involuntary, or merger delisting) rates are greater for $Low\ Agility$ firms over time, and which is consistent with the results of Table 9. Whereas, voluntary delisting (e.g., going dark and going private without subsequent trading), which follows the considerations of mitigating agency conflicts, decreasing registration or compliance costs, or alternative sources of financing, does not show a consistent pattern between $High\ Agility$ and $Low\ Agility$ firms. On the other hand, both involuntary delisting and delisting for mergers, which are akin to bankruptcy, liquidation, failure to meet listing requirements, and distress, are more frequent among $Low\ Agility$ firms over time.

Thus, the results in the Appendix A Table A11 support the role of high level of agility in firm survival, which would otherwise have been (involuntary) firm delisting.

1.4.7 Endogeneity

The previous results show that $Agility$ increases both product market performance and survival likelihood; however, the results could be driven by the endogeneity of $Agility$. More specifically, there could be unobservable and thus omitted factors that are correlated with $Agility$ and product market performance or survival likelihood. Also, it is plausible that firms expecting good future prospects in terms of competitiveness in the product market or survival likelihood could have arranged their operation in a more agile way. To relieve those endogeneity concerns, I estimate IV estimations in the subsample of the pharmaceutical industry. In particular, I again exploit two exogenous variations induced by the FDA introduced in Section 4.3., drug approval rates and approval times, as IVs of $Agility$.

While the results in Section 4.3. show that the drug approval rates and approval times correlate with $Agility$ for the pharmaceutical firms, there is little reason to believe that they have a direct influence on the product market performance or survival likelihood other than through their association with firm's introduction of new drug products, and hence, $Agility$. However, one might argue that individual firms can affect those two variations for some reason; in fact, the Prescription Drug User Fee Act (PDUFA), which was first introduced in 1992, requires drug developers to pay user fees when they submit drug applications to the FDA. The FDA explains, "… Since the passage of PDUFA, user fees have played an important role in expediting the drug approval process". As previous studies (e.g., Vernon, Golec, Lutter, and Nardinelli, 2009; Gabay, 2018) note, the FDA used the collected fees to hire more staff and upgrade the data system to expedite the drug review process. Thus, it might be plausible that firms seeking agility paid high user fees with many applications to shorten the approval times. However, this plausible effect is unlikely to present in this paper's identification for two reasons; first, the effect is likely to be concentrated in the early years after the introduction of PDUFA in 1992, which is quite a long time (10 years) before this paper's sample period. Second, it is not clear whether a firm tries to pay high user fees where the benefit accrues to all the industry rivals as well as itself. On the other hand, drug approval rates are likely to depend on the quality of submitted drugs rather than individual firms' agility levels; firms will submit as high-quality drugs as possible regardless of their agility levels.

On the other hand, it is problematic if lobbying activities of the pharmaceutical firms influence the FDA's drug approval process. Alternatively, the lobbying activities may affect the political economy surrounding the pharmaceutical industry (e.g., election outcomes of the FDA Commissioner) that can impact the FDA's decisions. To rule out the possibility of this omitted variable problem, I include the firm-level lobbying expenditures, $Lobby\ (\$mil)$, as a control variable in the IV estimations.[32] Also, one-year lagged firm flexibility variables are used as additional instruments since $Agility$ is likely to be affected by those variables, as seen in Section 4.4.

[Insert Table 10 here]

---

[32] The firm-level lobbying expenses are available from the Center for Responsive Politics (https://www.opensecrets.org/).

Table 10 Column 1 and 2 display IV regression results confirming the positive (negative) effect of $Agility$ on product market performance (delisting likelihood). First stage regressions are qualitatively similar to regression results of Table 7 (i.e., $Agility$ is positively associated with the drug approval rates and inverse of drug approval times) with slightly different magnitudes of coefficients probably because of the additional instruments (i.e., one-year lagged firm flexibility variables) and further dropped observations, and thus, omitted in Table 10.

To enhance the external validity from the previous results, I also use difference-in-differences framework using industry-level regulation changes. Gutierrez and Philippon (2017) shows that a rise in regulation increases fixed cost component or introduces barriers to entry. Also, compliance costs increase with regulatory stringency, which are incurred when firms change their product sets or even when they try to maintain their current productions. As such, an increase in regulations can restrict firms' scope of product differentiation or assimilation, and hence, capacity to increase their agility in the industry, especially among firms with a low level of agility.

Following unexpected regulation increases, firms should depend on their pre-established agility levels to compete in the product market environment where firms' capability to increase agility is limited by exogenous regulation increases. Therefore, if agility really gives a competitive advantage, then the low agility firms, which have not reconfigured their product sets (and thus more affected by the regulation changes), should experience worse product market outcomes than the high agility firms, which already have expanded or concentrated their product sets, when there is an unexpected increase in industry regulations. Accordingly, the interaction effect between agility and regulation increases on the product market outcomes should be positive.

An advantage of this quasi-natural experiment is that different industries experience regulation jumps at different times. The staggered jumps in the regulations imply that the control group in year t contains not only industries that never face a regulation jump but also industries that have already experienced one or will experience one later on but not in year t. Therefore, the concerns that the experiment could be confounded by other unrelated, concurrent events are mitigated. Also, another advantage of this identification strategy is that a regulation increase in an industry is not perfectly foreseeable or overseen by the industry since one single industry is regulated by multiple government agencies (on average xxx agencies per industry), and regulations from one government agency apply to multiple industries (on average xxx industries per government agency). Hence, the identification is unlikely to be contaminated by the predictability or unobservable factors such as lobbying activity or political connection of firms.

Following Gutierrez and Philippon (2017) and Duan, Larkin, and Ng (2019), I use the RegData US datasets from McLaughlin (2020) to identify the industry-level regulation jumps in 1997 – 2018.[33] The RegData US provides the level of regulations ("Industry Regulation Index") applied to each NAICS industry in each year, as introduced in Al-Ubaydli and McLaughlin (2017). As regulations become more stringent over time (i.e., have time trends), I define an industry's regulation increase as a $Regulation\ Jump$ if its magnitude is three times greater than the median magnitude of the industry's regulation increases in the period in order to capture the sizeable increases in regulations. Table 10 Columns 3 and 4 report the difference-in-differences estimation results in which the interaction between $Agility$ and $Regulation\ Jump$ significantly increases the market share growth and decreases the delisting probability, respectively.

Taken together, the results of IV regression and difference-in-differences estimation relieve the concerns that the endogeneity of $Agility$ could drive the main results.

[33] The RegData US dataset is available from (https://www.quantgov.org/download-data).

1.4.8 Benefits of Agility

In this section, I investigate possible channels through which agile firms attain competitive benefits in terms of the product market performance and survival. More specifically, agile firms may be willing and able to respond more proactively when facing industry-wide common shocks relative to rigid counterparts. In order to check whether this is the case, I focus on two large and prevalent types of corporate investments: R&D and acquisitions. To the extent that the both types require time and resources until completion, agile firms may undertake investments in R&D or acquisitions more proactively to win the R&D race or competition in the takeover market. For the analysis, I construct $Industry\ M\&A\ Wave$ defined as the ratio of the transaction value for each year and industry (classified by the 3-digit SIC code) to the total assets of all Compustat firms in the same year and industry following Schlingemann, Stulz, and Walkling (2002) and Uysal (2011). Analogously, I create $Industry\ R\&D\ Intensity$ as the ratio of R&D value for each year and industry to the total assets of all Compustat firms in the same year and industry.

In addition, I examine whether agile firms can maintain their better product market performance when confronted by industry-level import tariff cuts. Tariff cuts lessen trade barrier and raise import penetration, escalating pressures from foreign rivals (Bernard, Jensen, and Schott, 2006). Given that agile firms, by definition, respond intensively to encroachment of their domestic rivals (as measured by $External\ Fluidity$), it is likely that they are also responsive to challenges from foreign rivals (as measured by $Tariff\ Cut$), and hence, have better product market performance than rigid firms. I follow the procedures in the previous literature (e.g., Valta, 2012; Xu, 2012) to identify the major tariff cuts at the SIC 3-digit level. For each industry-year, I first calculate the tariff rate as the ratio of duties collected from the industry's imports to the dutiable value of imports.[34] Next, to identify meaningful changes in trade barrier, I classify a negative tariff change as a $Tariff\ Cut$ if its size is 3 times greater than the median magnitude of the industry's negative tariff changes. Also, following Frésard (2010), I exclude tariff cuts that are followed by comparable positive changes (i.e., 80% of the negative tariff changes) in the next two subsequent years, or, are not preceded by tariff cuts in the past year. Also, negative tariff changes smaller than 1% are excluded from tariff cuts.

[Insert Table 11 here]

Table 11 Column 1 demonstrates that firms ramp up R&D following industry-wise intense R&D investments on average, and the sensitivity of R&D to industry-wise R&D investments increases with agility. In addition, Column 2 and 3 show that the relation holds for the next two years even though average firms do not appear to significantly increase their R&D investments. Next, Column 5 implies that firms' acquisition investments significantly increase with industry-wise M&A waves only among those with a high agility level. The coefficients of the interaction between $Agility$ and $Tariff\ Cut$ are significantly positive in Column 7, 8, and 9, indicating that the effect of agility on market share growth is magnified in the tariff cuts, and thus, trade barrier reductions.[35] The results also serve to alleviate the endogeneity concern arising between agility

[34] The import data is available from Feenstra, Romalis, and Schott (2002) and Schott (2010) and downloaded from Professor Peter Schott's website (https://sompks4.github.io/sub_data.html). I am grateful to Professor Peter Schott for making this data available.

[35] An interesting observation is that the coefficient of $Tariff\ Cut$ is either positive or insignificant. This is consistent with the empirical results in the past literature (e.g., Bernard, Jensen, and Schott, 2006; Frésard, 2010). Some firms

and market share growth by establishing difference-in-difference regressions; major tariff reductions do not reflect individual firms' policy or decision and are not completely predictable by industry or market conditions (Xu, 2012; Frésard and Valta, 2016). Therefore, the positive coefficient of the interaction between $Agility$ (measured in year t) and $Tariff\ Cut$ (measured in year t+1, t+2, and t+3) implies that the sensitivity of market share growth to agility is greater for firms that face unpredicted tariff cuts than firms that do not. Overall, a firm's agility is beneficial in strengthening its competitiveness, especially when facing industry-wide common shocks such as R&D or acquisition waves, or trade barrier reductions.[36]

1.4.9 Seeking Agility

Prior studies have established that firms attempt to acquire innovation and technology by acquiring target firms having accumulated innovation and technology (Harford, 2005; Bena and Li, 2014; Harford, 2005; Phillips and Zhdanov, 2013; Sevilir and Tian, 2012). In the same vein, rigid firms are likely to acquire agile firms to the extent that agility is a determinant of product market performance and survival rates. On the other hand, a firm, which is already agile, may have fewer incentives to acquire another agile firm.

---

will increase their domestic market share facing tariff cuts, whereas others lose their share accordingly. However, the findings do not undermine the role of agility in improving market share growth under tariff cuts in Table 10.

[36] However, the relations are not observed for CAPEX or advertisement expenses. I presume that they are less discretionary types of investments or demand less time or resources relative to R&D or acquisitions, and hence, interpret that firms do not find it much useful to increase their investments in CAPEX or advertisement rapidly even when facing industry-wide shocks of CAPEX or advertisement.

The acquisition of CELGENE CORP, which rank high in Table 5 for its agility, by BRISTOL-MYERS SQUIBB, a big player in the pharmaceutical industry, in 2019 provides an example of this. In an interview after the acquisition, Executive Vice President Christopher Boerner expressed:[37]

"The integration of Celgene makes us an even stronger combined company… This merger was the culmination of a long-term strategy at Bristol Myers Squibb to combine the reach and resources of an established pharmaceutical company with the **agility** of a biotech. The integration presented a fresh opportunity to **take some of the lessons from our new colleagues about simplifying how we operate and moving with greater speed**, and marry them with the scale, resources and centralized capabilities that existed at Bristol Myers Squibb."[38]

In order to examine the possibilities within the sample, I observe acquisition attempts of each sample firm (in year t) up to five years (i.e., year t+1, t+2,…, t+5). More specifically, the latest acquisition attempt within five years is collected for each firm-year observation.[39] Within

---

[37] "Building a company for the future". https://www.bms.com/life-and-science/news-and-perspectives/building-a-company-during-pandemic-with-celgene-integration.html

[38] Even though the acquisition deal is allegedly from "seeking agility" motive according to the interview, it could be the case that it was from another motive, for example, "killer acquisition" (Cunningham, Ederer, and Ma, 2021). More specifically, BRISTOL-MYERS SQUIBB might have acquired CELGENE CORP to interrupt innovation and preempt future competition given that CELGENE CORP was active in both its own innovation and licensing deals with other drug-makers. However, the assessment of these other motivations is beyond the scope of this study.

[39] The best way for estimation might be to observe acquisition attempts of each sample firm in year t+1. However, it keeps too few observations (22 observations).

the intersection of the sample and SDC database, observations with non-missing agility values of both acquirer and target are used for the estimation.

[Insert Table 12 here]

Table 12 Column 1 exhibits that the agility of acquirers and that of targets have a negative association. In addition, under the consideration that acquirers can only observe the contemporaneous, not future, agility of target firms (i.e., 10-K business description of target firm, which is available to acquiring firm, is observable at the latest fiscal year-end of the target firm), I also run the regression of target's agility right before the deal on acquirer's agility in Column 2. The results show that the agilities of acquirer and target are negatively correlated.

Next, I investigate the dynamics of the absolute difference between acquirer's $Agility$ and target's $Agility$. More specifically, the absolute deviation of acquirer's $Agility$ in t, t+1,…, t+5 from target's $Agility$ in t is observed where t is the year when their acquisition is completed.

[Insert Fig 4 here]

In Fig 4, the mean and median of absolute $Agility$ difference are plotted across t, t+1,…, t+5. The difference continues to drop two years after the deal completion (year t+1 and t+2) and returns to the initial level afterward. The results indicate that acquirers absorb the targets' agility after deal completions even though the absorption rate gradually decreases.

1.4.10 Costs of Agility

The previous section explores how agility brings competitive benefits under industry-wide shocks, however, it does not directly assess the costs of agility. Agile firms choose either product deviation or assimilation when confronting competitive threats, and these choices entail costs. For instance, firms could pioneer new markets, innovate, and increase advertisement to differentiate their products that are encroached. Meanwhile, firms can assimilate their product sets to that of rivals by augmenting the current product lines, locking in customers, or lowering product prices. The costs of such actions should be reflected in profitability. In sum, firms can increase agility at the expense of current profitability. To identify sizeable changes in agility, I characterize $Agility\ Jump$ ($Drop$) as the positive (negative) changes in $Agility$ from the previous year that are three times greater than the median of positive (negative) changes. The medians are defined at year, industry, or industry-year level, separately.

[Insert Table 13 here]

Table 13 Column 1 reports that $Agility\ Jump$ (from t to t+1) is significantly associated with a 1.2 percentage points decrease in ROA (from t to t+1) when the median is defined at the year level. Column 2 exhibits a similar coefficient estimate of $Agility\ Jump$ when the median is defined at industry level. The results imply that sizeable increases in agility bring decreases in profitability as measured by ROA. Interestingly, Column 3 shows that $Agility\ \ Drop$ is significantly associated with 0.7 percentage points increase in ROA (when the median is defined at industry-year level), indicating that firms can increase profitability by reducing agility. In unreported results, the change in ROA from t to t+3 (or t+5) is insignificantly associated with both $Agility\ Jump$ and $Agility\ Drop$, indicating that only short-term profitability is affected by an abrupt change in agility.

The results show that firms exercise agility at the expense of concurrent profitability and explain why not all firms maintain a high level of agility despite its competitive benefits. On the other hand, there could be other aspects of costs of agility. For example, firms might be willing to bear the costs of reshaping their governance, organizational, or operational structure to secure decentralization, and hence agility. Or, they might need to rebalance capital structures or adjust cash ratios to achieve financial flexibility, which can promote agility. However, it is empirically challenging to incorporates these types of costs because it is difficult to observe their magnitudes and timing. I acknowledge these limitations of the cost analysis presented in this paper.

1.4.11 Stock Return Predictability

Failure to build up agility leads to loss in market share, and eventually, likelihood of firm discontinuation according to the previous results. Therefore, if agility is negatively associated with priced distress risk, then agile firms are expected to earn lower stock returns than rigid firms. Besides, firms that cannot maintain agility will find it difficult to deal with uncertainty which arrives randomly, such as competition or technology shocks, and hence, investors raise the required rate of return. Meanwhile, to the extent that agility carries firm innovativeness, agile firms bear innovation risk which is priced and earn higher returns.

I examine the ability of agility to predict stock returns using monthly Fama-MacBeth (1973) cross-sectional regressions with controlling for beta, size, book-to-market (Fama and French, 1992), momentum (Jegadeesh and Titman, 1993), short term reversal (Jegadeesh, 1990), illiquidity (Amihud, 2002), industry concentration (Hou and Robinson, 2006), profitability, asset growth (Cooper, Gulen, and Schill, 2008; Fama and French, 2015), and idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang, 2006) where four return holding periods are considered; 1-month, 3-month, 6-month, and annual returns.

[Insert Table 14 here]

Table 14 presents the average slope coefficients whose standard errors are Newey-West adjusted. Column 1 of Table 14 presents the average slop coefficients of -0.108, which translates into 13 basis points increase in return per month for a one standard deviation decrease in $Agility$. The results for longer holding period are consistent with the 1-month results although the magnitudes of the slopes are smaller, suggesting that the return predictability is not a short term phenomenon. Overall, the results point to the risk associated with low agility, rather than innovation risk, also implying that agility unlikely carries innovativeness.

1.4.12 Robustness & Additional Tests

1.4.12.1 Robustness: Estimation Window of Agility

$Agility$ is estimated by firm-by-firm regression of (3), which requires 5-year consecutive observations for a firm's $Agility$ value. $Agility$ has considerable time-series variation even within each firm due to the short estimation window (i.e., 5 years), and thus, one might argue that $Agility$ has a limitation in measuring true agility level if it fluctuates too much over time within a firm. Also, it is arguable that a longer estimation window can make the estimated measure more reliable. However, the estimation window could be extended but with some expenses; first, sample observations would be dropped due to the shrunken sample period. For example, a 10-year estimation window pushes the starting year of the sample period forward to 2008, which would have been 2003 for a 5-year estimation window. Second, extending the estimation window downsizes the weight on more recent observations that are critical as far as $Agility$ measures the speed of a firm's response to competitive threats it encounters.

To ensure that the main results are robust to changes in the estimation window, I also estimate $Agility$ through firm-by-firm regression of (3) with a longer estimation window of 6, 7,…, or 10 years. Table A4 in the Appendix A revisits the main regression results (i.e., Tables 8 and 9) when a 10-year estimation window is used, and it finds that the main results are robust to the change in the estimation window. The results for the estimation window of 6, 7, 8, or 9 years are also qualitatively invariant and thus not reported.

1.4.12.2 Robustness: Magnitude of Competitive Threats

A firm's $Agility$ is defined as the degree of its product assimilation or deviation relative to its rivals' products (i.e., $Internal\ Fluidity$) when the rivals' threats (i.e., $External\ Fluidity$) arise, but some threats are too small to merit any responses or even detect. In that case, the firm's $Agility$ value may inflate its actual agility level since the observed $Internal\ Fluidity$ has nothing to do with competitive threats. Or, a firm's $Agility$ value could just represent how innovative it is, not how agile it is, particularly when its $External\ Fluidity$ is too small; for instance, an innovative firm, as the first mover in the market, may change its product even though there is no encroachment from rivals, and its $Agility$ would be estimated to be very high for $Internal\ Fluidity$ being high whereas $External\ Fluidity$ being low or even close to zero. If then, the firm's $Agility$ would capture its innovativeness, not its agility. To address these potential measurement problems, I redefine $Agility$ from firm-by-firm regression of (3) where the observations are eliminated if their $External\ Fluidity$ values are in the bottom quintile of the same year. Next, the main regressions in Tables 8 and 9 are implemented by using the redefined $Agility$. The results are reported in Table A5 in the Appendix A, and they show qualitatively similar estimates to that of Tables 7 and 8. If anything, the magnitudes and significance of the coefficients of $Agility$ and $High\ Agility$ are larger than that in Tables 7 and 8.

1.4.12.3 Robustness: Falsification Tests

For more robustness of the main results, I also perform a series of falsification tests to see if the main effects are still observable when the original $Agility$ is replaced by "fictitious" $Agility$ (which is introduced in Section 3). "Fictitious" $Agility$ is created from 1,000 times of simulations as in Section 3, and each of "fictitious" $Agility$ is included artificially as the main independent variable of estimation models in Tables 8 and 9 rather than the original $Agility$ variable. I then re-estimate the falsification tests and plot a histogram of the distribution of coefficient estimates for "fictitious" $Agility$. A dashed vertical line is also drawn to represent the true estimates in Tables 8 and 9. If the main effects were just coincidental outcome, then we would expect to see a distribution where similar coefficient estimates as in Tables 8 and 9 were observed in sufficiently many simulations.

Appendix A Figure A3 shows the resulting histograms that are all centered around zero, implying that the main effects are absent when "fictitious" $Agility$ is used. In addition, it supports that the positive effects of $Agility$ on product market performance and survival probabilities are unlikely driven randomly.

1.4.12.4 Robustness: Reporting Quality of 10-K Filings

Even though Item 101 in Regulation S-K requires business descriptions in 10-K filings be representative and accurate, firms might omit their product information in the business descriptions intentionally or unintentionally. In any event, their business descriptions would not be reliable sources for the measures $Internal\ Fluidity$, $External\ Fluidity$, and hence $Agility$.

Previous literature (e.g., Verrecchia, 1983; Maksimovic and Pchler, 2001) suggests that disclosing proprietary information to product market competitors can decrease a firm's competitive advantage. Verrecchia and Weber (2006) and Boone, Floros, and Johnson (2016) show that firms redact proprietary information by receiving permission for confidential treatments from the SEC, especially among young and small firms. On the other hand, large firms with diverse products may omit information of their products unintentionally due to the complexity of their product portfolios, or at least some changes in their products could be less noticeable within their large product sets. Taken together, these possibilities would lead to business descriptions for these firms that are less informative, and thus, their measured $Agility$ less accurate.

To minimize these possibilities, I first exclude firms that are younger than 5 years old or appear in the sample for the first time. Columns 1 through 6 of Table A6 in the Appendix A confirm the results of Tables 8 and 9 even after excluding these young firms. Next, Columns 7 through 12 again show consistent results with Tables 8 and 9 when firms whose size is in top 20% of the sample are excluded.

1.4.12.5 Product Differentiation vs. Assimilation

Given that the sensitivity of product differentiation or assimilation to competitive threats (i.e., agility) brings better product market outcomes, it is also worth investigating whether differentiation or assimilation is more effective in inducing better outcomes. For this purpose, I contrast outcomes between assimilators (i.e., firms with positive $\beta_{i,t}$s in Equation (3)) and differentiators (i.e., firms with negative $\beta_{i,t}$s in Equation (3)) by defining the following variables:

$$Agility_{it,+} = \begin{cases} Agility_{it} & if\ \beta_{i,t} > 0 \\ 0 & otherwise \end{cases}$$

$$Agility_{it,-} = \begin{cases} Agility_{it} & if\ \beta_{i,t} < 0 \\ 0 & otherwise \end{cases}$$

In this way, the coefficient of $Agility_{it,+}$ ($Agility_{it,-}$) represents the effect of agility on product market outcomes among assimilators (differentiators) while satisfying $Agility_{it} = Agility_{it,+} + Agility_{it,-}$.[40]

Table A7 in the Appendix A shows that $Agility_{+}$ and $High\,Agility_{+}$ have significantly positive effects on product market performance and survival likelihood, whereas $Agility_{-}$ and $High\,Agility_{-}$ do not, implying that product assimilation rather than differentiation is likely to bring better product market outcomes. However, in every column of Table A7, the coefficients of $Agility_{+}$ ($High\,Agility_{+}$) and $Agility_{-}$ ($High\,Agility_{-}$) have the same sign as $Agility$ ($High\,Agility$), and thus, it is potentially possible that $Agility_{-}$ or $High\,Agility_{-}$ can have some significant effects with increased power of tests from, for example, extended sample period. More specifically, it is plausible that product differentiation takes longer time to take effect compared to product assimilation. On the other hand, product assimilation appears ex-post optimal in the results, but it is not clear which strategy is ex-ante more optimal.

---

[40] $High\,Agility_{it,+}$ and $High\,Agility_{it,-}$ are defined in a similar way. However, $Low\,Agility_{it,+}$ and $Low\,Agility_{it,-}$ are redundant since $Low\,Agility$ group firms already have $Agility$ values close to zero (i.e., β_{it}s are close to zero).

1.4.12.6 Quasi-agility

A firm's $Agility$ is measured as the change of its product set relative to rivals' products under their threats, however, the change of its products could be centered around its own products in the past. More specifically, a firm's product set might either converge to or diverge from its past product set rather than rivals' past product set. However, to the extent that the responsiveness relative to rivals' products is more effective in resolving competitive threats, the responsiveness relative to its own products would bring lower improvement in product market outcomes. To explore this, I replace $(W_{it+1} - W_{it}) \cdot D_t$ (i.e., $Internal\ Fluidity$) by $(W_{it+1} - W_{it}) \cdot W_{it}$ in firm-by-firm regression of (3) to define $Quasi\text{-}agility$. Column 1 through 3 in Panel A and B of the Appendix A Table A8 show that $Quasi\text{-}agility$ increases market share growth and survival likelihood. However, the coefficients of $Quasi\text{-}agility$ lose significance when $Agility$ is included in Column 4 through 6 in Panel A and B, implying that a firm's product responsiveness that centers on rivals' products rather than its own products is more beneficial in the adverse shift of competitive landscape.

1.4.12.7 Residual Agility

Is agility a mere composite of various dimensions of firm flexibility? Even though the local linear regression results in Fig 3 and the Appendix A Fig A2 show that agility is not a necessary and sufficient condition of each dimension of firm flexibility, those firm flexibility measures might together constitute agility. It could be the case, then, that the previous results are accounted for by the effect of firm flexibility, not agility, on the product market outcomes. To examine this possibility, I run regression of $Agility$ in t on firm flexibility measures from each flexibility category in t-1 that are most significant in the local linear regression results in Fig 3 (i.e., $Net\ Leverage$ from financial flexibility, $Board\ Size$ from governance flexibility, $Firm\ Size$ from organizational flexibility, $CAPEX/AT$ from operating flexibility) in each industry. As a result, $Residual\ Agility$, the residual from the regression, is orthogonal to those flexibility variables, and can be interpreted as the component of $Agility$ not explained by firm flexibility.

Next, the main regressions in Tables 8 and 9 are implemented by using $Residual\ Agility$. The results are reported in Table A9 in the Appendix A, and they show qualitatively similar estimates to that of Tables 8 and 9. Also, the results remain unchanged when predicted value of $Agility$ is additionally included in the unreported regressions, and which implies that the unexplained component of $Agility$ serves as a more significant role in product market outcomes. In addition, $Residual\ Agility$, which is obtained from the regression of $Agility$ in t on the contemporaneous firm flexibility variables in t (not t-1), presents similar coefficient estimates. The results indicate that even agility of firms, which arrange their firm structure in a way such that both firm flexibility and agility are enhanced simultaneously, improves product market performance.

1.4.12.8 Manufacturing Industry

Corporate agility can be more relevant for manufacturing firms than firms in other industries such as public services or construction industry. In the meantime, the previous results in Table 6 show that manufacturing firms have dispersion in agility, implying that the benefits from agility can vary even within the industry. More specifically, low-Q manufacturing industries (SIC 2-digit 27, 30, 32, 33, 34, 35, 37, 38) appear to have low level of agility presumably because they benefit less from agility than high-Q manufacturing industries. Table A10 in the Appendix A explores these possibilities.

Panel A reports coefficients of $Agility$, $High\ Agility$, and $Low\ Agility$ that are more statistically and economically significant than in Tables 8 and 9. The results indicate that manufacturing firms can enjoy more benefit from high agility than other industry firms. In the meantime, the results in Panel B imply that the benefit is less realized for low-Q manufacturing firms.

1.4.12.9 Product Homogeneity

Product assimilation or differentiation may not be an effective response to the rivals' competitive threats for industries producing homogeneous goods compared to those not. Product assimilation may be less effective in homogeneous goods industries where the ability of price discrimination is limited due to regulations (e.g., Robinson-Patman Act in 1936) or industry-wide conditions (e.g., price fixing) (Hay and Kelley, 1974). On the other hand, product differentiation can be less effective in homogeneous goods industries because pioneering new markets and customers is challenging. In this sense, the virtue of agility might not be much realized in the homogeneous goods industries.

I use the product classification from Rauch (1999), where products at 4-digit Standard International Trade Classification (SITC) level are categorized into three subsets: those traded on organized exchanges, those which are reference-priced, and differentiated goods. Following the literature, I group the first two categories into homogeneous goods and compare the effects of

$Agility$ on product market outcomes between industries producing homogenous goods and those producing differentiated goods.[41]

Panel A of Table A12 demonstrates the positive effects of $Agility$ on product market outcomes for industries producing differentiated goods, consistent with Tables 8 and 9. However, the pattern is not observed for industries producing homogeneous goods in Panel B. If anything, Column 6 of Panel B shows that $Low\ Agility$ firms have a lower likelihood of delisting, indicating that firms irresponsive to competitive threats rather have a higher likelihood of survival in homogeneous goods industries.

1.5 Conclusion

This paper studies how corporate agility affects product market performance and firm survival rates. Motivated by the research of Alchian (1950) and Lehn (2018) on corporate agility, this paper introduces a novel measure of agility derived from business descriptions in firms' SEC 10-K filings. I analyze the characteristics and diagnostics of the newly constructed measure of agility to affirm its validity. I establish internal fluidity (i.e., the degree of product assimilation) has a negative sensitivity to external fluidity (i.e., the degree of rivals' threats) and the sensitivity depends on a firm's status or industry conditions. Thereby, I confirm that firms either increase or decrease their internal fluidity when external fluidity changes and define agility as the (absolute

[41] Each 4-digit SITC is matched with 4-digit U.S. SIC code using the concordance table from Tang (2012). I use "liberal" classification from Rauch (1999), however, the results are invariant when "conservative" classification is used. I am grateful to Professors James Rauch and Heiwai Tang for making this data available.

value of) sensitivity of internal fluidity to external fluidity. Also, the agility measure is stable in that it does not vary much with different permutations of input parameters (i.e., common word threshold, local vs. main dictionary, etc.). Additionally, the measure is fairly persistent over time within the same firm. Lastly, I find that two industrywide exogenous shocks in the pharmaceutical industry (i.e., new drug approval time and approval rates) are associated with the agility measure further validating the measure as a proxy for the true level of agility.

I observe that firm flexibility (i.e., financial flexibility, governance flexibility, organizational flexibility, operating flexibility) promotes firm agility but not vice versa. These results suggest that agility is a unique firm characteristic distinct from other firm flexibility variables used in prior literature. Also, I find evidence that agility significantly increases market share growth, especially in the short run. In the long run, greater firm agility increases the survival likelihood (i.e., decreases the probability of delisting).

Further, the results show that agile firms ramp up R&D investments (acquisition investments) following industry-wide R&D (M&A) waves more intensively than rigid firms. The results also suggest that agile firms have better product market performance than rigid firms when facing industry-level tariff reductions. In addition, acquirers' agility measures and targets' agility measures are generally negatively correlated implying that firms potentially seek to increase agility via acquisitions. On the other hand, firms increase agility at the expense of short-term profitability.

Lastly, I find that agility is a negative predictor of future returns even after controlling for other firm risk and characteristics in the Fama-MacBeth (1973) cross-sectional regressions. The results indicate that firms that fail to build up agility involve priced risk.

One limitation of this study is that the measurement of agility depends on the product market space (due to observability and definability) and may not capture agility that would otherwise have been observed in other types of business environmental changes such as consumer demand changes, technological changes, social norm changes, or legal environment changes. However, I believe this paper's approach can be extended to these specific changes; for example, a financial institution's agility might be measurable as the degree of changes in its financial products (or portfolio) as a response to the increased similarity of rival institutions' products (or portfolio). If then, the financial institution's agility might bear the same relationship to performance in the financial market as this study's agility does to performance in the product market. Also, the degree of product changes in pharmaceutical firms (e.g., vaccine developments) in the pre- and post-COVID 19 pandemic period may allow a more meticulous investigation of corporate agility.

In sum, this paper introduces a new measure of corporate agility and examines how it affects firm performance and survival likelihood, which has not been deeply studied in the literature. Thus, my paper contributes to a better understanding of this very important topic.

2.0 Second Essay: Is Innovation Always Beneficial? Externalities of Innovation on Product Market Relationship

2.1 Introduction

Technology innovation has been regarded as an important corporate investment decision and outcome (e.g., Schumpeter, 1911; Solow, 1957; Hall et al., 2009; Hsu et al., 2015). While previous studies highlight the role of innovation in firm productivity, growth and survival, a firm's innovation also can affect the other stakeholders as well as the firm itself and its security holders. In other words, stakeholders, such as its supplier, customer, competitor, employee, and even government, can be affected through their economic relationship with the innovative firm even if they don't have direct monetary stake in the innovative firm. While the innovation literature mostly focuses on the spillover effect of innovation on customer or supplier firm, the literature has so far paid little attention to how innovation shapes the dynamics between customer and supplier. [42] This paper helps bridge that gap by investigating how a firm's innovation affects the relationship with its customer or supplier firm as the innovation changes its bargaining power.

---

[42] For example, one source of such externality takes place in the technology dimension. More specifically, Hsu (2011) finds that firms can save innovation costs by taking advantage of innovation made by their competitors or geographically close firms. Bloom et al. (2013) investigates a positive effect from knowledge spillovers and negative business stealing effects from rival firms. Li (2018) finds that supplier experience improved performance from its customer innovation and emphasizes the positive externality of innovation. Whereas, this paper focuses on the negative externality from the innovator's bargaining power.

The relationship between Apple and Samsung illustrates how innovation of one party is critical to its counterparty in the trade relationship. With its advanced screen technology, Samsung has been the major supplier of Apple and now Apple relies heavily on the OLED screens supplied by Samsung because the supplier has a technological merit that it is the only supplier which can mass-produce OLED screens.[43] The growing dependence of Apple on Samsung implies its weak bargaining power against Samsung, for instance, over its pricing on OLED screens (in fact, this component is said to be one reason why iPhone X has a steep price tag). Samsung could charge the price of its OLED at least to the price of OLED from alternative suppliers. Also, we would expect Apple to be granted less trade credit or allowed for shorter payment delay by Samsung due to its stronger dependence on Samsung than before.

The changed dynamics stemming from one party's innovation can show up in various ways; for instance, trade credit (or payment delay), cash before delivery (or advanced payment), delivery delay, pricing on traded product, length of customer-supplier trade relationship, or long-term supply contract can appear or be affected as relative bargaining power between two firms changes. In this paper, I specifically focus on trade credit for the following reasons. To the extent that trade credit proxies for relative bargaining power as documented in the literature, it can also be a good measure for identification process of this paper. Also, given that contract-level variables (such as product price or contract terms) are not observable, trade credit, which is observable in annual filings, can be the important measures of bargaining power. Additionally, as the importance

[43] In fact, the market demand of iPhone XR (a more budget friendly version in the iPhone X lineup) fell short of expectations, and which is allegedly due to the lower quality of display (LCD screen) and camera compared to the previous iPhone X lineup (X and XS). As a result, Apple is looking to drop LCD screens from its iPhone lineup (starting with the 2020 iPhone) and switching to OLED screens.

of trade credit in the balance sheet of US firms grows, investigation of determinants which potentially influence the trade credit policy is interesting in its own right. [44]

On this ground, I investigate how a firm's innovation affects the trade credit provision of its supplier. [45] First, customer's more active innovation can generate higher degree of appropriation of quasi-rent and lead to more extension of trade credit from supplier ("holdup channel"). The innovation can generate completely new technology and products which enable the innovator to switch to another trade relationship and end up terminating the current relationship. [46] Meanwhile, note that this quasi-rent is not necessarily identical to the monopoly rent as explained in Klein et al. (1978). Going back to Apple and Samsung case, Apple cannot give up OLED-screen iPhones since the next best use of the devices (before installing screens) is only through equipping the devices with LCD screens, and which couldn't satisfy consumers just as turned out in the poor sales record of iPhone XR. Thus, we can say that Apple's assets (i.e., iPhone devices) are specialized to Samsung's product (i.e., OLED screen). Also, there is no market closure or restriction on other screen makers in the OLED screen market. Even if free and open

[44] Freeman (2020) documents that trade credit constitutes 73% of short-term liabilities among Compustat firms as of 2016.

[45] In this paper, I only focus on the innovation from the customer side because the Compustat segment file provides important customers of each supplier (i.e., customers comprising 10% or more of each supplier's total sales). Hence, the data only identifies whether a firm is an important customer of a firm, but not whether a firm is an important supplier of a firm.

[46] However, it is not clear whether it is supplier or customer that leads to the decision of increased trade credit; customer firm may demand more trade credit with its strengthened bargaining power, but it is also possible that supplier may voluntarily offer more trade credit. Even if it is the decision of supplier side, the explanation is still consistent with the holdup hypothesis. Unfortunately, the decision process is not observable even in the 10-K filings.

competition for entry is possible, other screen suppliers cannot just catch up Samsung's technology because it is too costly for them.[47] In other words, their lack of innovation enables Samsung to be the major supplier of Apple. Even if the example demonstrates the holdup of Apple ("customer") by Samsung ("innovative supplier"), the inverse relation (i.e., holdup of supplier by innovative customer) is also applicable.

To the extent that the customer innovation creates holdup problem, the effect should be more pronounced for suppliers with higher asset specificity (i.e., more relationship-specific investments) compared to those with lower asset specificity (i.e., less relationship-specific investments). This is because, as Klein et al. (1978) claims, specialized assets create quasi-rents that are appropriable by counterparties due to their low salvage value.

On the other hand, it is also possible that supplier is able to extend more trade credit with increased demand from customer ("demand channel"). Customer's innovation can lead to more active transactions with its supplier and thus more solid trade relationship between them if the innovation increases customer's demand for input products and/or decreases supplier's cost when supplier has a fixed cost of production. Accordingly, the supplier might be willing to extend more trade credit to customer. If then, supplier's provision of trade credit increases mechanically after customer's innovation, and which has nothing to do with the change in relative bargaining power supported by the holdup channel. If this channel is at work, then we should expect that the

[47] In fact, Apple is collaborating with LG Display as another supplier to break its reliance on Samsung, but this strategy is not going as planned due to technological limitations. Apple needs smaller, power-efficient displays, which require a different manufacturing process from the one LG uses to create its larger OLED panels.

supplier's sales to the customer or the customer's cost of goods sold increases after customer's innovation.

Another possibility arises from the monetary innovation cost of customer; after innovation, the customer might ask more trade credit to cover its innovation cost ("financing channel"). If the customer lacks liquidity and cannot pay its supplier in full before it recoups the innovation cost from its final sales, then it might request more trade credit. This channel is accounted for by the change in the liquidity, not change in the bargaining power, from the innovation. If this channel holds, then we should observe that the supplier extends even more trade credit to innovative customer which is more credit- or cash-constrained.

My approach to this study is as follows. I first document descriptive statistics on the sample to how customer and supplier in the sample differ in firm characteristics dimensions. Also, using a firm's patenting activity as the proxy for its innovation level, I report how suppliers whose customer has no innovation activity and those whose customer has positive innovation activity differ. As for the main results, I find that supplier extends more trade credit 1, 2, and 3 years after its customer increases innovation activity and the effect is both statistically and economically significant. Since industry-specific market condition can shape the trade credit, I perform a battery of additional tests using different combination of fixed effects, such as supplier industry-year fixed effect. Next, because the possible channels (i.e., holdup, demand, and financing channel) predict the same outcome and are not mutually exclusive, I examine which mechanism drives the result using cross-sectional heterogeneity tests. Given that the impact of customer innovation on supplier's trade credit is stronger when the supplier's asset specificity is high, it is likely that holdup problem between customer and supplier drives the main effect. Whereas, I do not observe any results which are implied by the demand and financing channel.

A potential concern with the main results is that a supplier may motivate its customer to increase innovation activity with its ability to provide a large amount of trade credit. Alternatively, a supplier being capable of extending much trade credit could attract innovative customers in the first place. Another concern is that customer innovation could be correlated with unobservable confounding factors such as product market or political conditions that affect supplier's trade credit decision. To further limit the potential effect of endogeneity, I conduct two-stage least squares (2SLS) regression with two instrumental variables (IVs) following Hsu et al (2015). More specifically, I use average R&D expenditures per patent and average duration from application filing to issue or grant of patent in customer's industry level as the two IVs. Because these two measures proxy for monetary cost and time cost of innovation at customer's industry level, respectively, they should affect customer's incentive to innovate but are unlikely to be related to supplier's trade credit policy. The 2SLS test confirms that the observed main effects are not driven by potential endogeneity.

Next question I address is whether the technological class of customer's innovation affects the positive sensitivity of supplier's trade credit provision to customer's innovation. If the customer's innovation is closely related to the supplier's existing product technology, and hence, is likely to be relationship-specific, then it should mitigate the holdup problem. Consistent with this prediction, I find that the positive sensitivity of supplier's trade credit to customer innovation decreases when customer's new patent cites supplier's existing patent, or, customer's new patent class overlaps with existing patent classes of supplier. On the other hand, it is not observed that the sensitivity changes when customer's patent cites its own existing patents, or, its patent class overlaps with its original patent classes. Again, these results are consistent with the holdup channel. In addition, the results highlight the difference between "product innovation" and “process innovation”. The innovation literature (Levin and Reiss, 1988; Cohen and Klepper, 1996; Lin and Saggi, 2002; Lin, 2009) classifies corporate innovation into two types: innovation to generate new product (i.e., product innovation) and innovation to increase the productivity of existing assets (i.e., process innovation). Customer’s product innovation can give the customer the opportunity to switch to another supplier and increase its bargaining power against its original supplier. To the extent that deviation of customer’s technology space from that of supplier is interpreted as customer’s making product innovation, the result implies that product innovation can cause holdup problem. In the meantime, it is not clear whether customer’s process innovation increases or decreases its bargaining power. On one hand, customer, for instance, can develop a new product with its extra resources attained additionally from its process innovation. In turn, the customer will be able to hold up its supplier with the new product. On the other hand, it is also possible that customer’s process innovation increases its production efficiency and lowers its production costs where the extra surplus can be appropriated by its supplier. To the extent that the overlapping between new technology space and original technology space within a firm implies process innovation, the results indicate that process innovation neither increases nor decreases bargaining power.

Next, I explore how customer innovation shapes financial and investment decision of supplier. A supplier, when faced with holdup by its customer, might change its financial and investment policy to protect itself from the holdup. The supplier might need to maintain conservative policies to cover the increased trade credit provision, cover the cost of searching new customer, build a new factory line for self-production of final product, prepare the cost of vertical acquisition of the customer, and so on. At the same time, it can increase its own innovative activity to increase bargaining power against its customer. It may also learn from customer’s innovation for the purpose of providing input products customized for customer's new product, and thus, preventing the customer from switching to another supplier. In fact, the result shows that suppliers seem to adopt more conservative financial policy through holding higher cash holdings and lessening payout when customers innovate. At the same time, suppliers increase their own innovation activities after their customers innovate. Moreover, their patents cite patents of their customers more frequently, that is, they learn from customers' innovation.[48] This analysis implies that customer innovation influences supplier's internal policy as well as its policy in the dimension of interfirm relationship (i.e., trade credit policy).

This paper contributes to the literature in three ways. First, my study emphasizes the negative externality of innovation, which has not been much documented in the innovation literature. Some studies (e.g., Hall et al (2010)) note that a firm's innovation can affect the productivity of other firms within the same industry, or, even other firms in distant regions. In this paper, I focus on the impact of innovation along the supply chain. Li (2018) finds that customer innovation increases the profitability of its supplier through the knowledge diffusion channel and demand channel. On the contrary, this paper emphasizes that customer innovation can cause negative externalities on supplier through the holdup channel. Also, this paper is related to the product market literature which investigates the externalities along the supply chain. It documents that customer-supplier relationship is influenced by various dimensions of counterparty risk:

[48] In an untabulated logistic regression, it is not more likely for customer-supplier relationship to be terminated after customer innovation. In fact, only 15 customer-supplier pairs out of 13,093 pairs execute vertical integrations in my sample. Thus, it is plausible that suppliers try to maintain their trade relationship with customers even after customer innovation (which potentially results in holdup problem) by adopting conservative financial policy and customizing their innovation for customers.

downstream merger activities (Fee and Thomas, 2004), bankruptcy risk (Hertzel et al., 2008), takeover risk (Cen et al., 2016), and so on. This paper argues that customer-supplier relationship, as measured by trade credit, is affected by counterparty's innovation. Lastly, this paper explains post-contractual opportunistic behavior, which is emphasized in the transaction cost theory literature (Klein et al., 1978; Williamson, 1979; Rhodes-Kropf and Robinson, 2008), especially after innovation.

2.2 Data Description

The data for customer-supplier relationship is obtained from Compustat which is collected for Cohen and Frazzini (2008). It is based on Compustat Segment file and uses a phonetic matching algorithm to match customer names with their PERMNOs. The data for patenting activity is collected for Kogan et al (2017) and is based on Google Patents Data[49]. It has an advantage that it includes more detailed information about patent (e.g., patent class code, citation information) relative to the US Patent Office (USPTO) data. I first define *Principal Customer* as the customer which takes the largest sales portion of each supplier in each year to construct customer-supplier pairs.[50] Next, I merge the customer-supplier data with the patent data at the *Principal Customer*

[49] The patent data is provided on Noah Stoffman's website. The website address is https://kelley.iu.edu/nstoffma/

[50] I focus only on principal customers because they are likely to be most influential in supplier's corporate policy (e.g., trade credit provision) among all customers with their greatest sales portion. Also, SFAS No. 14 requires suppliers report customers which take at least 10% of total sales, and thus, I exclude customers other than principal customers to minimize the selection bias.

level. Observations are treated as zero patents when patent information is missing. The database of Cohen and Frazzini (2008) covers the period from 1980 to 2011, and, the patent data of Kogan et al (2017) has the period from 1926 to 2010. Thus, my sample period spans from 1980 to 2010 and my sample consists of 39,003 customer-supplier-year observations (13,093 customer-supplier pairs).

The main dependent variable, *Trade Credit*, is the proportion of supplier's trade receivable attributable to its Principal Customer and is calculated as

$$Trade\ Credit_t = \frac{Trade\ Receivable_t \times \frac{Sales\ to\ Principal\ Customer_t}{Total\ Sales_t}}{Total\ Assets_t}$$

The main independent variable, *Customer Innovation*, is measured by Principal Customer's patenting activities and is calculated as

$$Customer\ Innovation_t = log\ (1 + The\ Number\ of\ Patents\ of\ Principal\ Customer_t)$$

[Insert Table 15 here]

Table 15 shows summary statistics for my sample. Customer and supplier firms are different in various dimensions as documented in Panel A. For example, customer firms are larger in size, more profitable (i.e., higher ROA), and hold less cash balances. In Panel B, suppliers with positive customer innovation are larger, less levered, and hold more cash than those with zero customer innovation. Also, suppliers undertake more R&D and make more innovation when they have customers with positive innovation. On the other hand, suppliers extend more trade credit when customers have positive innovative activities, but the difference is not significant.

2.3 Empirical Results

In this section, I perform various regression tests to analyze the hypotheses explained in Section 1.

2.3.1 Base Line Results: Customer Innovation and Supplier's Trade Credit

In this section, I test whether supplier extends more trade credit after customer innovation using panel OLS regressions. The regression models include $Customer\ Innovation$ (the main independent variable) and several supplier firm characteristics such as size, MTB, and ROA measured at year t. Also, the models contain year fixed effects and supplier-industry fixed effects (3-digit SIC code) to control for economic conditions. The dependent variable, $Trade\ Credit$, allows time lags of 1 to 3 years since it might take time for customer innovation to take effect along supply chain. In addition, all models control for serial correlation by clustering the standard errors at customer-supplier pair level.

[Insert Table 16 here]

Table 16 exhibits that customer innovation induces more trade credit provided by supplier. The coefficients of $Customer\ Innovation$ are both statistically and economically significant in all specifications. For example, a one standard deviation increase in $Customer\ Innovation$ leads to 0.319 percentage points increase in $Trade\ Credit$ after 3 years. Given that the dependent variable $Trade\ Credit$ is scaled by supplier's total assets, the effect size is substantial.

[Insert Table 17 here]

Further, to rule out the possibility that industry-specific market condition can be correlated with both customer innovation and supplier trade credit, I perform a battery of additional tests using different combination of fixed effects such as supplier's industry-year fixed effects and customer's industry-year fixed effects. In all specifications, the coefficients of $Customer\ Innovation$ is statistically significant at a 1% level. Therefore, the result implies that the baseline effect is robust after controlling for time-varying customer or supplier industry effects.

2.3.2 Mechanisms

In Section 3.1., I observe that supplier provides more trade credit after customer innovates. Since the possible channels (i.e., holdup, demand, and financing channel) predict the same outcome and are not mutually exclusive, I examine which mechanism drives the result using cross-sectional heterogeneity tests.

2.3.2.1 Holdup Channel

According to the holdup channel, customer's more active innovation can generate higher degree of appropriation of quasi-rent and lead to more extension of trade credit from supplier. Customer innovation can generate completely new technology and products which enable the customer to switch to another supplier and end up terminating the current relationship.

Klein et al. (1978) explains that holdup problem becomes more serious as the assets of exploited party are more relationship-specific since specialized assets create quasi-rents that are appropriable by counterparties due to their low salvage value. Thus, the holdup channel predicts that supplier with higher asset specificity extends even more trade credit when faced with customer innovation.

To measure supplier's asset specificity, I introduce four proxies of asset specificity since it is hard to observe how much firms' assets are relationship-specific individually.[51]

$$Asset\ Specificity_1 = \frac{Sales\ to\ Principal\ Customer}{Average\ Sales\ to\ all\ Customers}$$

$$Asset\ Specificity_2 = \frac{1}{log\ (1 + The\ Number\ of\ Alternative\ Customers)}$$

$$Asset\ Specificity_3 = 1 - \frac{Tangible\ Assets}{Total\ Assets}$$

$$Asset\ Specificity_4 = log\ (1 + The\ Number\ of\ Years\ of\ Trade\ Relationship\ with\ Principal\ Customer)$$

$Asset\ Specificity_1$ and $Asset\ Specificity_2$ utilize the information of customer firms of each supplier as identified in the Cohen and Frazzini (2008) data. $Asset\ Specificity_1$ measures the current sales dependence on $Principal\ Customer$ and is likely to be positively associated with the degree of specificity of supplier's assets to its $Principal\ Customer$. $Asset\ Specificity_2$ measures inverse of the number of $Alternative\ Customers$. Here, $Alternative\ Customers$ of a supplier are the customer firms which are in the same industry as $Principal\ Customer$ and whose suppliers are in the same industry as the supplier, and hence, $Alternative\ Customers$ are the firms which the supplier can potentially switch to without adjusting its current product line.

On the other hand, $Asset\ Specificity_3$ is related to intangible assets which are likely to be specific. For example, a supplier's knowledge or human capital can be already specific to current customer. The last measure, $Asset\ Specificity_4$, measures the length of trade relationship

[51] Fan (2000) focuses on a single industry ("petrochemical industry") and estimates asset specificity of a firm in the industry using its input material. However, concentrating on a single industry limits the data coverage of this paper.

with $Principal\ Customer$ in the sense that supplier's assets could have been specialized to its customer through years of trade relationship.

Using each measure of asset specificity, I first divide the sample into "High" asset specificity and "Low" asset specificity groups with its median value. I then contrast the coefficients of $Customer\ Innovation$ estimated in the two groups.

[Insert Table 18 here]

In Column 1 and 2 of Table 18, the coefficient of $Customer\ Innovation$ is statistically significant only among the high asset specificity group when $Asset\ Specificity_1$ is used. Even if Column 3, 5, and 7 show that the coefficients of $Customer\ Innovation$ are significantly positive among low asset specific group, but the magnitude is smaller than that among high asset specific group in Column 4, 6, and 8. In the meantime, note that the results in fact contradict an alternative explanation that is seemingly related to, but not perfectly in accordance with, the holdup explanation; when a supplier's customer makes innovation, it may spontaneously extend trade credit as an investment expecting some benefits, such as technological spillover, from the customer's innovation.[52] This can simultaneously occur even when the supplier faces (potential) threat from customer arising from its greater bargaining power (i.e., when the holdup problem arises), and thus, this explanation differs from the holdup mechanism. However, the results of

[52] This alternative explanation is based on the benefits which are different from the avoidance of losses from holdup problem; in other words, the benefits don't include, for instance, the continuation of the current trade relationship which is endangered under the holdup problem.

Table 18 do not support this explanation in that both high and low asset specificity groups can enjoy the same benefits according to the explanation. On the other hand, consistent with the holdup channel, Table 18's results imply that it is high asset specificity firms that can enjoy more benefit (or avoid more potential losses from the holdup problem) by extending more trade credit rather than low asset specificity firms. Overall, the results are consistent with the prediction of holdup channel that supplier with high asset specificity extends even more trade credit when faced with customer innovation than that with low asset specificity.

2.3.2.2 Demand Channel

Previous section exhibits the results which are consistent with the holdup channel, but an alternative mechanism, demand channel, might be at work. Customer innovation can lead to more active transactions with its supplier and thus more solid trade relationship between them if the innovation increases customer's demand for input products and/or decreases supplier's cost when supplier has a fixed cost of production. Accordingly, the supplier might be willing to extend more trade credit to customer. If then, supplier's provision of trade credit increases mechanically after customer's innovation, and which has nothing to do with the change in relative bargaining power supported by the holdup channel. If this hypothesis holds, then we should expect that the supplier's sales to the customer or the customer's cost of goods sold increases after customer's innovation. More specifically, I construct two customer-level variables as follows and test whether they are affected by Customer Innovation.

$$Customer\ Sales = Sales\ to\ Principal\ Customer$$

$$\frac{COGS}{TA} = \frac{Principal\ Customer's\ Cost\ of\ Goods\ Sold}{Principal\ Customer's\ Total\ Assets}$$

[Insert Table 19 here]

In the regressions, I run regressions with customer-level control variables (e.g., size, MTB, ROA) and customer industry fixed effects because the dependent variables are measured at customer-level. Also, I allow up to 3 years of time lag because the effect could show up with some time lag.

Table 19 shows that neither $Customer\,Sales$ nor $\frac{COGS}{TA}$ is influenced by $Customer\ Innovation$. The coefficients are not significantly different from zero and effect is not observed even after 3 years of time lag. In sum, the demand channel is not supported by the regression results.

2.3.2.3 Financing Channel

Prior results support the holdup channel but are inconsistent with the demand channel, and this section explores possibility of another channel: financing channel. After innovation, the customer might ask more trade credit to cover its innovation cost. If the customer lacks liquidity and cannot pay its supplier in full until it recoups the innovation cost from its final sales, then it might request more trade credit. If this hypothesis holds, then we should observe that the supplier extends even more trade credit to innovative customer which is more credit- or cash-constrained.

To test whether this hypothesis is true, I use three customer-level financial measures: cash ratio, payout, and leverage. The financing channel predicts that supplier extends even more trade credit when its customer has low cash ratio, high payouts, and/or high leverage. To check these possibilities, I run regression with interaction between $Customer\,Innovation$ and each customer-level financial measure.

[Insert Table 20 here]

In Table 20, none of the interaction variables is significantly different from zero. Thus, the results imply that the sensitivity of supplier trade credit to customer innovation doesn't vary across firms with different liquidity. Overall, the financing channel is not supported by the results.

2.3.3 Endogeneity

A potential concern with the prior result is that a supplier may motivate its customer to increase innovation activity with its ability to provide a large amount of trade credit. Alternatively, a supplier being capable of extending much trade credit could attract innovative customers. Also, it could be case that customer innovation is correlated with unobservable confounding factors such as product market conditions that affect supplier's trade credit decision. To address this potential endogeneity, I conduct 2SLS regression with two IVs following Hsu et al (2015). More specifically, I use average R&D expenditures per patent and average duration from application filing to issue or grant of patent in customer's industry-year level as the two IVs.[53] Because these two measures proxy for monetary cost and time cost of innovation at customer's industry level, respectively, they should affect customer's incentive to innovate but are unlikely to be related to supplier's trade credit policy. To check whether the baseline result is robust to endogeneity

[53] When industry-year level instruments are not available, average R&D expenditures per patent and average duration from application filing to issue or grant of patent, measured in firm level using the past three-year information, are used as the instruments.

problems, I re-estimate the OLS coefficients of Customer Innovation in Table 2 in the 2SLS regression framework.

[Insert Table 21 here]

Table 21 Column 1 reports the results of the first-stage regression.[54] Consistent with Hsu et al (2015), $Time\ Cost_{t-1}$ and $Monetary\ Cost_{t-1}$ are inversely related to $Customer\ Innovation_t$. The reported IV F-statistics, Durbin's p-value, and overidentification p-value support that the monetary and time costs of innovation are valid instruments regarding weak IV problem, exogeneity condition, and overidentification restriction problem, respectively.

Table 21 Column 2 and 3 show the insignificant coefficients of (predicted) $Customer\ Innovation_t$ possibly due to endogeneity or lowered test power from the decreased sample size, however, Column 4 shows that the positive effect of customer's innovation on trade credit extension is not driven by the endogeneity issues.

For more robustness, I also use difference-in-differences test with Wrongful Discharge Laws (WDL) as an exogenous shock to the customer's innovation activities. Acharya, Baghai, and Subramanian (2013) and Bena, Ortiz-Molina, and Simintzi (2020) show that WDLs are state-level legal changes that spur firm innovation by protecting employees against unjust dismissal. WDLs were adopted by several U.S. states since the 1970s to early 1990s, more specifically, consist of

[54] Table 7 Column 1 demonstrates the first-stage regression for the specification in Column 4 where the dependent variable is trade credit in year t+3. The first-stage regression results for Column 2 (year t+1) and 3 (year t+2) are qualitatively identical, and thus, are omitted for brevity.

"good faith exception (GF)", "implied contract exception (IC)", and "public policy exception (PP)". I exploit the staggered adoption of WDLs in the states where the customers' headquarters are located, but the suppliers' headquarters are not, to avoid any confounding effects of WDLs on trade credit decisions.[55]

[Insert Table 22 here]

Table 22 shows that customer's IC has positive impacts on trade credit even though GF and PP do not have a significant effect. The results demonstrate that WDLs, which spur customer's innovation, increase trade credit, indicating that the positive effect of customer's innovation on trade credit extension is not likely obtained from the endogeneity bias.

2.3.4 Technological Space of Customer Innovation

In this section, I examine whether the technological class of customer's innovation affects the positive sensitivity of supplier's trade credit provision to customer's innovation. If the customer's innovation is closely related to the supplier's existing product technology, and hence, is likely to be relationship-specific, then it should mitigate the holdup problem. To measure the relatedness of customer's innovation to supplier's technology, I use the citation and technology class information recorded in Kogan et al (2017)'s data. More specifically, $Cite_t$ is the indicator variable which equals to 1 if a customer's patent (issued in year t) cites any of its supplier's patent

---

[55] I follow the coding from Autor, Donohue, and Schwab (2006). I am grateful to Professor Autor for making this data available on his website.

(issued previously as of year t). $Class\ Overlap_t$ is the indicator variable which equals to 1 if technology class of customer's patent (issued in year t) overlaps with historical technology classes of supplier's patents (issued previously as of year t).

[Insert Table 23 here]

In Table 23, the interaction between $Customer\ Innovation$ and $Cite_t$ has negative associations with $Trade\ Credit$ even though it is significantly negative only in Column 1. On the other hand, the interaction between $Customer\ Innovation$ and $Class\ Overlap_t$ has negative associations with $Trade\ Credit$ in all specifications. Consistent with this prediction, I find that the positive sensitivity of supplier's trade credit to customer innovation decreases when customer's patent cites supplier's existing patent, or, customer's patent class overlaps with existing patent classes of supplier. Again, these results are consistent with the holdup channel.

[Insert Table 24 here]

On the other hand, it is not observed that the sensitivity changes when customer's patent cites its own existing patents, or, its patent class overlaps with its original patent classes. In Table 24, the interaction between $Customer\ Innovation$ and $Cite_t^{Own}$ (or $Class\ Overlap_t^{Own}$) is not significantly different from zero.

Arguably, the results in Table 23 and 24 may highlight the difference between "product innovation" and "process innovation". The innovation literature (Levin and Reiss, 1988; Cohen and Klepper, 1996; Lin and Saggi, 2002; Lin, 2009) classifies corporate innovation into two types:

innovation to generate new product (i.e., product innovation) and innovation to increase the productivity of existing assets (i.e., process innovation). Customer's product innovation can give itself the opportunity to switch to another supplier and increase its bargaining power against its original supplier. To the extent that deviation of customer's technology space from that of supplier is interpreted as customer's making product innovation, the result implies that product innovation can cause holdup problem. In the meantime, it is not clear whether customer's process innovation increases or decreases its bargaining power. On one hand, customer, for instance, can develop a new product with its extra resources attained additionally from its process innovation. In turn, the customer will be able to hold up its supplier with the new product. On the other hand, it is also possible that customer's process innovation increases its production efficiency and lowers its production costs where the extra surplus can be appropriated by its supplier. To wit, increased production efficiency can enable the supplier to hold up the customer. To the extent that the overlapping between new technology space and original technology space within a firm implies process innovation, the result indicates that the impact of customer's process innovation on its bargaining power is neutral.

2.3.5 Financial and Investment Decision of Supplier

In this section, I explore how customer innovation shapes financial and investment decision of supplier. A supplier, when faced with holdup by its customer, might change its financial and investment policy to protect itself from the holdup. The supplier might need to maintain conservative policies, for instance, to cover the increased trade credit provision, cover the cost of searching new customer, build a new factory line for self-production of final product, prepare the cost of vertical acquisition of the customer, and so on. At the same time, it can increase its own innovative activity to increase bargaining power against its customer. It may also learn from customer's innovation for the purpose of providing input products customized for customer's new product, and thus, preventing the customer from switching to another supplier.

To examine these possibilities, I test whether supplier's financial variables (i.e., cash ratio, payout, leverage) and investment variables (i.e., R&D expenditures, Supplier Innovation, Technology Spillover). $Supplier\ Innovation$ is the logarithm of 1 plus the number of patents of supplier. $Technology\ Spillover$ is defined as the logarithm of the ratio of the number of customer's past patents cited by supplier's patent at year t over the number of supplier's patent at year t.

[Insert Table 25 here]

Table 25 demonstrates that suppliers seem to adopt more conservative financial policy through holding higher cash holdings and lessening payout when customers innovate. The sensitivity of supplier's leverage to customer's innovation is not significantly different from zero. At the same time, Column 5 shows that suppliers increase their own innovation activities after their customers innovate. Moreover, Column 6 implies that their patents cite patents of their customers more frequently, that is, they learn from customers' innovation. However, the impact of customer's innovation on supplier's R&D expenditures is positive but statistically insignificant.

This analysis implies that customer innovation influences supplier's internal policy as well as its policy in the dimension of interfirm relationship (i.e., trade credit policy). [56]

2.3.6 Robustness

2.3.6.1 Measurement of Trade Credit

The previous results show that suppliers extend more trade credit to their customers where the trade credit is measured as the proportion of a supplier's trade receivable attributable to its Principal Customer and customer innovation is measured by Principal Customer's patenting activities. These measurements rely on the assumption that a supplier provides its customers with trade credit proportionate to their portions of sales. Meanwhile, Freeman (2020) explains that a supplier extends less trade credit to its customer with higher sales dependence to avoid credit concentration. Thus, this section loosens the assumption and examines whether the main results are robust.

First, I use a supplier's aggregated trade credit (i.e., total trade receivables) as the dependent variable and aggregated patenting activities of all other customers as well as Principal Customer as the independent variable. In this way, the concern of the measurement error in trade credit received by Principal Customer can be mitigated by measuring trade credit and patents in

---

[56] In an untabulated logistic regression, it is not more likely for customer-supplier relationship to be terminated after customer innovation. In fact, only 15 customer-supplier pairs out of 13,093 pairs execute vertical integrations in my sample. Thus, it is plausible that suppliers try to maintain their trade relationship with customers even after customer innovation (which potentially results in holdup problem) by adopting conservative financial policy and customizing their innovation for customers.

the aggregated level. Panel A of Appendix B Table B1 aggregate the patenting activities by counting the number of patents of all customers, and Panel B use the number of patents of all customers averaged using sales portion as the weights. The results are robust to the aggregation of trade credit and patenting activities.

Second, I focus on the suppliers whose Principal Customers are most influential customers in order to minimize any confounding effects of the other customers and their relationship with the suppliers. More specifically, the sample is restricted to the suppliers that have Principal Customer as the sole customer, or the suppliers whose Principal Customer takes more than 80% of the suppliers' sales. Panel C and D of Appendix B Table B1 report the regression results with the restricted samples, and the results are robust to these restrictions.

2.4 Conclusion

This paper investigates negative externalities of innovation along supply chain by analyzing the effect of customer innovation on supplier trade credit. Main finding of this paper is that supplier extends more trade credit after customer makes innovation, and the effect is robust after controlling for various firm characteristics and industry-specific market conditions, and, to potential endogeneity issues.

Second, I analyze three possible channels (i.e., holdup, demand, and financing channels) which can derive the main effect. My results are only consistent with the holdup channel which predicts the stronger effect size of high asset specificity group than low asset specificity group.

Next, I claim that the technological relatedness of customer's innovation to supplier's innovation downsizes the positive sensitivity of supplier's trade credit provision to customer's innovation. Also, this result highlights that product innovation causes holdup problems, whereas process innovation neither strengthens nor weakens holdup problems.

Lastly, I find that supplier adopts more conservative financial policy (i.e., higher cash holdings and less payouts) and produces more innovation by learning from customer's innovation. Thereby, I conclude that customer innovation impacts supplier's internal policy as well as its policy in the dimension of interfirm relationship (i.e., trade credit policy). However, the trade relationship per se does not appear to terminate after customer innovation.

Overall, my results propose a unique channel through which corporate innovation can influence upstream or downstream firms. While this paper emphasizes the negative externalities of innovation along supply chain, a firm's innovation can have externalities on its other stakeholders such as employee, union, and government, and which is not deeply studied in the literature. For instance, a firm's innovation might endow its management with its increased bargaining power against its employees in the midst of wage negotiation process. I believe this research contributes to a better understanding of this topic.

3.0 Third Essay: Spillover Effect of Corporate Fraud: Evidence from Financial Constraints of Intra- and Inter-Industry Firms

3.1 Introduction

"Global Crossing's sudden implosion has done more than sting shareholders, creditors and employees. It's burdened the suffering telecom industry with new worries about solvency and accounting irregularities while prompting some investors to flee the sector. "Global Crossing was a wake-up call for a lot of people that didn't realize how bad the telecom sector had become,"...."

- March 14, 2002, Simon Avery, AP Business Writer

Previous studies investigate the influence of corporate fraud on a firm in several aspects such as credibility and credit ratings. For example, Chava, Cheng, Huang, and Lobo (2010) documents that class action lawsuits increase the cost of equity capital in the plaintiff firms. Deng, Willis, and Xu (2014) finds that fraud firms face higher cost of bank debt (i.e., higher loan spread and up-front fees, and, enhanced covenants and collateral requirement). Also, frauds can negatively affect the stock prices, and which proves the negative perception of market on the firm and reputational loss after frauds. For instance, Gande and Lewis (2009) shows that corporate fraud revelation induces value decline in the fraud firms. These effects may lead to fraud firms' facing greater financial constraints than before the frauds are publicized (or they are known to capital market indirectly before announcement.) Arena and Julio (2011) finds that future litigation risk is a determinant of cash holdings and investment decisions and explains that firms with higher litigation risk give up investment and hoard cash anticipating future settlement costs. In addition, the literature includes investigation of impact of litigation risk on IPO underpricing (Lowry and Shu, 2002) and M&A behavior (Gormley and Matsa, 2009).

Another strand of literature concentrates on the externality of a firm's event or policy on other firms. Overall, the literature falls into two main categories: intra-industry or inter-industry spillover effect. The first strand of literature investigates the externality of a firm's action or behavior on the peer firms in the same industry. In fact, the intra-industry spillover or contagion effect is studied using various corporate events, such as firm bankruptcy (Lang and Stulz, 1992), dividend announcement (Firth, 1996), mergers and acquisitions (Akhigbe and Martin, 2000), stock repurchases (Massa, Zahid, and Theo, 2007). In particular, Gande and Lewis (2009) observes that peer firms experience negative stock price reactions to the announcement of lawsuits within the same industry. Similarly, Yu, Zhang, and Zheng (2015) focuses on the effect of corporate fraud of China firms and observes the negative stock price response of peer firms within the same industry when a firm's fraud is announced. Also, the paper explains that this negative spillover effect can be mitigated for peer firms with good governance. On the other hand, Arena and Julio (2011) finds that fraud of a firm increases intra-industry firms' cash holding level and interprets that increase in the likelihood of a future lawsuit, caused by announcement of the fraud, induce peer firms to hoard more cash. In the meantime, Kumar and Langberg (2009) proves by its model that inflated performance report or disclosure by a firm can result in overinvestments of competitors, and the prediction is different from the result of Arena and Julio (2011). Consistent with Kumar and Langberg (2009), Beatty, Liao, and Yu (2013) empirically investigates high-profile firms' accounting frauds and finds that peer firms' investment is greater during the fraud period compared to the pre-fraud period. Thereby, the papers confirm that frauds have spillover effect on peer firms' corporate policy as well as stock price reaction. However, to my knowledge, there is no past research about the spillover effect of corporate fraud in the perspective of financial constraints.

In addition, some studies focus on the externality which ripples through product market relationship. This inter-industry externality is studied previously; Hertzel, Li, Officer, and Rodgers (2008) studies the spillover effect of bankruptcy filings along the supply chain and finds negative stock price effects for supplier firms (but not much for customer firms). Itzkowitz (2013), on the other hand, shows that suppliers in important relationships with customers hold more cash than other suppliers and the behavior is assumed to be based on the precautionary motive of suppliers before they lose important customers. Also, there is also research about information transfer between industries. For example, Ahern and Harford (2014) investigates propagation of merger waves along the product market chain. However, I cannot find past research about inter-industry (or supply chain) spillover effect of frauds regarding financial constraints up to now.

In this paper, I investigate whether corporate frauds affect financial constraints of intra-industry peer firms, customer or supplier industry firms. Using the securities class action lawsuits listed in the Securities Class Action Clearinghouse as the fraud sample, I obtain the information of cases such as plaintiff firm name, filing date, timeline of case, settlement cost, and so on. Even though firms are exposed to other types of lawsuits such as antitrust and copyright lawsuits, securities class action lawsuit sample is a useful database for this research given that securities class action lawsuits are filed by investors who purchased or sold securities of a firm during class period. That is, investors are likely to pay attention to the securities class action lawsuits and respond to them. In addition, the database provides detailed information about cases and is publicly available at the Securities Class Action Clearinghouse website

(http://securities.stanford.edu/filings.html) at Stanford University.

Also, I utilize dollar value of production or consumption on commodities of each industry which is obtainable from the U.S. Bureau of Economic Analysis (BEA) to identify important supplier or customer industries of a fraud industry (i.e., industry in which one or more frauds arise) in product market relationship. Thereby, the top-supplier and top-customer industries of each industry are found.

Using cash flow sensitivity of investment, annual payout ratios, and Standard & Poor's debt rating as the measures of financial constraints, I investigate how each measure of intra-industry firms, top-supplier industry firms, and top-customer industry firms respond to the announcement of frauds. The literature regarding financial constraints has suggested several measures for financial constraints, but each of them is subject to measurement error problem, and, several past studies raise doubts on the validity of each measure. Hence, I use the three measures and check if results are consistent with each other.

When a fraud occurs, then intra-industry firms can take advantage of decreased competition in the product market since fraud firms may produce less or consumption on their products may become rigid, and as a result, the other firms within the same industry can gain additional market share. Then, this "competitive effect" in the product market would alleviate the financial constraints in intra-industry firms. If this competitive effect generates the positive spillover effect, then concentrated industry will experience more positive spillover in terms of financial constraints than competitive industry when a fraud occurs within industry because firms would gain more market share in concentrated industry.

Whereas, investors may suspend financing fraud firms and find another firms for alternative investments when a fraud occurs. In that case, intra-industry firms of a fraud firm can be good places to transfer the investors' money. Especially, investors with diversification purpose would try to find another firm in the same industry as the fraud firm. If then, intra-industry firms will find it easier to receive financing and their financial constraints will be mitigated. This explanation for positive intra-industry spillover is not necessarily identical to the competitive effect explanation; while the competitive effect channel demonstrates that intra-industry firms receive gains from their enhanced product market performance, this explanation explains that those firms receive reflected benefit directly from capital market when a fraud arises. Then, the next question is, do intra-industry firms receive reflected benefit evenly? If the positive spillover stems from just transfer of liquidity to peer firms in the same industry ("liquidity effect"), then those firms will receive the reflected gain evenly, or at best, more visible firms will receive relatively more gain in intra-industry. On the other hand, investors may turn their attention from fraud firms to other peer firms and this will move their money. In turn, investors, who are subject to limited attention and monitoring ability, may pay more attention to less visible firms up to then. Thus, if the positive spillover is caused by transfer of attention ("attention effect"), then less visible firms will receive more financing. As such, a firm's visibility to investors is an important factor to differentiate between the liquidity effect and attention effect, and thus, I use the number of analysts covering the firm so as to measure its visibility.

In addition, I explore one additional channel which may lead to negative intra-industry spillover outcome while the competitive effect, liquidity effect, and attention effect results in positive intra-industry spillover outcome; peer firms in the same industry would receive reassessment from investors when a fraud of a firm is publicized ("reassessment effect"). That is, if fraud occurrence seems to be an inherent problem in that industry, then investors may focus on the likelihood of governance failure in intra-industry firms which are also likely to be susceptible to weak governance and fraud. Besides, given the anecdotal evidence that corporate frauds cluster within an industry, investors would reassess them. Consequentially, peer firms' financial constraints can rise and frauds can lead to negative intra-industry spillover effect. To investigate this possibility, I utilize Sarbanes-Oxley Act (SOX) which was introduced as a reaction to big corporate frauds such as Enron and WorldCom cases. To the extent that enactment of SOX was aimed at preventing frauds, I assume that investors' concern over future governance failure in peer firms has been relieved after SOX and reassessment effect would be weakened. Hence, if the reassessment effect provides a channel of negative spillover on intra-industry firms, then negative spillover should be mitigated in post-SOX period.

Next, I explore whether frauds impact financial constraints of top customer and top supplier industry firms positively or negatively. If a fraud arises and is detected or alleged, then the fraud firm's management, operation, and production can be brought to a halt due to fraud investigation and litigation process. As a result, firms which are closely related to the fraud firm in the product market chain may need to suspend their production. Also, they will face increased uncertainty in the case that they need to replace their customer or supplier which is under fraud investigation. As a result, decline in cash flows and imposition of searching costs and contracting costs will escalate their financial frictions even though the degree of information asymmetry or moral hazard problem stays the same within them; they need to borrow more. Unfortunately, I cannot find a proper observable measure to test this hypothesis even if this mechanism can be an instant explanation of negative spillover on supplier or customer firms' financial constraints.

On the other hand, there is a more direct channel through which spillover regarding financial constraints on supplier and customer industry firms is conveyed; the idea is that, if the fraud firm is in adverse selection due to its fraud investigation, then supplier firms which have provided trade credits may find it hard to collect the trade credits at the right time. Thereby, the supplier firms will face more financial frictions than before and hence experience negative spillover outcome. On the other hand, it is not certain whether customer firms which have been provided with trade credits from the fraud firm will face negative or positive spillover effect from fraud. All else equal, customers which have depended on the fraud firm's provision of trade credits may delay their repayment if the fraud firm suspends its operation and management, and which will alleviate their financial constraints for a while. Whereas, if a large amount of settlement money is imposed on the fraud firm and it urges the customer firms to reimburse the trade credits, then the customer firms should hasten the repayment unexpectedly. Then, their financial constraints would be aggravated. Therefore, whether frauds generate different degree of spillover effects on customer firms with different usage of trade credits is an empirical question.

Aside from the above explanation which supports the negative spillover effect on customer or supplier industry firms, it is also plausible that investors transfer their attention or liquidity from the fraud industry to other industries. This channel would result in positive spillover effect on the customer or supplier industries, however, the explanation is also applicable to all other industries and the positive spillover effect would be widespread over all other industries.

3.2 Data Description

3.2.1 Fraud Data

The sample for corporate fraud is obtained from the Securities Class Action Clearinghouse website (http://securities.stanford.edu/filings.html) at Stanford University for the period 1996 to 2017 and 4,377 securities class action lawsuits are identified. Among sued firms, only firms with tickers present in the Compustat universe are left in the sample. Also, if name of a sued firm is different from that of the matched Compustat firm, then it is excluded from the fraud sample to improve the quality of matching.[57] As Dyck, Morse, and Zingales (2010) explains, the potential problem in using the securities class action data is to include frivolous cases, but not to omit critical cases. Thus, I filter out cases using the following requirements; firms with total assets less than $750 million in the last fiscal year before the filing date are excluded,[58] and, this leaves 828 cases in the fraud sample. After that, settled cases in which the settlement is at least $2 million are included[59], and, 191 cases are left in the sample eventually. In each year, fraud industry is defined as the BEA IO industry where at least one corporate fraud is detected.

3.2.2 BEA IO Data

To identify supplier and customer industry of fraud industry, I use the benchmark IO relationships provided by the BEA following Becker and Thomas (2008) and Ahern and Harford (2014). The BEA provides dollar flows between all customer industries and supplier industries according to its industry classification ("IO industry classification"). The IO tables record the dollar flows based on the data from the Economic Census and are updated every five years. Since

[57] I searched google and each firm's website manually to see if the name has changed during the sample period.

[58] As Dyck, Morse, and Zingales (2010) notes, firm size or assets may decrease after fraud is detected or revealed.

[59] According to Choi, Nelson, and Pritchard (2009), the dollar value cutoff of $2 million in settlement is likely to sort out cases which have merit.

the fraud data cover the period 1996 to 2017, I use the IO tables for 1997, 2002, and 2007.[60] In each of the three years, a table for definition of IO industries, a make table, and a use table are provided. In the table for IO industry definition, IO industry codes and their description are reported, and, related NAICS codes are also reported for every IO industry. The make table shows the dollar value of each commodity produced by supplier industries. A commodity is any good, output, or service which is produced, and, multiple industries used to produce the same commodity. Typically, a supplier industry is dominated by one type of commodity. On the other hand, the use table records the dollar value of each commodity purchased by customer industries. For consistency, I use producers' prices throughout the data work.

In order to identify the product market relationship, I follow the matrix construction process following Becker and Thomas (2008) and Ahern and Harford (2014); first, I construct an Industry-by-Commodity matrix where each component represents the percentage of each commodity that is produced by each industry (i.e., market share of each industry for a commodity). Accordingly, this matrix is calculated from the values in the make table through dividing each element of the make table by the sum of all the elements in column which it belongs to. Next, I construct an Industry-by-Industry matrix where each component shows the dollar value flowing from the customer industry to the supplier industry by multiplying the above Industry-by-Commodity matrix (i.e., market share matrix) by the use table. The row and column represent supplier industries and customer industries, respectively. Therefore, each matrix component (i, j) divided by the total values of commodities that supplier industry i produced is equal to the

[60] As of September 2017, IO table for 2007 is the most recent information available since tables are updated every five years with a five-year lag.

proportion of supplier industry i's commodity outputs purchased by customer industry j. Thereby, the customer industry with the highest proportion is defined as the top customer industry of supplier industry i. Similarly, each matrix component (i, j) divided by the total values of commodities that customer industry j purchased is equal to the proportion of customer industry j's commodity inputs that are purchased from supplier industry i. Hence, the supplier industry with the highest proportion is defined as the top supplier industry of customer industry j.[61]

The above process of defining the top customer or top supplier industries is applied to each of the IO tables in 1997, 2002, and 2007. Also, I assume that the top customer or top supplier relationship of an industry is fixed until the next IO table is updated. For instance, the relationship defined by using the 1997 IO table is assumed to hold until 2001.

Next, I classify each fraud firm into IO industry using its NAICS code and the corresponding IO industry code. Accordingly, top customer or top supplier industry is identified for a fraud firm by merging the fraud sample and the BEA IO database.

3.2.3 Compustat Firm Data

To match the sample period of the fraud data, I focus on U.S. public firms whose information is available during the period 1996 to 2017 in the Compustat universe according to their fiscal years. For each firm-year observation, necessary firm variables are constructed and the

[61] Note that some industries have themselves as the top customer (supplier) industries, and, I choose the industry with the second highest proportion as the top customer (supplier) industry in order to differentiate between the spillover effect of frauds on intra-industry and that on top customer (supplier) industry.

definition of the variables is summarized in the Appendix C.[62] In particular, long- and short-term bond ratings variables are obtained through merging the Compustat Fundamental Annuals file and Rating file provided in the WRDS. Following the convention of previous research, financial firms (SIC code 6000-6999) and utilities (SIC code 4900-4999) are excluded from the Compustat sample. In addition, firm-year observation with total assets less than 30 million dollars in 2000 dollars are deleted from the sample.[63]

Next, for each Compustat firm-year observation, occurrence of fraud within the same industry, the bottom industry, or the top industry is identified by merging the Compustat sample and fraud-BEA IO merged sample. More specifically, if a fraud occurs within the same industry, then the indicator variable $Fraud_{Within}$ is equal to 1, and 0 otherwise. Similarly, if a fraud occurs within the bottom (top) industry along product market relationship in the last fiscal year, then the indicator variable $Fraud_{Bottom}$ ($Fraud_{Top}$)is equal to 1, and 0 otherwise. In the final sample, 12.1%, 8.1%, and 5.3% of the firm-year observations experience fraud within the same industry, the bottom industry, and the top industry, respectively. Table 26 shows the summary statistics for intra-industry, top-supplier, and top-customer industry firms. Also, Table 26 presents the statistics for industries which are not classified as either of the three industries.

[Insert Table 26 here]

---

[62] In each year, all variables (except indicator variables) are winsorized at the 1st and 99th percentiles to alleviate the influence of extreme values throughout the paper.

[63] Total assets values are calculated in 2000 dollars using the CPI index data from the U.S. Bureau of Labor Statistics. The empirical results of this paper are similar even if the different cutoff values for screening total assets are used; cutoff values of 10, 15, 20, or 25 million dollars in 2000 all lead to the similar empirical results.

3.3 Empirical Results

3.3.1 Overall Spillover in Financial Constraints

This section analyzes how financial constraints of firms in intra-industry, top industry, and bottom industry respond to corporate frauds. To measure financial constraints, I utilize cash flow sensitivity of investment, annual payout ratio, long-term bond rating, and short-term bond rating. Each of these is frequently used in research of financial constraints literature, but I use all those measures since they are proxies for financial constraints which are not directly observable to econometricians.

First, Fazzari, Hubbard, and Petersen (1988) introduces the sensitivity of a firm's investment to its cash flow as a measure of financial constraints. Under frictionless capital markets, a firm's investments should be a linear function of the value of its investment opportunities and not be affected by its financial status. That is, the firm can undertake investments freely according to the value of its potential investments. However, with the existence of friction in capital markets, a firm should choose projects among its investments opportunities and its investments deviate from the first-best level. Thus, the firm can increase its investment when more financing is available or its cash flows increase. This is the notion of using cash flow sensitivity of investment for measuring financial constraints. While there are critiques of this measure,[64] previous studies such as Rauh (2006) and Almeida and Campello (2007) claim that it is a good measure of financial constraints.

Next, Fazzari, Hubbard, and Petersen (1988) finds that financially constrained firms have lower payout ratios than unconstrained firms, and thus, I employ annual payout ratios as one of the financial constraints measures in this paper. A drawback of this measure is that payout can be decided by other consideration such as signaling purpose rather than the degree of financial constraints. Also, it is widely known that firms engage in dividend smoothing and try to avoid cutting dividend. As a result, it is plausible that a firm's payout ratio is static over time even though its financial constraints vary.

Standard & Poor's rates and reports credit rating grades of firms and several studies (e.g., Gilchrist and Himmelberg, 1995; Almeida, Campello, and Weisbach, 2004; Denis and Sibilkov, 2009) classify firms into financially constrained group and unconstrained group according to their rating scores. More specifically, the studies define that firms are classified into financially constrained group if their debt rating is not available in the past (i.e., they have never been rated by S&P before) but they have outstanding debt. Availability of debt rating of a firm is quite static over time, and therefore, I use the rating score itself to observe variation in rating score which is one of the dependent variables in this paper. I implement the numerical transformation procedure of letter grade following Dimitrov, Palia, and Tang (2015) and Anderson, Mansi, and Reeb (2003).

---

[64] Past studies including Kaplan and Zingales (1997), Erickson and Whited (2000), and Alti (2003) criticizes the use of investment-cash flow sensitivity for measuring financial constraints. The studies explain that cash flows capture investment opportunities and profitability as well, and thus the sensitivity is not a perfect measure for financial constraints.

To estimate responsiveness of financial constraints when frauds occur within intra-industry, top industry, or bottom industry, I use the following specification:

$$\frac{Inv}{K} = \beta_0 + \beta_1 \cdot \frac{CF}{K} + \beta_2 \cdot Fraud_{Within} + \beta_3 \cdot \frac{CF}{K} \times Fraud_{Within} + \beta_4 \cdot Fraud_{Top} + \beta_5 \cdot \frac{CF}{K} \times Fraud_{Top} + \beta_6 \cdot Fraud_{Bottom} + \beta_7 \cdot \frac{CF}{K} \times Fraud_{Bottom} + \beta_8 \cdot X + \epsilon$$

$$Payout\ Ratio = \beta_0 + \beta_1 \cdot Fraud_{Within} + \beta_2 \cdot Fraud_{Top} + +\beta_3 \cdot Fraud_{Bottom} + \beta_4 \cdot X + \epsilon$$

$$\Delta Debt\ Rating = \beta_0 + \beta_1 \cdot Fraud_{Within} + \beta_2 \cdot Fraud_{Top} + +\beta_3 \cdot Fraud_{Bottom} + \beta_4 \cdot X + \epsilon$$

where $\frac{Inv}{K}$ is the ratio of investments over beginning-of-period capital stock and $\frac{CF}{K}$ is the ratio of cash flows over beginning-of-period capital stock. *Payout Ratio* is the ratio of total payouts (i.e., dividend plus repurchase) over total assets. *Debt Rating* is the numerical value of long- or short-term debt rating. Higher value of *Debt Rating* corresponds to lower letter rating grade and hence lower credit score by definition. In the third equation, $\Delta Debt\ Rating$ (i.e., change in *Debt Rating* from last fiscal year) is used as the dependent variable. *X* is the vector of firm control variables including Market-to-book ratio, leverage, ROA, and so on. The control variables are obtained from firm information in the last fiscal year. I also include firm fixed effects to control for time-invariant component of financial constraints which are not captured by firm variables in X. Year dummies are included as well to control for U.S. economic condition.

Table 27 presents the estimates for the above specifications. Column (1) and (2) represent the OLS estimates for the cash flow sensitivity of investment. Next, column (3) and (4) are the OLS results for *Payout Ratio*. In sequence, column (5) and (6) represent the estimates for Debt Rating in ordered logistic regression model. Since $\frac{Inv}{K}$ is likely to be autocorrelated within a firm, I include the lagged value of it as an explanatory variable in column (1), and, change in $\frac{Inv}{K}$ from the last fiscal year is used as the dependent variable in column (2). In both specifications, the coefficient of $\frac{CF}{K} \times Fraud_{Within}$ is significantly negative. On the other hand, the coefficients of $\frac{CF}{K} \times Fraud_{Top}$ and $\frac{CF}{K} \times Fraud_{Bottom}$ are all significantly positive except the coefficient of $\frac{CF}{K} \times Fraud_{Top}$ in column (2). These results imply that the cash flow sensitivity of investment decreases for firms within the same industry as fraud firms. In contrast, the cash flow sensitivity of investment increases for firms in the top supplier or top customer industries of the industry in which a fraud occurs. Column (3) represents the result for *Payout Ratio* and the coefficient of $Fraud_{Within}$ is significantly positive. On the other hand, the coefficients of $Fraud_{Top}$ and $Fraud_{Bottom}$ are not significantly different from zero. In column (4), lagged *Payout Ratio* is included as an independent variable and the result is similar with that of column (3). Therefore, the results show that firms within the same industry as a fraud firm increase annual payout. In column (5), change in long-term debt rating is used as the dependent variable, and, the coefficients of $Fraud_{Within}$ and $Fraud_{Top}$ are significantly positive. Column (6) shows the result when change in short-term debt rating is used as the dependent variable, and, the coefficient of $Fraud_{Bottom}$ is significantly positive. Hence, long-term debt rating becomes worse for firms within the same industry or top customer industry and short-term debt rating becomes worse for firms in top supplier industry when frauds occur.

[Insert Table 27 here]

Overall, the results in Table 27 support that firms' financial constraints are mitigated when peer firms in the same industry commit frauds, and, financial constraints increase for firms in industries which are important to fraud firm's industry in the product market relationship. However, there are two points to be noted about the results. First, the fact that there is no significant impact of fraud on payout ratio in top supplier and top customer firms could be attributable to intention of firms to avoid cutting dividend and hence total payouts despite their escalated financial constraints. This should be an inherent problem in using payout ratio as financial constraint measure. Second, debt rating could be a more forward-looking measure of financial constraints than cash flow sensitivity of investment or payout ratio; while cash flow sensitivity of investment and payout ratio instantly capture today's financial constraints, debt rating (especially long-term debt rating) reflect the assessment of credit rating company about future constraints given that it is constructed as the reference indicator for investors. Therefore, degeneration of debt rating in intra-industry firms may imply credit rating company's intention to inform investors of the likelihood of future fraud events in intra-industry which is dominant over its assessment of today's financial constraints.

3.3.2 Channels for Intra-industry Spillover

3.3.2.1 Competitive Effect

If a fraud occurs, then intra-industry firms can take advantage of decreased competition in the product market and the other firms within the same industry can gain additional market share. Then, this competitive effect in the product market would alleviate the financial constraints in intra-industry firms. If the positive spillover effect is caused by competitive effect, then concentrated industry will experience more positive spillover in terms of financial constraints than competitive industry when a fraud occurs within industry because firms would gain more market share in concentrated industry.

To test this, I first obtain the HHI index for each IO industry and classify IO industries into high HHI industry group (i.e., concentrated industry group) and low HHI industry group (i.e., competitive industry group) in each year. Next, HHI_{High} (i.e., indicator variable which equals to 1 if HHI of an industry is higher than median for each year) is interacted with $\frac{CF}{K}$ and $Fraud_{Within}$ to differentiate change in cash flow sensitivity of investment among different HHI industry groups when frauds occur in the same industry. Table 28 shows the regression results when this three-way interaction is included in column (1) and (2). In column (1) and (2), the coefficients of $\frac{CF}{K} \times Fraud_{Within} \times HHI_{High}$ are significantly positive. This indicates that cash flow sensitivity of investment decreases more steeply for concentrated industries when a fraud occurs within the same industry. Column (3) and (4) show that $Fraud_{Within} \times HHI_{High}$ has significantly positive impact on annual payout ratio. Thus, increment in payout when a fraud occurs is more prominent in concentrated industries than competitive industries. However, $Fraud_{Within} \times HHI_{High}$ doesn't show a significant coefficient in column (5) and (6).

[Insert Table 28 here]

In sum, the results in Table 28 support that positive intra-industry spillover regarding financial constraints measured by cash flow sensitivity of investment and payout ratios is stronger in concentrated industries. Hence, it can be interpreted that competitive effect is a channel through which frauds induce positive spillover effect within the same industry.

3.3.2.2 Attention Effect vs. Liquidity Effect

When a fraud occurs, investors may suspend financing fraud firms and find another firms for alternative investments. In that case, intra-industry firms of a fraud firm can be good places to transfer the investors' money. Especially, investors with diversification purpose would try to find another firm in the same industry as the fraud firm. If then, intra-industry firms will find it easier to receive financing and their financial constraints will be mitigated. This explanation for positive intra-industry spillover is not necessarily identical to the competitive effect explanation; while the competitive effect channel demonstrates that intra-industry firms receive gains from their enhanced product market performance, this explanation explains that those firms receive reflected benefit directly from capital market when a fraud arises.

Then, the next question is, do intra-industry firms receive reflected benefit evenly? If the positive spillover stems from just transfer of liquidity to peer firms in the same industry ("liquidity effect"), then those firms will receive the reflected gain evenly, or at best, more visible firms will receive relatively more gain in intra-industry. On the other hand, investors may turn their attention from fraud firms to other peer firms and this will move their money. In turn, investors, who are subject to limited attention and monitoring ability, may pay more attention to less visible firms up to then. Thus, if the positive spillover is caused by transfer of attention ("attention effect"), then less visible firms will receive more financing.

To test whether liquidity effect or attention effect is at work for the positive spillover effect on intra-industry firms, I use analyst coverage as the proxy for visibility of a firm. More specifically, I obtain the number of analysts on I/B/E/S providing earnings forecasts in each firm and define $Analyst\ Coverage$ as the natural logarithm of the number. Table 29 column (1) and (2) present the regression results when the interaction variable $\frac{CF}{K} \times Fraud_{Within} \times Analyst\ Coverage$ is included as an explanatory variable. In column (1) and (2), $\frac{CF}{K} \times Fraud_{Within} \times Analyst\ Coverage$ shows significantly positive coefficients. This implies that cash flow sensitivity of investment declines more for intra-industry firms with lower analyst coverage. Column (5) and (6) exhibit the positive coefficients of $Fraud_{Within} \times Analyst\ Coverage$, and, it denotes less downgrade in both long- and short-term debt ratings for firms with lower analyst coverage.

[Insert Table 29 here]

Therefore, Table 29 supports attention effect rather than liquidity effect as a possible channel of positive spillover effect on intra-industry firms of frauds. However, the positive spillover effect is not significantly different across firms with different visibility when payout ratios are used as the measure of financial constraints. One possible explanation for this is that more visible firms' intention to maintain or increase payouts (due to its visibility to investors) could be strong enough to cancel out relatively more positive spillover outcome on less visible firms.

3.3.2.3 Comparison of Possible Channels for Intra-industry Spillover

In the last previous subsections, the results in Table 28 and Table 29 support that the competitive effect and attention effect provide channels through which frauds alleviate the financial constraints of intra-industry peer firms. However, the two effects are not mutually exclusive; it is possible that both effects can be at work simultaneously, or, that one effect is dominant over another effect. Thus, I analyze the two effects at the same time in this subsection.

In addition, I explore one additional channel which may lead to negative intra-industry spillover outcome even though the results in Table 27 show positive spillover outcome overall; peer firms in the same industry would receive reassessment from investors when a fraud of a firm is publicized ("reassessment effect"). That is, if fraud occurrence seems to be an inherent problem in that industry, then investors may focus on the likelihood of governance failure in intra-industry firms which are also likely to be susceptible to weak governance and fraud. Besides, given the anecdotal evidence that corporate frauds cluster within an industry, investors would reassess them. Consequentially, peer firms' financial constraints can rise and frauds can lead to negative intra-industry spillover effect. To investigate this possibility, I utilize Sarbanes-Oxley Act (SOX) which was introduced as a reaction to big corporate frauds such as Enron and WorldCom cases. To the extent that enactment of SOX was aimed at preventing frauds, I assume that investors' concern over future governance failure in peer firms has been relieved after SOX and reassessment effect would be weakened. Hence, if the reassessment effect provides a channel of negative spillover on intra-industry firms, then negative spillover should be mitigated in post-SOX period. To check whether this channel is also at work, I define $PostSOX$ which is an indicator variable equal to one if the year of observation is 2002 or later.

In Table 30, I add $\frac{CF}{K} \times Fraud_{Within} \times HHI_{High}$, $\frac{CF}{K} \times Fraud_{Within} \times Analyst\ Coverage$, and $\frac{CF}{K} \times Fraud_{Within} \times PostSOX$ as the independent variables to investigate how cash flow sensitivity of investment varies across each of the three variables. In column (1) and (2), the coefficients of $\frac{CF}{K} \times Fraud_{Within} \times HHI_{High}$ and $\frac{CF}{K} \times Fraud_{Within} \times Analyst\ Coverage$ are significantly negative and positive, respectively, and which is consistent with the results of Table 28 and Table 29. The coefficients of $\frac{CF}{K} \times Fraud_{Within} \times PostSOX$ are both significantly positive in column (1) and (2), and thus, cash flow sensitivity of investment increases more after the enactment of SOX when frauds occur. In column (3) and (4), $Fraud_{Within} \times HHI_{High}$ shows a significantly positive impact on payout ratios as in Table 28, and, the coefficient of $Fraud_{Within} \times Analyst\ Coverage$ is not significantly different from zero as in Table 29. In addition, $Fraud_{Within} \times PostSOX$ doesn't exhibit a significant influence on payout ratios. Column (6) shows significantly positive impact of $Fraud_{Within} \times Analyst\ Coverage$ on change in short-term bond rating. In both column (5) and (6), the coefficients of $Fraud_{Within} \times PostSOX$ are significantly positive, and which means that frauds lead to more downgrade in both long- and short-term debt rating in post-SOX period than in pre-SOX period.

[Insert Table 30 here]

In sum, the competitive effect and attention effect are at work when financial constraints are measured by cash flow sensitivity of investment. When annual payout ratio (debt rating) is used as the financial constraint measure, the competitive effect (attention effect) is more dominant as the channel of positive spillover. In addition, every column of Table 30 implies that sensitivity of financial constraints to frauds for intra-industry firms increases, or at best, stays the same in post-SOX period compared to pre-SOX period. It doesn't support the reassessment effect story and hence negative spillover effect of frauds on intra-industry firms.

3.3.3 Channels for Supplier and Customer Industry Spillover

If a fraud arises and is detected or alleged, then the fraud firm's management, operation, and production can be brought to a halt due to fraud investigation and litigation process. As a result, firms which are closely related to the fraud firm in the product market chain may need to suspend their production. Also, they will face increased uncertainty in the case that they need to replace their customer or supplier which is under fraud investigation. As a result, decline in cash flows and imposition of searching costs and contracting costs will escalate their financial frictions even though the degree of information asymmetry or moral hazard problem stays the same within them; they need to borrow more. Unfortunately, I cannot find a proper observable measure to test this hypothesis even if this mechanism can be an instant explanation of negative spillover on supplier or customer firms' financial constraints.

On the other hand, there is a more direct channel through which spillover regarding financial constraints on supplier and customer industry firms is conveyed; the idea is that, if the fraud firm is in adverse selection due to its fraud investigation, then supplier firms which have provided trade credits may find it hard to collect the trade credits at the right time. Thereby, the supplier firms will face more financial frictions than before and hence experience negative spillover outcome. On the other hand, it is not certain whether customer firms which have been provided with trade credits from the fraud firm will face negative or positive spillover effect from fraud. All else equal, customers which have depended on the fraud firm's provision of trade credits may delay their repayment if the fraud firm suspends its operation and management, and which will alleviate their financial constraints for a while. Whereas, if a large amount of settlement money is imposed on the fraud firm and it urges the customer firms to reimburse the trade credits, then the customer firms should hasten the repayment unexpectedly. Then, their financial constraints would be aggravated.

To proxy for trade credit usage, I assign $Trade\ Credit_{Top}$ to be the ratio of accounts payable over total assets following Fisman and Love (2003) for top customer industry firms. Similarly, I assign $Trade\ Credit_{Bottom}$ to be the ratio of accounts receivable over total assets for top supplier industry firms. Table 31 reports the regression results when interactions between $Trade\ Credit$ and variables. In column (1) and (2), $\frac{CF}{K} \times Fraud_{Bottom} \times Trade\ Credit_{Bottom}$

shows significantly positive coefficients, and which denotes that top supplier firms' financial constraints increase more steeply as their trade credit increases. On the other hand, $\frac{CF}{K} \times Fraud_{Top} \times Trade\ Credit_{Top}$ shows significantly negative coefficients, and which means that top customer firms with high trade credit usage face less increase in financial constraints. Column (5) shows significantly negative coefficient of $Fraud_{Top} \times Trade\ Credit_{Top}$, and thus, top customer firms with high trade credit usage experience less downgrade in their debt ratings.

[Insert Table 31 here]

Overall, Table 31's results support that trade credit can be a linkage through which spillover regarding financial constraints can arise in top supplier and top customer industry firms.

3.4 Robustness Test

In this section, I implement three types of additional tests for the robustness of the main results.

3.4.1 Placebo Test: Matched Sample Analysis

While the main result in Table 27 demonstrates the negative (positive) spillover effect on intra-industry firms (top supplier and top customer industry firms) regarding financial constraints, it is not certain whether the spillover effects would have appeared even if the firms had not been in the intra-industry (top supplier and top customer industry) of the fraud firm. However, change in financial constraints of firms which were not in the intra-industry (top supplier and top customer industry) but similar to the intra-industry firms (top supplier and top customer industry firms) is observable, and, estimating the regression using the "matched" sample can provide a placebo test whether some other factors that are not controlled in the main regression drive the main results. To perform this placebo test, I match each sample observation with other observations having total assets between 70% and 130% of its total assets in each year among observations which are not "treated" (i.e., observations for which frauds don't occur in intra-industry, supplier industry, and customer industry). Next, the observation having the closest market-to-book ratio is defined as the matched sample. The firm control variables for the matched sample are also obtained from Compustat. For the placebo test, I replicate the regression using the matched sample as if the matched firms were "treated".

[Insert Table 31 here]

Table 31 presents the result of the main regression when the matched sample is used instead, and, the estimates are in sharp contrast to those for the treated firms. The positive spillover effect on intra-industry firms and negative spillover effect on top supplier and top customer industry firms are not observed in the regression; if any, $\mathrm{Fraud}_{\mathrm{Bottom}}$ shows a significantly positive coefficient in column (5), but which is not present in Table 2. Overall, the placebo test implies that the matched sample doesn't experience the spillover effect as the original sample, and hence, the main results are not driven by some other unobservable factors.

3.4.2 IV Estimation

It is not much likely that individual firm's investment-capital ratio, payout ratios, and debt rating can affect the occurrence of a fraud within intra-industry, supplier industry, or customer industry, but I also mitigate the possible endogeneity issue by employing IV estimation; for example, it can be argued that peer firms' aggressive investment or payout policy might motivate a firm in the same industry to commit fraud. Alternatively, it could be claimed that downgrade in supplier firm's debt rating might make its customer firm unstable and hence to engage in frauds.

To construct instrumental variables for $Fraud_{Within}$, $Fraud_{Top}$, and $Fraud_{Bottom}$, I take advantage of finding in Gande and Lewis (2009) that the number of lawsuits within the same industry has an explanatory power for the propensity to be sued. For each firm-year observation, I calculate the number of lawsuits over the year before the last year which may have an explanatory power for fraud occurrence in the last year within the same industry. Here, I don't restrict the lawsuits by the settlement cutoff (i.e., $2 million) because it is likely that small lawsuits affect the detection rates of frauds in the next year but don't influence the individual firm policy.[65] This variable is denoted as $Fraud\ Intensity_{Within}$ and is used as the instrumental variable for $Fraud_{Within}$. Similarly, the number of lawsuits over the year before the last year in the customer (supplier) industry is defined to be $Fraud\ Intensity_{Bottom}$ ($Fraud\ Intensity_{Top}$) and is used as the instrumental variable for $Fraud_{Bottom}$ ($Fraud_{Top}$). Accordingly, the instrumental variables are interacted with firm control variables which are interacted with $Fraud_{Within}$, $Fraud_{Top}$, and $Fraud_{Bottom}$, respectively.

---

[65] This is the necessary condition for using the number of previous lawsuits as a valid instrumental variable.

Table 8 presents the IV estimation results for main regression specification.[66]

[Insert Table 32 here]

3.4.3 Potential Issue about Industries Closely Related to Frauds

It is plausible that firms in some specific industries could drive the spillover effect reported in the regression results in the previous sections. More specifically, if there is an industry where fraud occurs frequently and the firms in that industry conventionally maintain low financial constraints compared to firms in other industries, then the positive intra-industry spillover effect could be driven by those firms. Alternatively, if there is an industry whose customer industry commits frauds frequently and the firms in that industry conventionally have high financial constraints compared to firms in other industries, then the negative spillover effect on top supplier and top customer industries could be nonexistent in reality.

To check this possibility, I observe four sectors where frauds occur most frequently (Technology, Services, Financial, Healthcare) and four industries which take the most portion of frauds occurrence in their own sector (Semiconductor, Telecommunication, Insurance, Pharmaceutical manufacturing). Next, I construct indicator variables for each of the four industries ("Semi", "Tele", "Ins", "Phar") and interaction variables between those indicators and main firm variables. In addition, I define an indicator variable, $\mathrm{Freq}_{\mathrm{Top}}(\mathrm{Freq}_{\mathrm{Bottom}})$ for industries which

[66] Specifications with respect to change in long- or short-term debt rating are estimated through ordered logit regression in the main result, and, IV estimation is impossible in this case.

are top customer (supplier) industries of “Semi”, “Tele”, “Ins”, and “Phar” so as to identify customer (supplier) industries which face frauds frequently from their supplier (customer) industry. Accordingly, their interactions with $\frac{CF}{K}$ are defined.

[Insert Table 33 here]

Table 33 shows the regression results when the above newly constructed indicator variables for the four industries (and their interactions with firm variables) and their top supplier or top customer industries are included. The coefficients of variables of interest have similar magnitude (and the same sign) as the coefficients in Table 27, and which implies that the above possibility attributable to industries which are closed related to frauds either industry-wise or product market network-wise is not persuasive.

3.5 Conclusion

This paper investigates spillover effect of corporate frauds on financial constraints of intra-industry, top supplier industry, and top customer industry firms. Using cash flow sensitivity of investment, annual payout ratios, and Standard & Poor’s debt rating as the measures for financial constraints, I examine how frauds affect other firms’ financial constraints. As a result, I find that intra-industry firms receive positive spillover effect (i.e., decrease in financial constraints), and, firms in top-supplier or top-customer industries receive negative spillover effect (i.e., increase in financial constraints) from frauds. As possible channels through which intra-industry firms experience positive spillover effect, I find that competitive effect and attention effect are at work.

Whereas, I observe that different trade credit usage leads to more (less) negative spillover effect on top-supplier (top-customer) firms. These results have implications for the literature regarding spillover effect of corporate frauds on different firms. Also, I believe consideration about characteristics of securities class action lawsuits (e.g., type of frauds, time to settle cases, amount of settlement cost) in intra- or inter-industry spillover effect would contribute to the literature.

Table 1: Summary statistics

Summary statistics are reported for the sample of 12,737 observations in the intersection of Compustat, CRSP, and 10-K database for the period of 2003-2018. First, firms in Compustat and CRSP are excluded if (i) they are financials (SIC code 6000-6999) or utilities (SIC code 4900-4949), (ii) they have a book value of equity less than $250,000, or (iii) they have asset value less than $500,000. After the screening procedure, firm-year observations with the fiscal year in 1997-2018 are included because the electronic filing on Edgar has been required since 1997. Next, firms whose $Agility$ can be estimated are only included in the final sample. Variable definitions are described in Appendix A Table A1. Panel A reports firm characteristics of the sample and Compustat-CRSP firms which meet the same screening condition as the sample but whose agility cannot be estimated. The last column shows the difference between the sample and Compustat-CRSP firms. Panel B reports firm characteristics of quintile groups of $Agility$. The last column shows the difference between Q1 (lowest $Agility$) firms and Q5 (highest $Agility$) firms. The symbol ***, **, and * denote statistical significance for two-tailed t-tests at the 1%, 5%, and 10% levels, respectively.

Panel A: Comparison between sample and Compustat-CRSP firms

	Sample	Compustat-CRSP	Compustat-CRSP – Sample (t)
$Cash/AT$	0.193	0.231	0.039*** (18.166)
$Leverage$	0.201	0.187	-0.013*** (-7.483)
$Dividend\ Payer$	0.418	0.282	-0.136*** (-29.067)
$Size$	6.534	5.359	-1.175*** (-58.626)
MTB	2.196	2.985	0.789* (2.025)
$Zscore$	0.126	-1.316	-1.442*** (-4.099)
ROA	0.078	-0.039	-0.118*** (-50.151)
$Tangibility$	0.248	0.305	0.057*** (24.753)
$R\&D/AT$	0.047	0.054	0.007*** (7.152)
Observations	12,712	78,075	

Panel B: Comparison between quintile groups of $Agility$

	Q1	Q2	Q3	Q4	Q5	Q1 – Q5 (t)
$Cash/AT$	0.183	0.187	0.196	0.194	0.204	-0.021*** (-3.515)
$Leverage$	0.208	0.200	0.197	0.206	0.191	0.017** (3.222)
$Dividend\ Payer$	0.440	0.429	0.405	0.405	0.410	0.030* (2.166)
$Size$	6.627	6.583	6.504	6.505	6.451	0.176** (3.086)
MTB	2.880	1.926	2.332	1.925	1.922	0.957 (0.912)
$Zscore$	-0.532	0.762	-0.640	0.535	0.498	-1.030 (-0.753)
ROA	0.086	0.084	0.074	0.074	0.074	0.013* (2.526)
$Tangibility$	0.262	0.258	0.252	0.239	0.227	0.035*** (5.607)
$R\&D/AT$	0.043	0.044	0.047	0.051	0.051	-0.008** (-2.825)
Observations	2,538	2,550	2,542	2,541	2,541	

Table 2: Summary statistics of text-based variables

Summary statistics of text-based variables ($Internal\ Fluidity$, $External\ Fluidity$, $\beta_{i,t+1}$, $Agility$) are reported for the sample of 12,737 observations in the intersection of Compustat, CRSP, and 10-K database for the period of 2003-2018. Variable definitions are described in equation (1), (2), and (3). Panel A displays the mean, standard deviation, minimum, and maximum of the variables when computed using a 5% threshold and local dictionary. Panel B displays the mean of the variables when permutations on the threshold level and dictionary version are allowed (e.g., 25% threshold with the main dictionary).

Panel A: Summary statistics of $Agility$, $Internal\ Fluidity$, and $External\ Fluidity$

	Mean	Standard Deviation	Min	Max
$Internal\ Fluidity$	-0.000014	0.000036	-0.001156	0.000299
$External\ Fluidity$	-0.000015	0.000035	-0.001213	0.000378
$\beta_{i,t+1}$	-0.048937	0.991680	-17.993642	20.252276
$Agility$	-1.191198	1.281941	-10.197084	3.008267
Observations	12,737			

Panel B: Permutation on dictionary version and threshold level

Dictionary	Local			Main		
Threshold Level	5%	10%	25%	5%	10%	25%
$Internal\ Fluidity$	-0.000014	-0.000022	-0.000046	-0.000006	-0.000010	-0.000021
$External\ Fluidity$	-0.000015	-0.000025	-0.000033	-0.000006	-0.000012	-0.000015
$\beta_{i,t+1}$	-0.048937	-0.070594	-0.059434	-0.070541	-0.069160	-0.102622
$Agility$	-1.191198	-1.143087	-1.010108	-1.227146	-1.154815	-1.053783
Observations	12,737	12,737	13,104	12,737	13,104	13,104

Table 3: Product assimilation vs. Product deviation

This table examines how firm choices between product assimilation and product deviation depend on threats of rivals as well as their interaction with firm status. The firm status variables are $Cash/AT$, Age , $Market\ Share\ Growth$, $R\&D/AT$, and industry HHI, and, are as defined in Appendix A Table A1. The dependent variable is $Internal\ Fluidity$. All specifications are estimated via OLS with year, firm, and industry fixed effects. Standard errors are clustered by firm. I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
$Variable$	$Cash/AT$	Age	$Market\ Share\ Growth$	$R\&D/AT$	HHI
$External\ Fluidity$	-0.026	-0.257***	-0.053***	-0.059***	-0.041
	(0.263)	(0.001)	(0.008)	(0.008)	(0.108)
$External\ Fluidity$ x $Variable$	-0.302**	0.013***	0.015***	-0.533***	-0.531**
	(0.014)	(0.004)	(0.004)	(0.001)	(0.021)
$Variable$	-0.000	0.000***	-0.000	-0.000	-0.000**
	(0.154)	(0.000)	(0.235)	(0.117)	(0.016)
Constant	-0.000	-0.000*	-0.000	-0.000	-0.000
	(0.751)	(0.083)	(0.397)	(0.678)	(0.751)
Observations	12,736	12,736	12,584	12,736	12,736
R-squared	0.254	0.255	0.254	0.253	0.253
Year FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y

Table 4: Persistence test

This table reports the mean persistence of $Agility$ measure. Each row of Panel A displays the proportion of firms in the corresponding $Agility$ quintile in year t, which remain in the same $Agility$ quintile in year t+1, t+2, …, t+5. Each row of Panel B shows the migration rates of firms in the corresponding $Agility$ quintile in year t to each of the $Agility$ quintiles in year t+1.

Panel A: 5-year follow-up of $Agility$ quintiles

Quintile (in year t)	Proportion of firms remaining in the same quintile (as of year t) in year				
	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
1	0.409	0.300	0.247	0.201	0.191
2	0.356	0.268	0.235	0.212	0.204
3	0.346	0.228	0.177	0.180	0.197
4	0.383	0.273	0.229	0.211	0.193
5	0.558	0.414	0.318	0.273	0.225

Panel B: Year-to-year follow-up of $Agility$ quintiles

Quintile (in year t)	Proportion of firms migrating in year $t+1$ to Quintile				
	1	2	3	4	5
1	0.409	0.257	0.161	0.106	0.067
2	0.260	0.356	0.193	0.119	0.072
3	0.166	0.183	0.346	0.197	0.108
4	0.103	0.121	0.198	0.383	0.196
5	0.072	0.076	0.102	0.193	0.558

Table 5: Firm-level agility

This table reports firms that score in the highest 30 according to their $Agility$ for the 1st half sample period (the year 2003-2010) and 2nd half sample period (the year 2011-2018) separately. Column 1 (2) includes the list of top 30 firms in the first (second) 8-year period based on $\overline{Agility}_{[2003,2010]}$ ($\overline{Agility}_{[2011,2018]}$), and which is computed as a firm's average $Agility$ only when it has at least 4 non-missing $Agility$ values in the period. Column 3 includes the list of top 30 firms based on $\overline{Agility}_{[2011,2018]}$) - $\overline{Agility}_{[2003,2010]}$. The firms on each list are in alphabetical order.

(1) $\overline{Agility}_{[2003,2010]}$	(2) $\overline{Agility}_{[2011,2018]}$	(3) $\overline{Agility}_{[2011,2018]}$ - $\overline{Agility}_{[2003,2010]}$
ADOBE INC	AKORN INC	ASGN INC
ASTRONICS CORP	ASGN INC	BEASLEY BROADCAST GROUP INC
ATRION CORP	BED BATH & BEYOND INC	BOOKING HOLDINGS INC
BED BATH & BEYOND INC	BEL FUSE INC	BOSTON SCIENTIFIC CORP
BEL FUSE INC	CEB INC	CDI CORP
CARMAX INC	CELGENE CORP	CHEESECAKE FACTORY INC
CEB INC	CMTSU LIQUIDATION INC	CONSTELLATION BRANDS
CELGENE CORP	COTT CORP QUE	COTT CORP QUE
CMTSU LIQUIDATION INC	CSS INDUSTRIES INC	CSS INDUSTRIES INC
COMMUNICATIONS SYSTEMS INC	FARO TECHNOLOGIES INC	CYBEROPTICS CORP
DATALINK CORP	FTI CONSULTING INC	CYTEC INDUSTRIES INC
DOVER MOTORSPORTS INC	GAIA INC	DST SYSTEMS INC
EXXON MOBIL CORP	GENVEC INC	ENDOLOGIX INC
FUEL TECH INC	GERON CORP	FASTENAL CO
GIBRALTAR INDUSTRIES INC	GRAY TELEVISION INC	FTI CONSULTING INC
GLATFELTER	HELIOS AND MATHESON ANALYTIC	GENTEX CORP
HONEYWELL INTERNATIONAL INC	INNODATA INC	GRAHAM HOLDINGS CO
INSIGNIA SYSTEMS INC	INTEGER HOLDINGS CORP	GRAY TELEVISION INC
INTEGER HOLDINGS CORP	INTRICON CORP	HELIOS AND MATHESON ANALYTIC
INTRICON CORP	JOE'S JEANS INC	INNOSPEC INC
JOE'S JEANS INC	KAMAN CORP	INTEGRATED DEVICE TECH INC
MERIT MEDICAL SYSTEMS INC	LIFETIME BRANDS INC	INTEST CORP
NEUROCRINE BIOSCIENCES INC	MCKESSON CORP	KFORCE INC
SEACOR HOLDINGS INC	PREMIERE GLOBAL SERVICES INC	KINDRED HEALTHCARE INC
SHIRE PLC	REGENERON PHARMACEUTICALS	PEPSICO INC
SNYDERS-LANCE INC	REPROS THERAPEUTICS INC	SPRINT CORP
THESTREET INC	STEPAN CO	STEPAN CO
TTEC HOLDINGS INC	TELECOMMUNICATION SYS INC	TOOTSIE ROLL INDUSTRIES INC
WEIS MARKETS INC	VERTEX PHARMACEUTICALS INC	TRIMBLE INC
WEST PHARMACEUTICAL SVSC INC	WEIS MARKETS INC	WASTE CONNECTIONS INC

Table 6: Industry-level agility

This table reports the fifteen most and fifteen least agile industries in SIC 2-digit level for the sample period of 2003 to 2018. Column 1 (2) includes the list of top (bottom) 15 industries with their time series average $Agility$ values ($\overline{Agility}_{[2003,2018]}$). Electric, Gas, & Sanitary Services (49) contains firms with SIC 2-digit codes of 49 except firms with SIC codes 4900-4949.

	(1) Most agile		(2) Least agile
$\overline{Agility}_{[2003,2018]}$	Industry (SIC 2)	$\overline{Agility}_{[2003,2018]}$	Industry (SIC 2)
-0.734	Apparel & Accessory Stores (56)	-1.490	Stone, Clay, & Glass Products (32)
-0.923	Furniture & Homefurnishings Stores (57)	-1.472	Electric, Gas, & Sanitary Services (49)
-0.940	General Merchandise Stores (53)	-1.347	Automative Dealers & Service Stations (55)
-0.996	Engineering & Management Services (87)	-1.345	Primary Metal Industries (33)
-1.041	Apparel & Other Textile Products (23)	-1.345	Oil & Gas Extraction (13)
-1.062	Wholesale Trade – Nondurable Goods (51)	-1.336	Heavy Construction, Except Building (16)
-1.080	Business Services (73)	-1.322	Miscellaneous Retail (59)
-1.088	Eating & Drinking Places (58)	-1.318	Rubber & Miscellaneous Plastics Products (30)
-1.099	Miscellaneous Manufacturing Industries (39)	-1.286	Transportation Equipment (37)
-1.119	Chemical & Allied Products (28)	-1.283	Printing & Publishing (27)
-1.130	Furniture & Fixtures (25)	-1.257	Fabricated Metal Products (34)
-1.157	Food & Kindred Products (20)	-1.256	Health Services (80)
-1.160	Transportation by Air (45)	-1.227	Communications (48)
-1.170	Electronic & Other Electric Equipment (36)	-1.221	Instruments & Related Products (38)
-1.176	Paper & Allied Products (26)	-1.209	Industrial Machinery & Equipment (35)

Table 7: Investigation of pharmaceutical industry

This table examines how $Agility$ of firms in the pharmaceutical industry is associated with the FDA's new drug approval time and rates. $Approval\ Time$ $(Priority)$ and $Approval\ Time$ $(Standard)$ are the median total approval times of priority and standard drugs, respectively, obtained from New Drug Application (NDA) and Biologic License Application (BLA) approval times for the period from 1993-2015. $Approval\ Rates$ is the approval rates for CDER NME NDA and BLA applications for the period from 1993-2015. The dependent variable is $Agility$. All specifications are estimated via OLS with year and firm fixed effects. Standard errors are clustered by firm. I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
	$Agility$	$Agility$	$Agility$
$\frac{1}{Approval\ Time\ (Priority)}$	324.536**	111.441**	
	(0.045)	(0.024)	
$\frac{1}{Approval\ Time\ (Standard)}$			117.307**
			(0.024)
$Approval\ Rates$	10.728***	10.102**	5.875***
	(0.010)	(0.011)	(0.006)
Constant	-53.335**	-26.017**	-14.295**
	(0.029)	(0.018)	(0.023)
Observations	849	691	691
R-squared	0.477	0.550	0.550
Firm Controls	N	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y

Table 8: Agility and product market performance

This table investigates the effect of $Agility$ on product market performance. The independent variables are measured at year t and the definitions are described in Appendix A Table A1. The dependent variable of Columns 1 and 2 is market share growth in year t+1. The dependent variables of Columns 3 and 4 are market share growth in year t+3 and t+5, respectively. All specifications are estimated via OLS with year, firm, and industry fixed effects. Standard errors are clustered by firm. I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) $Market\ Share\ Growth_{t+1}$	(2) $Market\ Share\ Growth_{t+1}$	(3) $Market\ Share\ Growth_{t+3}$	(4) $Market\ Share\ Growth_{t+5}$
$Agility$	0.083**	0.070*	0.095*	0.050
	(0.040)	(0.079)	(0.055)	(0.418)
$Cash/AT$		-0.713	1.076	2.451**
		(0.256)	(0.184)	(0.023)
$Leverage$		-0.960	-0.505	0.103
		(0.178)	(0.516)	(0.929)
$Dividend\ Payer$		0.057	0.304	0.264
		(0.750)	(0.127)	(0.315)
$Zscore$		0.028	0.026	-0.069
		(0.219)	(0.698)	(0.547)
$Size$		-0.327	-0.776***	-0.103
		(0.104)	(0.001)	(0.781)
Age		-0.081***	-0.055*	-0.236***
		(0.003)	(0.062)	(0.000)
MTB		-0.012	-0.050	-0.409**
		(0.894)	(0.600)	(0.016)
ROA		-2.304***	-1.147	4.247*
		(0.003)	(0.270)	(0.059)
$Tangibility$		-1.709	-0.496	-0.394
		(0.144)	(0.753)	(0.865)
$R\&D/AT$		-1.728	0.798	10.092***
		(0.428)	(0.789)	(0.008)
$Constant$	-1.142**	1.993	3.470**	2.069
	(0.013)	(0.135)	(0.027)	(0.419)
Observations	11,246	10,885	8,310	5,768
R-squared	0.348	0.348	0.429	0.433
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y

Table 9: Agility and firm survival

This table examines the effect of $Agility$ on firm survival likelihood. $High\ Agility$ ($Low\ Agility$) is an indicator variable equal to one if a firm's $Agility$ in year t is in the top (bottom) quintile within the same industry-year. All other independent variables are measured at year t, and the definitions are described in Appendix A Table A1. The dependent variables in Column 1, 2, and 3 (4, 5, and 6) are indicator variables equal to one if a firm is delisted from CRSP as of year t+1, t+3, and t+5, respectively. Specifications are estimated via logit (linear probability) models with year and industry fixed effects in Column 1, 2, and 3 (4, 5, and 6). I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
		Logit			LPM	
	$Delist_{t+1}$	$Delist_{t+3}$	$Delist_{t+5}$	$Delist_{t+1}$	$Delist_{t+3}$	$Delist_{t+5}$
$High\ Agility$	-0.129	-0.121*	-0.118*	-0.003	-0.005	-0.013*
	(0.205)	(0.062)	(0.057)	(0.507)	(0.492)	(0.076)
$Low\ Agility$	0.121	0.048	-0.106	0.003	0.014*	-0.004
	(0.334)	(0.559)	(0.201)	(0.648)	(0.095)	(0.700)
$Cash/AT$	-0.559**	-0.524***	0.202	-0.060**	-0.138***	0.045
	(0.047)	(0.004)	(0.259)	(0.016)	(0.000)	(0.223)
$Leverage$	1.525***	1.808***	1.653***	0.104***	0.226***	0.160***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Dividend\ Payer$	-0.406***	-0.456***	-0.494***	0.001	-0.021*	-0.019
	(0.000)	(0.000)	(0.000)	(0.885)	(0.078)	(0.136)
$Zscore$	-0.006	-0.013**	-0.005	-0.001***	-0.001	-0.002**
	(0.116)	(0.015)	(0.306)	(0.000)	(0.476)	(0.043)
$Size$	-0.186***	-0.194***	-0.179***	-0.048***	-0.084***	-0.049***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.017	-0.013	-0.014	0.015***	0.034***	0.038***
	(0.355)	(0.345)	(0.397)	(0.000)	(0.000)	(0.000)
MTB	-0.011	-0.015**	-0.254***	-0.001***	-0.000	-0.007*
	(0.201)	(0.022)	(0.000)	(0.000)	(0.633)	(0.084)
ROA	-0.489	-0.513**	-0.427*	-0.061**	-0.151***	-0.104**
	(0.122)	(0.027)	(0.078)	(0.018)	(0.000)	(0.010)
$Tangibility$	-0.418	-0.655***	-0.795***	-0.059	-0.045	-0.009
	(0.205)	(0.003)	(0.000)	(0.146)	(0.416)	(0.886)
$R\&D/AT$	0.247	-0.424	-0.411	-0.098*	-0.195**	-0.356***
	(0.661)	(0.280)	(0.337)	(0.089)	(0.013)	(0.000)
Observations	10,971	10,403	8,428	12,289	11,084	8,927
(Pseudo) R-squared	0.0415	0.0535	0.0638	0.432	0.687	0.803
Firm FE	N	N	N	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Table 10: Endogeneity

This table addresses the potential endogeneity by using IV estimation in the sample of the pharmaceutical industry and difference-in-differences framework with industry-level regulation increases. Columns 1 and 2 report second stage OLS and probit models based on the IV approach, respectively. Columns 3 and 4 display OLS and probit models in difference-in-differences estimation, respectively. The independent variables are measured at year t and the definitions are described in Appendix A Table A1. The dependent variables in Columns 1 and 2 (3 and 4) are market share growth and an indicator variable equal to one if a firm is delisted from CRSP as of year t+1, respectively. Age is dropped automatically because of the collinearity in Column 2. Columns 1 and 2 do not include industry fixed effects since only pharmaceutical industry is used as the sample. I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
	IV (Second Stage)		Diff-in-Diff	
	$Market\ Share\ Growth$	$Delist$	$Market\ Share\ Growth$	$Delist$
$Agility\ (Instrumented)$	1.298***	-0.509*		
	(0.000)	(0.074)		
$Agility$			0.076	0.027
			(0.107)	(0.484)
$Agility\ \times Regulation\ Jump$			0.176*	-0.198*
			(0.085)	(0.081)
$Regulation\ Jump$			0.249	-0.142
			(0.131)	(0.547)
Observations	604	590	8,998	9,111
R-squared	0.921		0.371	
Firm Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	N	N	Y	Y

Table 11: Benefits of agility

This table explores the benefits of agility. $Industry\ R\&D\ Intensity$, $Industry\ M\&A\ Wave$, $Tariff\ Cut$, and their interactions with $Agility$ are included as well as other firm control variables ($Cash/AT$, $Leverage$, $Dividend\ Payer$, $Zscore$, $Size$, Age, MTB, ROA, $Tangibility$, $R\&D/AT$). The independent variables are measured at year t (except *Tariff Cut*), and the definitions are described in Appendix A Table A1. *Tariff Cut* is measured as of year t+1, t+2, and t+3 in Column 7, 8, and 9, respectively. The dependent variables in Column 1, 2, and 3 are $R\&D/AT$ in year t+1, t+2, and t+3, respectively. The dependent variables in Column 4, 5, and 6 are $Acquisition\ Value/AT$ in year t+1, t+2, and t+3, respectively. The dependent variables in Column 7, 8, and 9 are $Market\ Share\ Growth$ in year t+1, t+2, and t+3, respectively. All specifications are estimated via OLS with year and industry fixed effects and firm control variables. I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) $\frac{R\&D}{AT}_{t+1}$	(2) $\frac{R\&D}{AT}_{t+2}$	(3) $\frac{R\&D}{AT}_{t+3}$	(4) $\frac{Acq.Val.}{AT}_{t+1}$	(5) $\frac{Acq.Val.}{AT}_{t+2}$	(6) $\frac{Acq.Val.}{AT}_{t+3}$	(7) $Mkt.Share\ Growth_{t+1}$	(8) $Mkt.Share\ Growth_{t+2}$	(9) $Mkt.Share\ Growth_{t+3}$
$Agility$	-0.001	-0.002	-0.001	0.001	-0.000	0.000	0.071*	-0.006	0.094*
	(0.440)	(0.176)	(0.504)	(0.492)	(0.855)	(0.968)	(0.075)	(0.900)	(0.057)
$Agility \times Industry\ R\&D\ Intensity$	0.144***	0.137***	0.126**						
	(0.000)	(0.010)	(0.031)						
$Industry\ R\&D\ Intensity$	0.318**	0.213	0.297						
	(0.026)	(0.295)	(0.209)						
$Agility \times Industry\ M\&A\ Wave$				0.021	0.023**	0.009			
				(0.157)	(0.032)	(0.490)			
$Industry\ M\&A\ Wave$				0.006	0.003	-0.005			
				(0.626)	(0.752)	(0.646)			
$Agility \times Tariff\ Cut$							1.963***	1.196***	1.177*
							(0.000)	(0.000)	(0.075)
$Tariff\ Cut$							3.877***	2.025***	1.758
							(0.000)	(0.001)	(0.178)
Observations	11,001	9,855	8,408	12,289	11,652	11,084	10,886	9,746	8,311
R-squared	0.589	0.413	0.366	0.036	0.036	0.033	0.348	0.380	0.429
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 12: Agility and acquisition

This table examines the association between the acquirer's $Agility$ and the target's $Agility$. The target firm in the latest acquisition attempt within five years (year t+1, t+2,…, t+5) is collected for each sample firm in year t. Within the intersection of the sample and SDC database, observations with non-missing $Agility$ values of both acquirer and target are used for the estimation. The independent variables are measured at year t, and the definitions are described in Appendix A Table A1. The dependent variable in Column 1 is $Agility$ of the target in the year of the acquisition attempt. The dependent variable in Column 2 is $Agility$ of the target in the preceding year of the acquisition attempt. All specifications are estimated via OLS with year fixed effects. I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) $Target's\ Agility$	(2) $Target's\ Agility$
$Acquirer's\ Agility$	-0.421**	-0.818***
	(0.014)	(0.003)
$Cash/AT$	-0.879	-4.346
	(0.506)	(0.246)
$Leverage$	0.427	-1.965
	(0.749)	(0.514)
$Dividend\ Payer$	0.365	0.129
	(0.431)	(0.878)
$Zscore$	-0.384	0.081
	(0.312)	(0.855)
$Size$	0.061	0.140
	(0.516)	(0.467)
Age	-0.116	-0.108
	(0.190)	(0.211)
MTB	0.708**	0.860*
	(0.021)	(0.085)
ROA	-3.921	-13.974
	(0.468)	(0.139)
$Tangibility$	-0.812	2.210
	(0.527)	(0.207)
$R\&D/AT$	3.818	9.451
	(0.285)	(0.196)
Constant	-2.423*	-2.846
	(0.084)	(0.142)
Observations	55	48
R-squared	0.484	0.532
Year FE	Y	Y

Table 13: Costs of agility

This table explores the costs of agility. $Agility\ Jump$ and $Agility\ Drop$ are included as well as other firm control variables ($Cash/AT$, $Leverage$, $Dividend\ Payer$, $Zscore$, $Size$, Age, MTB, ROA, $Tangibility$, $R\&D/AT$). The firm control variables are measured at year t, and the definitions are described in Appendix A Table A1. In Column 1, 2, and 3, $Agility\ Jump$ ($Drop$) is an indicator variable equal to one if a firm's positive (negative) change in Agility (i.e., $Agility_{t+1} - Agility_t$) is 3 times greater than the median of positive (negative) changes in Agility in the same year, industry, and industry-year, respectively. The dependent variable, $\Delta ROA_{t,t+1}$, is the change in ROA from year t to t+1 (i.e., $ROA_{t+1} - ROA_t$). All specifications are estimated via OLS with firm, year, and industry fixed effects and firm control variables. I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) $\Delta ROA_{t,t+1}$	(2) $\Delta ROA_{t,t+1}$	(3) $\Delta ROA_{t,t+1}$
$Agility\ Jump$	-0.012***	-0.011**	-0.001
	(0.003)	(0.013)	(0.660)
$Agility\ Drop$	-0.003	-0.003	0.007*
	(0.410)	(0.325)	(0.088)
$Cash/AT$	-0.061***	-0.061***	-0.062***
	(0.006)	(0.006)	(0.006)
$Leverage$	0.054***	0.054***	0.055***
	(0.004)	(0.004)	(0.003)
$Dividend\ Payer$	0.008	0.007	0.008
	(0.161)	(0.166)	(0.162)
$Zscore$	0.002	0.002	0.002
	(0.148)	(0.148)	(0.152)
$Size$	-0.022***	-0.022***	-0.022***
	(0.000)	(0.000)	(0.000)
Age	-0.002***	-0.002***	-0.002***
	(0.006)	(0.006)	(0.006)
MTB	0.002	0.002	0.002
	(0.148)	(0.147)	(0.152)
ROA	-0.729***	-0.729***	-0.728***
	(0.000)	(0.000)	(0.000)
$Tangibility$	-0.067**	-0.067**	-0.068**
	(0.042)	(0.041)	(0.039)
$R\&D/AT$	-0.091	-0.091	-0.090
	(0.322)	(0.321)	(0.324)
Constant	0.186***	0.184***	0.182***
	(0.001)	(0.001)	(0.001)
Observations	9,863	9,863	9,863
R-squared	0.471	0.471	0.470
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Industry FE	Y	Y	Y

Table 14: Stock return predictability

This table reports the average slopes (in percent) from Fama-MacBeth (1973) cross-sectional regressions for multiple holding period returns; 1-month, 3-month, 6-month, and annual returns. Excess returns from July of year t to June of year t+1 on $Agility$ and a set of control variables in fiscal year ending in year t-1 except log (ME) (measured at the end of June of year t), $Momentum$ (measured in the prior 11 months with a one-month gap), $Reversal$ (measured in the prior month), $Illiquidity$ (measured within the current month using daily returns and dollar trading volume), and $Id.Vol$ (measured in the prior 12 months with a one-month gap using daily returns). The definitions of the independent variables are described in Appendix A Table A1. The regressions only use stocks with lagged price greater than five dollars. The return data are from July of 2004 to December of 2020. Average R-squared is the average of the adjusted R-squared from the cross-sectional regressions. All specifications include industry fixed effects. Standard errors are Newey-West adjusted, and I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Ret_1	(2) Ret_3	(3) Ret_6	(4) Ret_{12}
$Agility$	-0.108***	-0.003***	-0.006***	-0.012***
	(0.004)	(0.007)	(0.002)	(0.000)
$Beta$	-0.218	-0.002	0.002	0.000
	(0.322)	(0.596)	(0.815)	(0.970)
log (ME)	-0.077*	-0.001	-0.001	-0.003
	(0.066)	(0.290)	(0.484)	(0.322)
log (BTM)	0.323	0.005	0.009	0.008
	(0.226)	(0.333)	(0.283)	(0.591)
$Momentum$	-0.739*	-0.021**	-0.034**	-0.037*
	(0.057)	(0.020)	(0.023)	(0.073)
$Reversal$	-3.520***	-0.046***	-0.049**	-0.097***
	(0.000)	(0.005)	(0.011)	(0.002)
$Illiquidity$	2.230	0.114	0.244	0.565*
	(0.553)	(0.176)	(0.133)	(0.089)
ROA	3.823**	0.100***	0.198***	0.224***
	(0.017)	(0.004)	(0.001)	(0.008)
$Id.Vol$	-15.305	-0.195	-0.281	-0.843
	(0.234)	(0.529)	(0.600)	(0.266)
HHI	6.882	0.052	0.158	0.339**
	(0.236)	(0.629)	(0.252)	(0.028)
$Asset\ Growth$	0.124	-0.001	0.001	-0.006
	(0.753)	(0.921)	(0.960)	(0.715)
Observations	96,944	96,944	96,944	96,945
Average R-squared	0.423	0.426	0.432	0.432
Industry FE	Y	Y	Y	Y

Table 15: Summary statistics

Panel A	Customer		Supplier		(3)	
Firm Variables	$Mean$	$Std.Dev.$	$Mean$	$Std.Dev.$	$Diff$	t
$Size$	9.199	2.229	4.332	2.231	4.87^{***}	(299.47)
MTB	1.818	3.976	2.294	6.487	-0.48^{***}	(-11.11)
ROA	0.136	0.614	0.015	0.664	0.12^{***}	(25.92)
$Leverage$	0.253	0.177	0.279	0.527	-0.03^{***}	(-9.12)
$Cash/TA$	0.096	0.117	0.191	0.226	-0.10^{***}	(-73.22)
$CAPEX/TA$	0.075	0.056	0.073	0.098	0.00^{*}	(2.17)
$R\&D/TA$	0.046	0.067	0.080	0.234	-0.03^{***}	(-26.48)
$Innovation$	2.314	2.593	0.446	0.996	1.87^{***}	(132.78)
Observations	39003		39003		78006	

Panel B	$Customer\ Innovation = 0$		$Customer\ Innovation > 0$			
Supplier Variables	$Mean$	$Std.Dev.$	$Mean$	$Std.Dev.$	$Diff$	t
$Size$	4.204	2.166	4.439	2.278	-0.24^{***}	(-10.42)
MTB	2.272	4.311	2.313	7.852	-0.04	(-0.60)
ROA	0.011	0.809	0.018	0.514	-0.01	(-1.00)
$Leverage$	0.291	0.478	0.270	0.565	0.02^{***}	(4.02)
$Cash/TA$	0.173	0.211	0.205	0.236	-0.03^{***}	(-13.90)
$CAPEX/TA$	0.075	0.114	0.072	0.082	0.00^{**}	(3.24)
$R\&D/TA$	0.067	0.245	0.090	0.224	-0.02^{***}	(-9.58)
$Innovation$	0.334	0.854	0.539	1.091	-0.21^{***}	(-20.88)
$Trade\ Credit$ (%)	4.206	5.171	4.236	4.876	-0.03	(-0.48)
Observations	17673		21330		39003	

Table 16: Baseline regression

This table shows results of OLS regressions examining the effect of customer's innovation on supplier's trade credit provision. The dependent variable is the proportion of supplier's trade receivable attributable to its principal customer at year t+1, t+2, and t+3 in columns 1, 2, and 3, respectively. The main independent variable is the natural logarithm of one plus the number of patents of principal customer at year t. All other independent variables are measured in year t at supplier's level. Standard errors are clustered at customer-supplier pair level and reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
VARIABLES	$Trade\ Credit_{t+1}$	$Trade\ Credit_{t+2}$	$Trade\ Credit_{t+3}$
$Customer\ Innovation_t$	0.122***	0.123***	0.123***
	(0.000)	(0.000)	(0.001)
$Size_t$	-0.671***	-0.635***	-0.632***
	(0.000)	(0.000)	(0.000)
MTB_t	0.003	-0.008	-0.027
	(0.424)	(0.142)	(0.527)
ROA_t	1.159***	0.220	-0.546
	(0.000)	(0.677)	(0.393)
$CAPEX/TA_t$	-2.940***	-3.077***	-3.499***
	(0.000)	(0.000)	(0.001)
$Leverage_t$	-0.111	0.011	-0.053
	(0.631)	(0.972)	(0.875)
$Cash/TA_t$	-3.734***	-3.395***	-3.187***
	(0.000)	(0.000)	(0.000)
$R\&D/TA_t$	0.960	-0.011	-0.936
	(0.284)	(0.991)	(0.461)
$Constant$	6.978***	6.960***	7.142***
	(0.000)	(0.000)	(0.000)
Observations	19,042	13,973	10,450
R-squared	0.206	0.210	0.228
Year FE	Y	Y	Y
Industry FE	Y	Y	Y

Table 17: Multiple fixed effects

This table shows results of OLS regressions examining the effect of customer's innovation on supplier's trade credit provision with different combination of fixed effects. The dependent variable is the proportion of supplier's trade receivable attributable to its principal customer at year t+1. The main independent variable is the natural logarithm of one plus the number of patents of principal customer at year t. All other firm control variables are measured in year t at supplier's level. Year, supplier's industry, customer's industry, supplier's industry-year, and customer's industry-year fixed effects are included. Standard errors are clustered at customer-supplier pair level and reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

VARIABLES	(1) $Trade\ Credit_{t+1}$	(2) $Trade\ Credit_{t+1}$	(3) $Trade\ Credit_{t+1}$	(4) $Trade\ Credit_{t+1}$	(5) $Trade\ Credit_{t+1}$
$Customer\ Innovation_t$	0.122***	0.143***	0.134***	0.149***	0.132***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
$Constant$	6.978***	8.107***	4.979***	5.478***	6.232***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	19,042	19,042	19,042	19,042	19,042
R-squared	0.206	0.167	0.239	0.388	0.316
Firm Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	N	N
Supplier Industry FE	Y	N	Y	N	Y
Customer Industry FE	N	Y	Y	Y	N
Supplier Industry X Year FE	N	N	N	Y	N
Customer Industry X Year FE	N	N	N	N	Y

Table 18: Holdup channel

This table compares the OLS estimates of customer's innovation between subgroups divided according to supplier's asset specificity. The dependent variable is the proportion of supplier's trade receivable attributable to its principal customer at year t+1 in every column. The main independent variable is the natural logarithm of one plus the number of patents of principal customer at year t. All other independent variables are measured in year t at supplier's level. The sample is divided into low asset specificity and high asset specificity group using the median value of asset specificity. In each odd (even) column, firms with low (high) asset specificity are used in the regression. Standard errors are clustered at customer-supplier pair level and reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Asset\ Specificity_1$		$Asset\ Specificity_2$		$Asset\ Specificity_3$		$Asset\ Specificity_4$	
VARIABLES	Low	High	Low	High	Low	High	Low	High
$Customer\ Innovation_t$	0.036	0.157**	0.153***	0.181***	0.100***	0.176***	0.102***	0.153***
	(0.262)	(0.013)	(0.003)	(0.000)	(0.008)	(0.001)	(0.002)	(0.001)
$Constant$	1.961**	4.937***	6.641***	5.795***	3.720***	1.671	4.832***	4.650***
	(0.014)	(0.007)	(0.000)	(0.000)	(0.000)	(0.495)	(0.000)	(0.000)
Observations	3,605	3,727	5,449	5,932	9,464	9,578	7,771	8,590
R-squared	0.391	0.357	0.216	0.285	0.288	0.291	0.231	0.313
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y	Y	Y	Y	Y

Table 19: Demand channel

This table reports the results of OLS regressions examining the effect of customer's innovation on two customer-level variables: supplier's sales to the customer and customer's cost of goods sold. In column 1, 2, and 3, the dependent variable is supplier's sales to the principal customer at year t+1, t+2, and t+3, respectively. In column 4, 5, and 6, the dependent variable is the ratio of principal customer's cost of goods sold over its total assets at year t+1, t+2, and t+3, respectively. The main independent variable is the natural logarithm of one plus the number of patents of principal customer at year t. All other independent variables are measured in year t at customer's level. Standard errors are clustered at customer level and reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

VARIABLES	(1) $Customer\ Sales_{t+1}$	(2) $Customer\ Sales_{t+2}$	(3) $Customer\ Sales_{t+3}$	(4) $COGS/TA_{t+1}$	(5) $COGS/TA_{t+2}$	(6) $COGS/TA_{t+3}$
$Customer\ Innovation_t$	6.383	9.182	7.547	0.014	0.012	0.009
	(0.408)	(0.283)	(0.420)	(0.141)	(0.280)	(0.465)
$Constant$	-179.135**	-226.049**	-243.517**	2.027***	1.942***	1.951***
	(0.027)	(0.022)	(0.044)	(0.000)	(0.000)	(0.000)
Observations	12,288	9,024	6,714	17,621	17,278	16,920
R-squared	0.195	0.314	0.342	0.695	0.756	0.755
Customer Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y	Y	Y

Table 20: Financing channel

This table shows the OLS estimates of customer's innovation and its interaction with customer's financial variable on supplier's trade credit provision. The dependent variable is the proportion of supplier's trade receivable attributable to its principal customer at year t+1 in column 1, 4, and 7. The same dependent variable is measured at year t+2 (t+3) in column 2, 5, and 8 (3, 6, and 9). The main independent variable is the natural logarithm of one plus the number of patents of principal customer at year t. In column 1, 2, and 3, the main independent variable is interacted with the customer's leverage in year t. In column 4, 5, and 6, the main independent variable is interacted with the customer's cash to asset ratio in year t. In column 7, 8, and 9, the main independent variable is interacted with the customer's payout ratio in year t. All other independent variables are measured in year t at supplier's level. Standard errors are clustered at customer-supplier pair level and reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

VARIABLES	(1) $Trade\ Credit_{t+1}$	(2) $Trade\ Credit_{t+2}$	(3) $Trade\ Credit_{t+3}$	(4) $Trade\ Credit_{t+1}$	(5) $Trade\ Credit_{t+2}$	(6) $Trade\ Credit_{t+3}$	(7) $Trade\ Credit_{t+1}$	(8) $Trade\ Credit_{t+2}$	(9) $Trade\ Credit_{t+3}$
$Customer\ Innovation_t$	0.115***	0.145***	0.172***	0.118***	0.125**	0.125**	0.125***	0.127***	0.115**
	(0.005)	(0.002)	(0.001)	(0.009)	(0.019)	(0.034)	(0.002)	(0.006)	(0.023)
$Customer\ Innovation_t$	0.067	-0.015	-0.099						
$\times\ Customer\ Leverage_t$	(0.652)	(0.923)	(0.535)						
$Customer\ Innovation_t$				0.115	0.128	0.166			
$\times\ Customer\ Cash/TA_t$				(0.537)	(0.576)	(0.535)			
$Customer\ Innovation_t$							-0.124	-0.041	0.518
$\times\ Customer\ Payout_t$							(0.688)	(0.911)	(0.198)
$Customer\ Leverage_t$	-0.586*	-0.346	-0.270						
	(0.092)	(0.307)	(0.449)						
$Customer\ Cash/TA_t$				-0.536	-0.750	-1.234			
				(0.366)	(0.339)	(0.184)			
$Customer\ Payout_t$							3.229***	3.914***	1.433
							(0.005)	(0.006)	(0.368)
Observations	18,948	13,923	10,414	18,970	13,937	10,424	18,980	13,944	10,429
R-squared	0.240	0.247	0.268	0.239	0.247	0.268	0.240	0.248	0.269
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 21: 2SLS regression

This table shows the second stage estimates of customer's innovation in 2SLS regressions. The dependent variable is the proportion of supplier's trade receivable attributable to its principal customer at year t+1, t+2, and t+3 in column 1, 2, and 3, respectively. The main independent variable is the natural logarithm of one plus the number of patents of principal customer at year t. All other independent variables are measured in year t at supplier's level. In the first stage regression, monetary cost (i.e., average R&D expenditures per patent) and time cost (i.e., average duration from application filing to issue or grant of patent) of innovation measured at customer's industry level are used as the instrumental variables for the main independent variable. Standard errors are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
			Second Stage	
VARIABLES	First Stage	$Trade\ Credit_{t+1}$	$Trade\ Credit_{t+2}$	$Trade\ Credit_{t+3}$
$Time\ Cost_{t-1}$	-0.065***			
	(0.010)			
$Monetary\ Cost_{t-1}$	-0.319***			
	(0.000)			
$Customer\ Innovation_t$		-0.076	0.164	0.707**
		(0.717)	(0.477)	(0.019)
$Size_t$		-0.699***	-0.637***	-0.643***
		(0.000)	(0.000)	(0.000)
MTB_t		-0.001	-0.016***	-0.029
		(0.802)	(0.001)	(0.305)
ROA_t		1.005***	-0.649**	-1.103***
		(0.000)	(0.041)	(0.010)
$CAPEX/TA_t$		-1.512*	-2.238**	-1.801
		(0.071)	(0.022)	(0.145)
$Leverage_t$		0.032	0.023	0.160
		(0.843)	(0.924)	(0.647)
$Cash/TA_t$		-3.747***	-3.360***	-2.224***
		(0.000)	(0.000)	(0.000)
$R\&D/TA_t$		1.141***	-0.233	-0.926
		(0.001)	(0.649)	(0.194)
$Constant$		3.314	1.140	-11.720
		(0.431)	(0.854)	(0.132)
Observations	4,057	7,983	5,680	4,057
R-squared	0.600			
IV F-statistics	43.22			
Durbin's p-value	0.063			
Overidentification p-value	0.639			
Year FE	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y

Table 22: Diff-in-diff regression

This table shows the second stage estimates of customer's innovation in diff-in-diff regressions. The dependent variable is the proportion of supplier's trade receivable attributable to its principal customer at year t+1, t+2, and t+3 in column 1, 2, and 3, respectively. The main independent variables are implied contract exception (IC), good faith exception (GF), and public policy exception (PP) measured at the state level where a customer's headquarter is located. All other independent variables are measured in year t at supplier's level. Standard errors are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

VARIABLES	(1) $Trade$ $Credit_{t+1}$	(2) $Trade$ $Credit_{t+2}$	(3) $Trade$ $Credit_{t+3}$
IC	0.440**	0.666***	0.678**
	(0.042)	(0.009)	(0.026)
GF	-0.136	0.159	0.068
	(0.655)	(0.664)	(0.872)
PP	-0.219	-0.074	-0.003
	(0.370)	(0.784)	(0.991)
Observations	9,080	6,843	5,271
R-squared	0.258	0.276	0.311
Firm Controls	Y	Y	Y
Year FE	Y	Y	Y
Supplier Industry FE	Y	Y	Y
Customer Industry FE	Y	Y	Y

Table 23: Overlapping of technology space between customer and supplier

This table shows the OLS estimates of customer's innovation and its interaction with technological relatedness between customer and supplier. The dependent variable is the proportion of supplier's trade receivable attributable to its principal customer at year t+1, t+2, and t+3 in column 1, 2, and 3 (4, 5, and 6), respectively. The main independent variable is the natural logarithm of one plus the number of patents of principal customer at year t. In column 1, 2, and 3, the main independent variable is interacted with an indicator variable which equals to 1 if a customer's patent (issued in year t) cites any of its supplier's patent (issued previously as of year t). In column 4, 5, and 6, the main independent variable is interacted with an indicator variable which equals to 1 if technology class of customer's patent (issued in year t) overlaps with historical technology classes of supplier's patents (issued previously as of year t). All other independent variables are measured in year t at supplier's level. Standard errors are clustered at customer-supplier pair level and reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

VARIABLES	(1) $Trade\ Credit_{t+1}$	(2) $Trade\ Credit_{t+2}$	(3) $Trade\ Credit_{t+3}$	(4) $Trade\ Credit_{t+1}$	(5) $Trade\ Credit_{t+2}$	(6) $Trade\ Credit_{t+3}$
$Customer\ Innovation_t$	0.248***	0.271***	0.291***	0.278***	0.308***	0.341***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Customer\ Innovation_t$	-0.190*	-0.130	-0.131			
$\times Cite_t$	(0.065)	(0.314)	(0.374)			
$Customer\ Innovation_t$				-0.159**	-0.185**	-0.234**
$\times Class\ Overlap_t$				(0.027)	(0.032)	(0.018)
$Cite_t$	0.647	0.447	0.498			
	(0.259)	(0.526)	(0.541)			
$Class\ Overlap_t$				0.779**	1.071***	1.421***
				(0.012)	(0.005)	(0.001)
$Constant$	4.866***	4.832***	5.113***	4.873***	4.801***	4.987***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11,464	8,530	6,380	11,464	8,530	6,380
R-squared	0.259	0.260	0.274	0.259	0.261	0.275
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y	Y	Y

Table 24: Overlapping of technology space between customer and itself in the past

This table shows the OLS estimates of customer's innovation and its interaction with technological relatedness with itself in the past. The dependent variable is the proportion of supplier's trade receivable attributable to its principal customer at year t+1, t+2, and t+3 in column 1, 2, and 3 (4, 5, and 6), respectively. The main independent variable is the natural logarithm of one plus the number of patents of principal customer at year t. In column 1, 2, and 3, the main independent variable is interacted with an indicator variable which equals to 1 if a customer's patent (issued in year t) cites any of its patents (issued previously as of year t). In column 4, 5, and 6, the main independent variable is interacted with an indicator variable which equals to 1 if technology class of customer's patent (issued in year t) overlaps with any of its historical technology classes of patents (issued previously as of year t). All other independent variables are measured in year t at supplier's level. Standard errors are clustered at customer-supplier pair level and reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

VARIABLES	(1) $Trade$ $Credit_{t+1}$	(2) $Trade$ $Credit_{t+2}$	(3) $Trade$ $Credit_{t+3}$	(4) $Trade$ $Credit_{t+1}$	(5) $Trade$ $Credit_{t+2}$	(6) $Trade$ $Credit_{t+3}$
$Customer\ Innovation_t$	0.374**	0.451***	0.538***	0.185***	0.201***	0.211***
	(0.014)	(0.004)	(0.008)	(0.000)	(0.001)	(0.004)
$Customer\ Innovation_t$	-0.149	-0.196	-0.258			
$\times\ Cite_t^{Own}$	(0.317)	(0.206)	(0.197)			
$Customer\ Innovation_t$				0.060	0.079	0.084
$\times\ Class\ Overlap_t^{Own}$				(0.179)	(0.132)	(0.150)
$Cite_t^{\mathrm{Own}}$	0.216	0.261	0.307			
	(0.408)	(0.383)	(0.387)			
$Class\ Overlap_t^{\mathrm{Own}}$				-0.206	-0.291	-0.085
				(0.245)	(0.154)	(0.699)
$Constant$	4.852***	4.731***	4.945***	5.175***	5.162***	5.354***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	11,464	8,530	6,380	11,464	8,530	6,380
R-squared	0.258	0.260	0.274	0.258	0.260	0.274
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Supplier Industry FE	Y	Y	Y	Y	Y	Y
Customer Industry FE	Y	Y	Y	Y	Y	Y

Table 25: Financial and investment decision of supplier

This table reports the results of OLS regressions examining the effect of customer's innovation on financial and investment decisions of supplier. In column 1, 2, and 3, the dependent variables are financial variables of supplier (cash to asset ratio, payout ratio, and leverage) in year t+1. In column 4, 5, and 6, the dependent variables are investment variables of supplier (R&D to asset ratio, logarithm of one plus the number of supplier's patents, and logarithm of the ratio of the number of customer's past patents cited by supplier's patents over the number of supplier's patents) in year t+1. The main independent variable is the natural logarithm of one plus the number of patents of principal customer at year t. All other independent variables are measured in year t at customer's level. Standard errors are clustered at supplier level and reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

VARIABLES	(1) $Cash/TA_{t+1}$	(2) $Payout_{t+1}$	(3) $Leverage_{t+1}$	(4) $R\&D/TA_{t+1}$	(5) $Supplier\ Innovation_{t+1}$	(6) $Tech\ Spillover_{t+1}$
$Customer\ Innovation_t$	0.001***	-0.001***	-0.001	0.001	0.012**	0.026***
	(0.001)	(0.009)	(0.502)	(0.214)	(0.019)	(0.000)
$Constant$	0.014	-0.001	0.041	0.074***	-0.225	-0.059
	(0.168)	(0.785)	(0.435)	(0.001)	(0.284)	(0.758)
Observations	26,072	26,078	26,040	16,560	27,931	27,931
R-squared	0.751	0.053	0.418	0.214	0.362	0.282
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Table 26: Summary statistics

	Intra-industry			Top-supplier industry			Top-customer industry			Other industry		
Variable	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min
Market-to-book	2.165	42.497	0.296	1.730	38.998	0.296	1.57	42.497	0.296	1.845	54.415	0.248
Log(Assets)	5.868	11.043	-0.548	5.998	10.953	0.472	6.348	11.248	0.102	6.059	11.561	-2.187
Leverage	0.220	3.346	0	0.253	2.530	0	0.288	3.722	0	0.250	4.771	0
Sales Growth	0.333	14.069	-0.999	0.311	14.069	-0.999	0.239	14.069	-0.999	0.255	14.069	-1.000
ROA	0.038	0.456	-7.479	0.093	0.456	-5.316	0.102	0.456	-5.316	0.079	0.458	-7.479

Table 27: Overall spillover in financial constraints

This table shows OLS estimates in column (1) through (4), and, ordered logit regression estimates in column (5) and (6). $Fraud_{Within}$ equals to 1 if fraud occurs within the same industry, and 0 otherwise during last fiscal year. $Fraud_{Top}$($Fraud_{Bottom}$) equals to 1 if fraud occurs in the supplier (customer) industry for which the firm is in the top-customer (top-supplier) industry, and 0 otherwise during last fiscal year. I also include their interactions with $\frac{CF}{K}_t$ in column (1) and (2). Each model contains firm- and year-fixed effects. Standard errors are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	$\frac{Inv}{K}_t$ (1)	$\Delta\frac{Inv}{K}$ (2)	$Payout\ Ratio_t$ (3)	$Payout\ Ratio_t$ (4)	$\Delta Long-term\ Bond\ Rating$ (5)	$\Delta Short-term\ Bond\ Rating$ (6)
$Fraud_{Within}$	-0.012*	-0.002	0.001**	0.001*	0.160***	0.083
	(0.006)	(0.010)	(0.001)	(0.001)	(0.038)	(0.095)
$\frac{CF}{K}_t \times Fraud_{Within}$	-0.004***	-0.005***				
	(0.000)	(0.001)				
$Fraud_{Top}$	0.018**	0.018	-0.001	-0.001	0.148***	0.029
	(0.008)	(0.013)	(0.001)	(0.001)	(0.046)	(0.112)
$\frac{CF}{K}_t \times Fraud_{Top}$	0.002***	-0.000				
	(0.001)	(0.001)				
$Fraud_{Bottom}$	0.002	-0.010	0.001	0.001	0.059	0.275**
	(0.009)	(0.015)	(0.001)	(0.001)	(0.054)	(0.130)
$\frac{CF}{K}_t \times Fraud_{Bottom}$	0.007***	0.009***				
	(0.001)	(0.002)				
$\frac{\mathrm{Inv}}{\mathrm{K}}_{t-1}$	0.067***					
	(0.002)					
$Payout\ Ratio_{t-1}$				0.055***		
				(0.002)		
$\frac{CF}{K}_t$	-0.007***	-0.007***				
	(0.000)	(0.000)				
$\frac{CF}{K}_{t-1}$			0.000***	0.000***	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)
MTB_{t-1}	0.052***	0.013***	0.000*	0.000***	-0.034***	-0.030**
	(0.001)	(0.002)	(0.000)	(0.000)	(0.005)	(0.014)
$\mathrm{Log(Assets}_{t-1})$	-0.188***	-0.163***	0.002***	0.002***	-0.043***	0.042**
	(0.003)	(0.005)	(0.000)	(0.000)	(0.007)	(0.018)
$\mathrm{Leverage}_{t-1}$	-0.207***	0.016	-0.026***	-0.032***	0.348***	0.456***
	(0.011)	(0.019)	(0.001)	(0.001)	(0.046)	(0.106)
$\mathrm{Sales\ Growth}_{t-1}$	0.022***	-0.126***	-0.001***	-0.001***	-0.096***	-0.013
	(0.002)	(0.003)	(0.000)	(0.000)	(0.010)	(0.028)
ROA_{t-1}	0.072***	0.104***	0.021***	0.021***	-0.658***	-0.483***
	(0.010)	(0.017)	(0.001)	(0.001)	(0.052)	(0.109)
Age_t	-0.003	0.015***	0.001***	0.001***	0.015***	0.024***
	(0.002)	(0.003)	(0.000)	(0.000)	(0.001)	(0.002)
Observations	83,165	83,165	83,118	75,365	83,118	83,118
R-squared	0.515	0.275	0.435	0.454		

Table 28: Competitive effect as a channel for intra-industry spillover

This table shows OLS estimates in column (1) through (4), and, ordered logit regression estimates in column (5) and (6). $Fraud_{Within}$ equals to 1 if fraud occurs within the same industry, and 0 otherwise during last fiscal year. I also include its interactions with $\frac{CF}{K}_t$ and HHI_{High} in column (1) and (2). Each model contains firm- and year-fixed effects. Standard errors are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	$\frac{\text{Inv}}{\text{K}}_t$ (1)	$\Delta\frac{\text{Inv}}{\text{K}}$ (2)	$Payout\ Ratio_t$ (3)	$Payout\ Ratio_t$ (4)	ΔLong − term Bond Rating (5)	ΔShort − term Bond Rating (6)
$Fraud_{Within}$	-0.009	-0.000	0.000	0.000	0.196***	0.069
	(0.006)	(0.010)	(0.001)	(0.001)	(0.042)	(0.104)
$\frac{CF}{K}_t \times Fraud_{Within}$	-0.003***	-0.002**				
	(0.000)	(0.001)				
$\frac{CF}{K}_t \times Fraud_{Within} \times HHI_{High}$	-0.002**	-0.010***				
	(0.001)	(0.001)				
$Fraud_{Within} \times HHI_{High}$			0.003***	0.002*	0.018	0.202
			(0.001)	(0.001)	(0.076)	(0.188)
$\frac{\text{Inv}}{\text{K}}_{t-1}$	0.067***					
	(0.003)					
$Payout\ Ratio_{t-1}$				0.056***		
				(0.002)		
$\frac{CF}{K}_t$	-0.007***	-0.007***				
	(0.000)	(0.000)				
$\frac{CF}{K}_{t-1}$			0.000***	0.000***	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)
MTB_{t-1}	0.052***	0.012***	0.000*	0.000***	-0.035***	-0.031**
	(0.001)	(0.002)	(0.000)	(0.000)	(0.005)	(0.013)
$\text{Log(Assets}_{t-1})$	-0.187***	-0.163***	0.002***	0.002***	-0.042***	0.041**
	(0.003)	(0.005)	(0.000)	(0.000)	(0.007)	(0.018)
Leverage_{t-1}	-0.206***	0.018	-0.026***	-0.032***	0.356***	0.463***
	(0.011)	(0.019)	(0.001)	(0.001)	(0.046)	(0.106)
$\text{Sales Growth}_{t-1}$	0.022***	-0.126***	-0.001***	-0.001***	-0.095***	-0.012
	(0.002)	(0.003)	(0.000)	(0.000)	(0.010)	(0.028)
ROA_{t-1}	0.072***	0.105***	0.021***	0.021***	-0.650***	-0.474***
	(0.010)	(0.017)	(0.001)	(0.001)	(0.052)	(0.110)
Age_t	-0.003	0.015***	0.001***	0.001***	0.015***	0.024***
	(0.002)	(0.003)	(0.000)	(0.000)	(0.001)	(0.002)
Observations	83,165	83,165	83,118	75,365	83,118	83,118
R-squared	0.514	0.275	0.435	0.454		

Table 29: Attention effect vs. liquidity effect as a channel for intra-industry spillover

This table shows OLS estimates in column (1) through (4), and, ordered logit regression estimates in column (5) and (6). $Fraud_{Within}$ equals to 1 if fraud occurs within the same industry, and 0 otherwise during last fiscal year. I also include its interactions with $\frac{CF}{K}_t$ and $Analyst\ Coverage$ in column (1) and (2). Each model contains firm- and year-fixed effects. Standard errors are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	$\frac{\text{Inv}}{\text{K}}_t$ (1)	$\Delta\frac{\text{Inv}}{\text{K}}$ (2)	$Payout\ Ratio_t$ (3)	$Payout\ Ratio_t$ (4)	ΔLong − term Bond Rating (5)	ΔShort − term Bond Rating (6)
$Fraud_{Within}$	-0.009	0.000	0.001	0.001	0.160***	0.010
	(0.006)	(0.010)	(0.001)	(0.001)	(0.043)	(0.107)
$\frac{CF}{K}_t \times Fraud_{Within}$	-0.004***	-0.006***				
	(0.000)	(0.001)				
$\frac{CF}{K}_t \times Fraud_{Within}$	0.002***	0.002***				
$\times\ Analyst\ Coverage$	(0.000)	(0.001)				
$Fraud_{Within}$			0.000	0.000	0.055*	0.147**
$\times\ Analyst\ Coverage$			(0.000)	(0.001)	(0.030)	(0.071)
$\frac{\text{Inv}}{\text{K}}_{t-1}$	0.067***					
	(0.002)					
$Payout\ Ratio_{t-1}$				0.055***		
				(0.002)		
$\frac{CF}{K}_t$	-0.007***	-0.007***				
	(0.000)	(0.000)				
$\frac{CF}{K}_{t-1}$			0.000***	0.000***	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)
MTB_{t-1}	0.053***	0.013***	0.000*	0.000***	-0.036***	-0.033**
	(0.001)	(0.002)	(0.000)	(0.000)	(0.005)	(0.013)
$\text{Log}(\text{Assets}_{t-1})$	-0.187***	-0.162***	0.002***	0.002***	-0.043***	0.038**
	(0.003)	(0.005)	(0.000)	(0.000)	(0.007)	(0.018)
Leverage_{t-1}	-0.206***	0.017	-0.026***	-0.032***	0.360***	0.470***
	(0.011)	(0.019)	(0.001)	(0.001)	(0.046)	(0.106)
$\text{Sales Growth}_{t-1}$	0.022***	-0.126***	-0.001***	-0.001***	-0.095***	-0.012
	(0.002)	(0.003)	(0.000)	(0.000)	(0.010)	(0.028)
ROA_{t-1}	0.072***	0.104***	0.021***	0.021***	-0.650***	-0.473***
	(0.010)	(0.017)	(0.001)	(0.001)	(0.052)	(0.109)
Age_t	-0.003	0.015***	0.001***	0.001***	0.015***	0.024***
	(0.002)	(0.003)	(0.000)	(0.000)	(0.001)	(0.002)
Observations	83,165	83,165	83,118	75,365	83,118	83,118
R-squared	0.514	0.275	0.435	0.454		

Table 30: Comparison of possible channels for intra-industry spillover

This table shows OLS estimates in column (1) through (4), and, ordered logit regression estimates in column (5) and (6). $Fraud_{Within}$ equals to 1 if fraud occurs within the same industry, and 0 otherwise during last fiscal year. I also include its interactions with $\frac{CF}{K}_t$, HHI_{High}, and $Analyst\ Coverage$ in column (1) and (2). Each model contains firm- and year-fixed effects. Standard errors are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Firm control variables such as market-to-book ratio and ROA are included in the estimations but not reported in the table.

VARIABLES	$\frac{\text{Inv}}{\text{K}}_t$ (1)	$\Delta\frac{\text{Inv}}{\text{K}}$ (2)	$Payout\ Ratio_t$ (3)	$Payout\ Ratio_t$ (4)	ΔLong − term Bond Rating (5)	ΔShort − term Bond Rating (6)
$Fraud_{Within}$	-0.014**	-0.003	-0.001	-0.001	-0.004	-0.299*
	(0.006)	(0.010)	(0.001)	(0.001)	(0.065)	(0.161)
$\frac{CF}{K}_t \times Fraud_{Within}$	-0.020***	-0.011***				
	(0.001)	(0.002)				
$\frac{CF}{K}_t \times Fraud_{Within} \times HHI_{High}$	-0.004***	-0.010***				
	(0.001)	(0.002)				
$\frac{CF}{K}_t \times Fraud_{Within} \times Analyst\ Coverage$	0.001***	0.001*				
	(0.000)	(0.001)				
$\frac{CF}{K}_t \times Fraud_{Within} \times PostSOX$	0.020***	0.010***				
	(0.001)	(0.002)				
$Fraud_{Within} \times HHI_{High}$			0.003**	0.002*	-0.029	0.120
			(0.001)	(0.001)	(0.077)	(0.187)
$Fraud_{Within} \times Analyst\ Coverage$			0.000	0.000	0.046	0.127*
			(0.000)	(0.001)	(0.030)	(0.071)
$Fraud_{Within} \times PostSOX$			0.002	0.001	0.267***	0.430**
			(0.001)	(0.001)	(0.073)	(0.182)
$Firm\ Controls$	Y	Y	Y	Y	Y	Y
Observations	83,165	83,165	83,118	75,365	83,118	83,118
R-squared	0.516	0.276	0.435	0.454		

Table 31: Matched sample analysis

This table shows OLS estimates in column (1) through (4), and, ordered logit regression estimates in column (5) and (6) using the matched sample instead of the original sample. $Fraud_{Within}$ equals to 1 if fraud occurs within the same industry, and 0 otherwise during last fiscal year. $Fraud_{Top}(Fraud_{Bottom})$ equals to 1 if fraud occurs in the supplier (customer) industry for which the firm is in the top-customer (top-supplier) industry, and 0 otherwise during last fiscal year. I also include their interactions with $\frac{CF}{K}_t$ in column (1) and (2). Each model contains firm- and year-fixed effects. Standard errors are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Firm control variables such as market-to-book ratio and ROA are included in the estimations but not reported in the table.

	$\frac{\text{Inv}}{\text{K}}_t$	$\Delta\frac{\text{Inv}}{\text{K}}$	$Payout\ Ratio_t$	$Payout\ Ratio_t$	ΔLong − term Bond Rating	ΔShort − term Bond Rating
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
$Fraud_{Top}$	0.016**	0.019	-0.001	-0.001	0.297***	0.126
	(0.008)	(0.013)	(0.001)	(0.001)	(0.062)	(0.149)
$\frac{CF}{K}_t \times Fraud_{Top}$	0.002***	0.001				
	(0.001)	(0.001)				
$\frac{CF}{K}_t \times Fraud_{Top} \times \text{Trade Credit}_{\text{Top}}$	-0.009***	-0.013***				
	(0.001)	(0.002)				
$Fraud_{Top} \times \text{Trade Credit}_{\text{Top}}$			0.000	0.001	-0.194**	-0.138
			(0.001)	(0.001)	(0.084)	(0.204)
$Fraud_{Bottom}$	0.001	-0.013	0.002*	0.002	0.025	0.153
	(0.009)	(0.015)	(0.001)	(0.001)	(0.076)	(0.185)
$\frac{CF}{K}_t \times Fraud_{Bottom}$	0.006***	0.006***				
	(0.001)	(0.002)				
$\frac{CF}{K}_t \times Fraud_{Bottom} \times \text{Trade Credit}_{\text{Bottom}}$	0.008***	0.013***				
	(0.002)	(0.004)				
$Fraud_{Bottom} \times \text{Trade Credit}_{\text{Bottom}}$			-0.001	-0.001	0.120	0.261
			(0.002)	(0.002)	(0.103)	(0.247)
$Firm\ Controls$	Y	Y	Y	Y	Y	Y
Observations	83,165	83,165	83,118	75,365	83,118	83,118
R-squared	0.514	0.275	0.435	0.454		

Table 32: IV estimation

This table shows IV estimates in column (1) through (4). $Fraud_{Within}$ equals to 1 if fraud occurs within the same industry, and 0 otherwise during last fiscal year. $Fraud_{Top}$($Fraud_{Bottom}$) equals to 1 if fraud occurs in the supplier (customer) industry for which the firm is in the top-customer (top-supplier) industry, and 0 otherwise during last fiscal year. I also include their interactions with $\frac{CF}{K}_t$ in column (1) and (2). The instrumental variables are $Fraud\ Intensity_{Within}$, $Fraud\ Intensity_{Top}$, and $Fraud\ Intensity_{Bottom}$, and, their interactions with $\frac{CF}{K}_t$. Each model contains year-fixed effects. Standard errors are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$\frac{Inv}{K}_t$	$\Delta\frac{Inv}{K}$	$Payout\ Ratio_t$	$Payout\ Ratio_t$
VARIABLES	(1)	(2)	(3)	(4)
$Fraud_{Within}$	0.111***	0.093	0.012***	0.007*
	(0.038)	(0.060)	(0.003)	(0.004)
$\frac{CF}{K}_t \times Fraud_{Within}$	-0.040***	-0.062***		
	(0.012)	(0.018)		
$Fraud_{Top}$	-0.076***	-0.085**	-0.003*	-0.002
	(0.025)	(0.038)	(0.002)	(0.002)
$\frac{CF}{K}_t \times Fraud_{Top}$	0.084***	0.112***		
	(0.017)	(0.027)		
$Fraud_{Bottom}$	0.129***	0.018	-0.004*	-0.001
	(0.028)	(0.043)	(0.002)	(0.002)
$\frac{CF}{K}_t \times Fraud_{Bottom}$	0.017***	0.003		
	(0.006)	(0.009)		
$Firm\ controls$	Y	Y	Y	Y
Observations	83,165	83,165	83,118	75,365

Table 33: Potential issue about industries closely related to frauds

This table shows OLS estimates in column (1) through (4), and, ordered logit regression estimates in column (5) and (6). $Fraud_{Within}$ equals to 1 if fraud occurs within the same industry, and 0 otherwise during last fiscal year. $Fraud_{Top}$($Fraud_{Bottom}$) equals to 1 if fraud occurs in the supplier (customer) industry for which the firm is in the top-customer (top-supplier) industry, and 0 otherwise during last fiscal year. I also include their interactions with $\frac{CF}{K}_t$ in column (1) and (2). In addition, indicator variables $Semi, Tele, Ins$, and $Phar$ and their interaction with $\frac{CF}{K}_t$ are included. Each model contains firm- and year-fixed effects. Standard errors are reported in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Firm control variables such as market-to-book ratio and ROA are included in the estimations but not reported in the table.

VARIABLES	$\frac{\mathrm{Inv}}{\mathrm{K}}_t$	$\Delta\frac{\mathrm{Inv}}{\mathrm{K}}$	$Payout\ Ratio_t$	$Payout\ Ratio_t$	ΔLong − term Bond Rating	ΔShort − term Bond Rating
	(1)	(2)	(3)	(4)	(5)	(6)
$Fraud_{Within}$	-0.012**	-0.002	0.001**	0.001*	0.171***	0.138
	(0.006)	(0.010)	(0.001)	(0.001)	(0.039)	(0.097)
$\frac{CF}{K}_t \times Fraud_{Within}$	-0.004***	-0.005***				
	(0.000)	(0.001)				
$Fraud_{Top}$	0.019**	0.017	-0.001	-0.001	0.137***	-0.040
	(0.008)	(0.013)	(0.001)	(0.001)	(0.048)	(0.117)
$\frac{CF}{K}_t \times Fraud_{Top}$	0.002***	-0.001				
	(0.001)	(0.001)				
$Fraud_{Bottom}$	0.002	-0.009	0.001	0.001	0.053	0.278**
	(0.009)	(0.014)	(0.001)	(0.001)	(0.054)	(0.131)
$\frac{CF}{K}_t \times Fraud_{Bottom}$	0.009***	0.011***				
	(0.001)	(0.002)				
$Semi$			0.001	-0.001	0.072	-0.165
			(0.005)	(0.005)	(0.074)	(0.186)
$\frac{CF}{K}_t \times Semi$	-0.005**	-0.014***				
	(0.002)	(0.003)				
$Tele$			0.004*	0.004**	0.372***	0.632***
			(0.002)	(0.002)	(0.078)	(0.172)
$\frac{CF}{K}_t \times Tele$	0.001	-0.005***				
	(0.001)	(0.001)				
Ins			-0.009	-0.009	-1.267*	0.050
			(0.022)	(0.022)	(0.722)	(2.358)
$\frac{CF}{K}_t \times Ins$	-0.036**	-0.005				
	(0.017)	(0.029)				
$Phar$			0.000	-0.002	-0.159**	-0.533***
			(0.006)	(0.007)	(0.071)	(0.176)
$\frac{CF}{K}_t \times Phar$	0.003***	0.004***				
	(0.000)	(0.001)				
$\mathrm{Freq_{Top}}$			0.001	0.001	-0.039	0.101

			(0.004)	(0.004)	(0.079)	(0.193)
$\frac{CF}{K}_t \times Freq_{Top}$	-0.028***	0.062***				
	(0.004)	(0.007)				
$Freq_{Bottom}$			0.001	0.000	-0.078	-0.080
			(0.006)	(0.007)	(0.169)	(0.427)
$\frac{CF}{K}_t \times Freq_{Bottom}$	0.036***	0.037***				
	(0.008)	(0.013)				
Firm controls	Y	Y	Y	Y	Y	Y
Observations	83,165	83,165	83,118	75,365	83,118	83,118
R-squared	0.516	0.277	0.435	0.454		

Figure 1: Industry-wise agility

These figures exhibit the time-series values of $Agility$ in the industry level; Figure 1A plots yearly averages of $Agility$ for the industries of software (SIC 3-digit code 737), pharmaceutical (283), metal (331-339, 341-349), and oil and gas (131, 291-299) industries. Figure 1B plots yearly averages of $Agility$ for the industries of household items (201-209, 231-239, 541-549, 561-566, 581) and non-household items (011-179, 351-359, 371-379). Figure 1C plots yearly averages of $Agility$ for less regulated industry (231-239, 271-279, 391-399, 501-509, 511-519, 531, 539, 541-549, 551-559, 561-566, 571-573, 581, 591-599, 701-899) and more regulated industry (011-149, 211-214, 241, 261, 283, 311, 384, 385, 401-497, 801-809). Figure 1D plots yearly averages of $Agility$ for high-Q industry and low-Q industry.

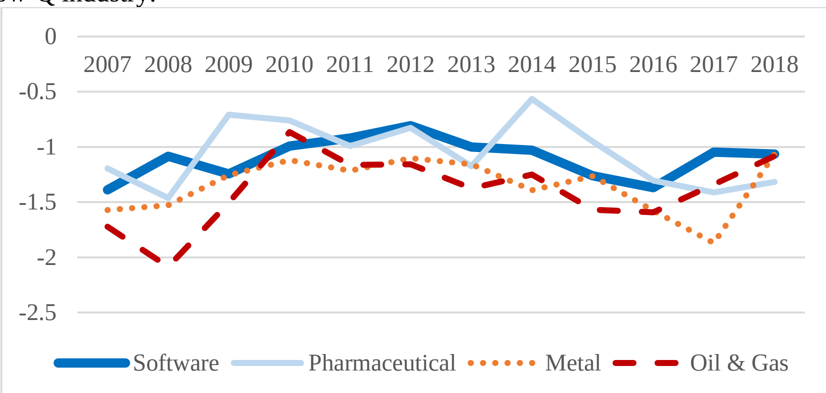


Figure 1A

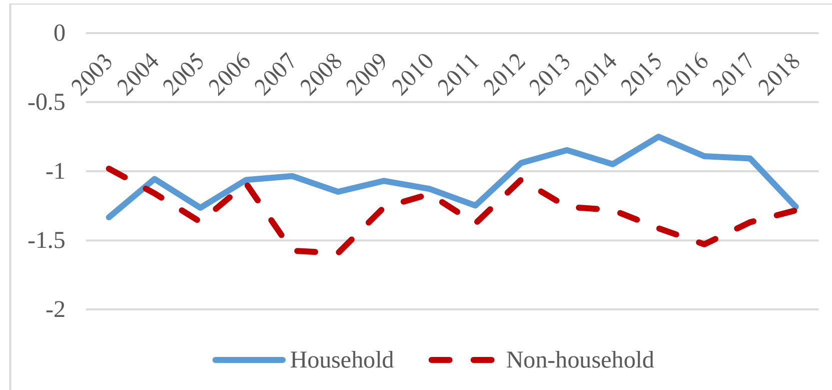


Figure 1B

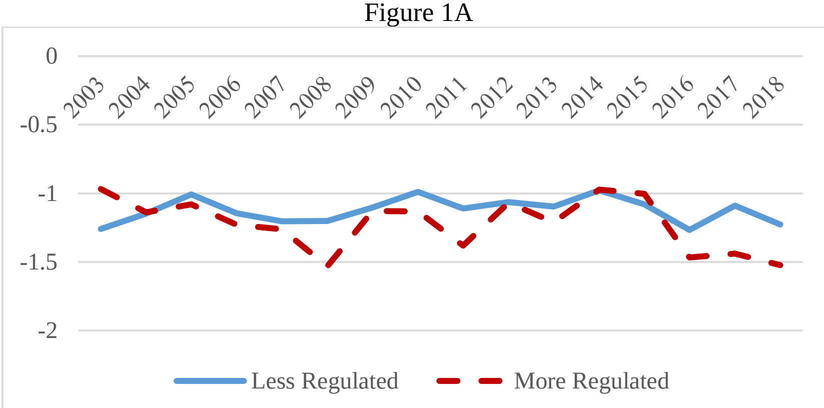


Figure 1C

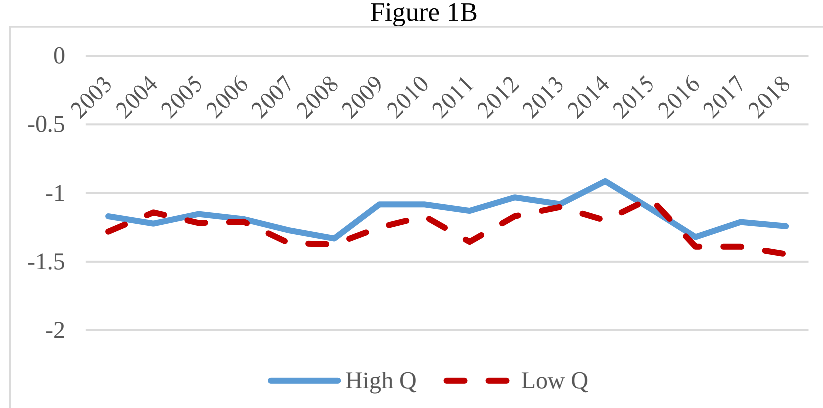


Figure 1D

Figure 2: Investigatin of pharmaceutical industry

These figures present the time series of average $Agility$ in the pharmaceutical industry, the FDA's new drug approval rate, and new drug approval times. $Approval\ Rates$ is the approval rates for CDER NME NDA and BLA applications for the period from 1993-2015. $Approval\ Time$ $(Priority)$ and $Approval\ Time$ $(Standard)$ are the median total approval times of priority and standard drugs, respectively, obtained from New Drug Application (NDA) and Biologic License Application (BLA) approval times for the period from 1993-2015. Figure 2A shows the time trends of average $Agility$ and $Approval\ Rates$. Figure 2B shows the time trends of average $Agility$ and the inverse of $Approval\ Time$ $(Priority)$. The left vertical axis represents the average $Agility$ and the right vertical axis represents the $Approval\ Rates$ $(Approval\ Time$ $(Priority))$ in Figure 2A (2B). $Approval\ Rates$ and $Approval\ Time$ $(Priority)$ are separately plotted because they are on different scales and have differential time-series variations.

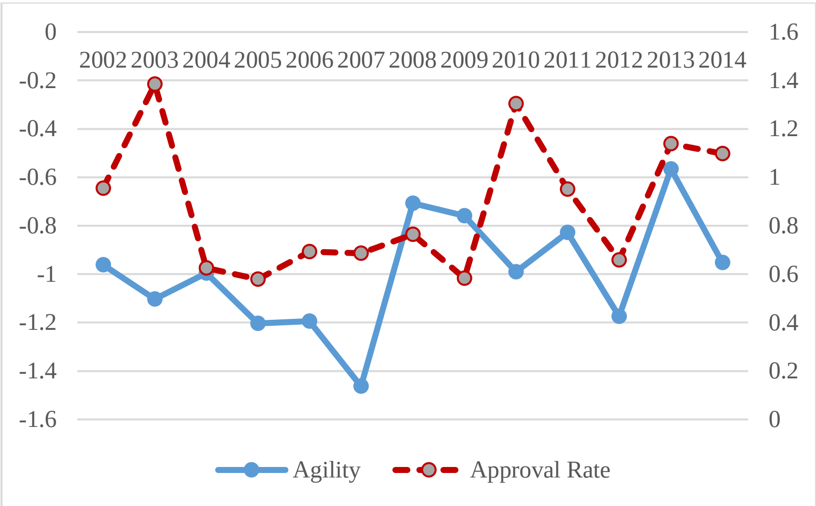


Figure 2A

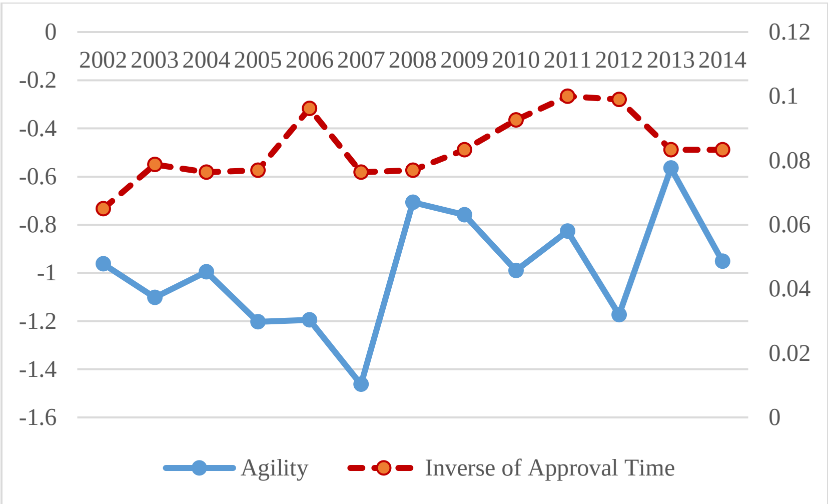
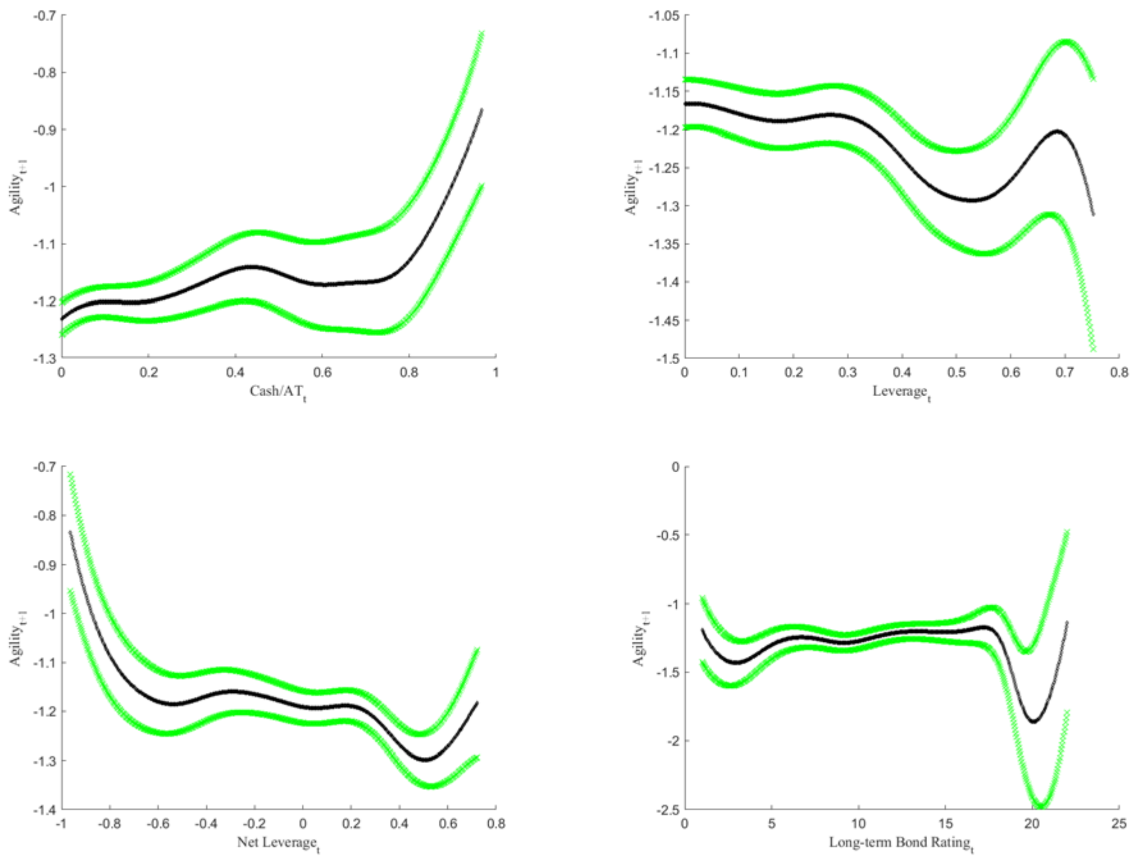


Figure 2B

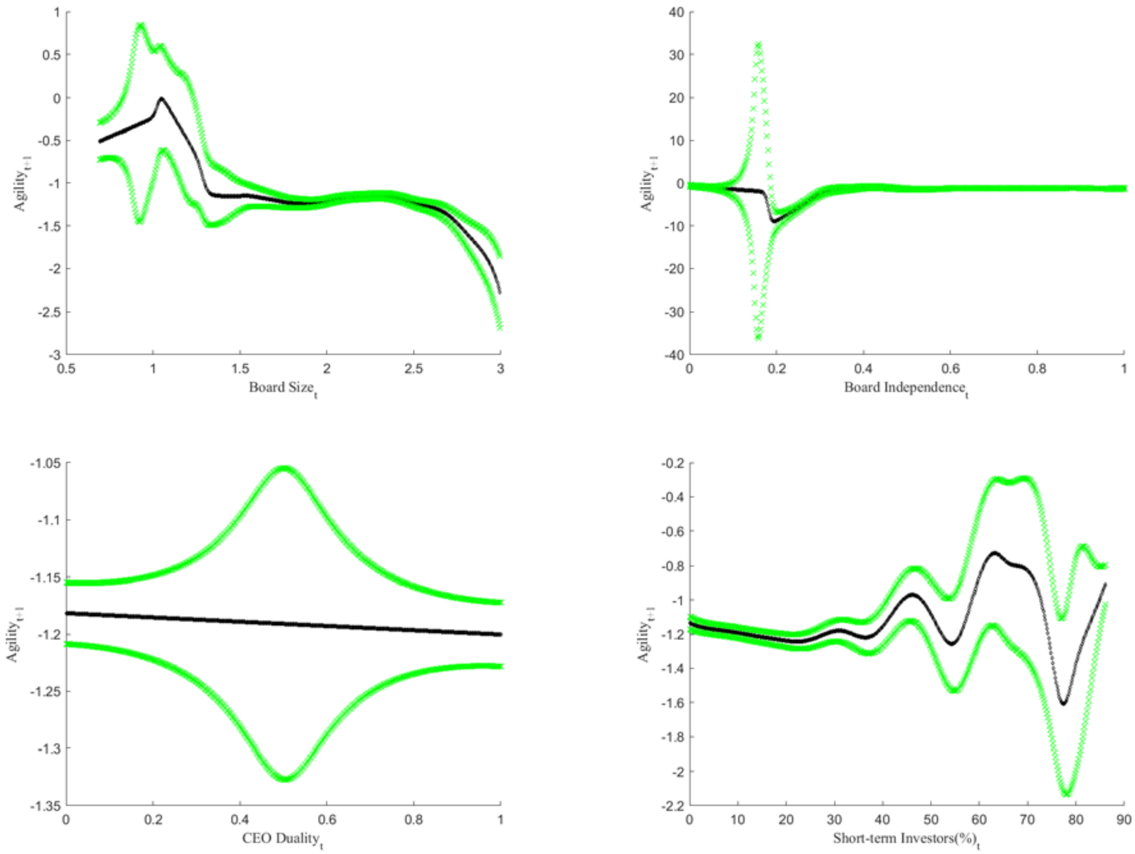
Figure 3: Local linear regression of agility (in year t) on firm variables (in year t-1)

These figures present how $Agility$ (in year t) changes with firm flexibility measures (in year t-1). Firm flexibility measures are categorized into financial flexibility measures (Cash/AT, Leverage, Net Leverage, Long-term Bond Rating), governance flexibility measures (Board Size, Board Independence, CEO Duality, Short-term Investors (%)), and organizational flexibility measures (Firm Age, Firm Size, Number of Business Segments, Firm Herfindahl Index). I estimate a local linear regression of $Agility$ (in year t) on each firm flexibility measures (in year t-1) with Gaussian kernel function and Silverman's rule-of-thumb bandwidth choice. Vertical and horizontal axes represent $Agility$ and firm flexibility variables, respectively. The black (green) line represents the local linear regression estimates (95% confidence interval).

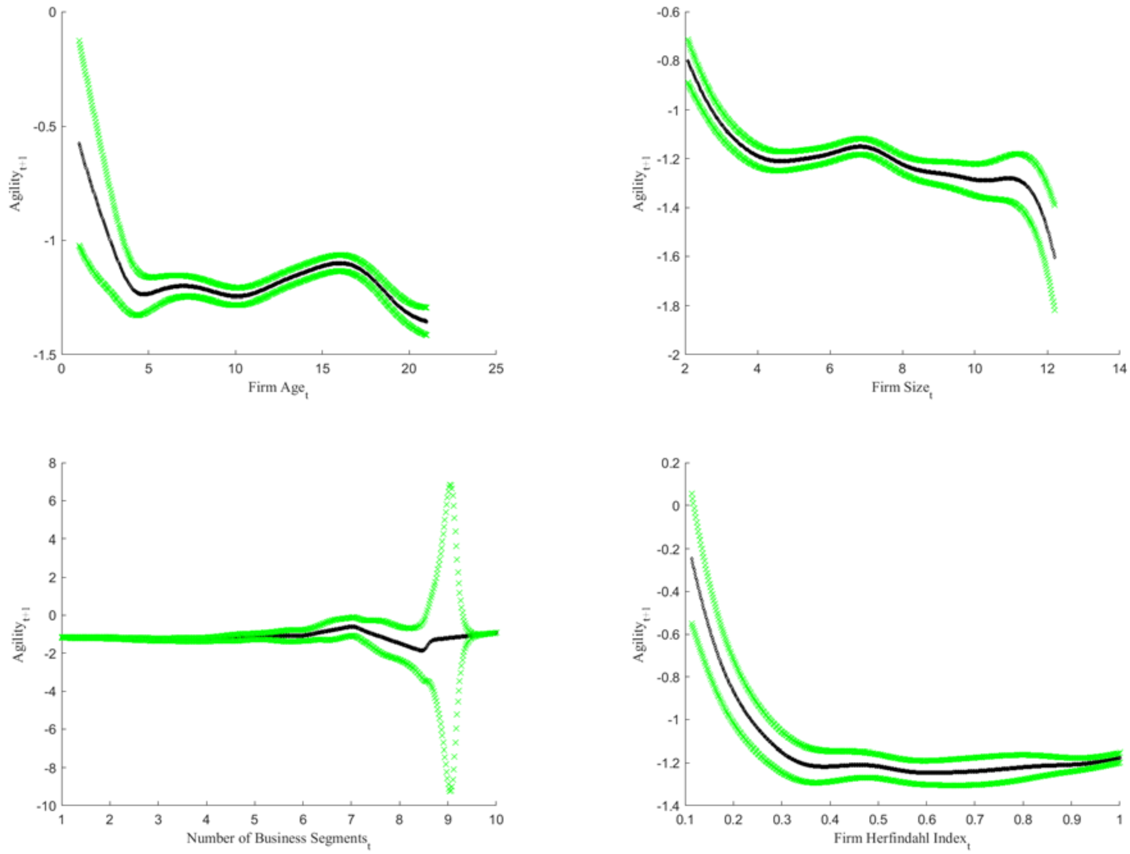
Panel A: Financial flexibility measures



Panel B: Governance flexibility measures



Panel C: Organizational flexibility measures



Panel D: Operating flexibility measures

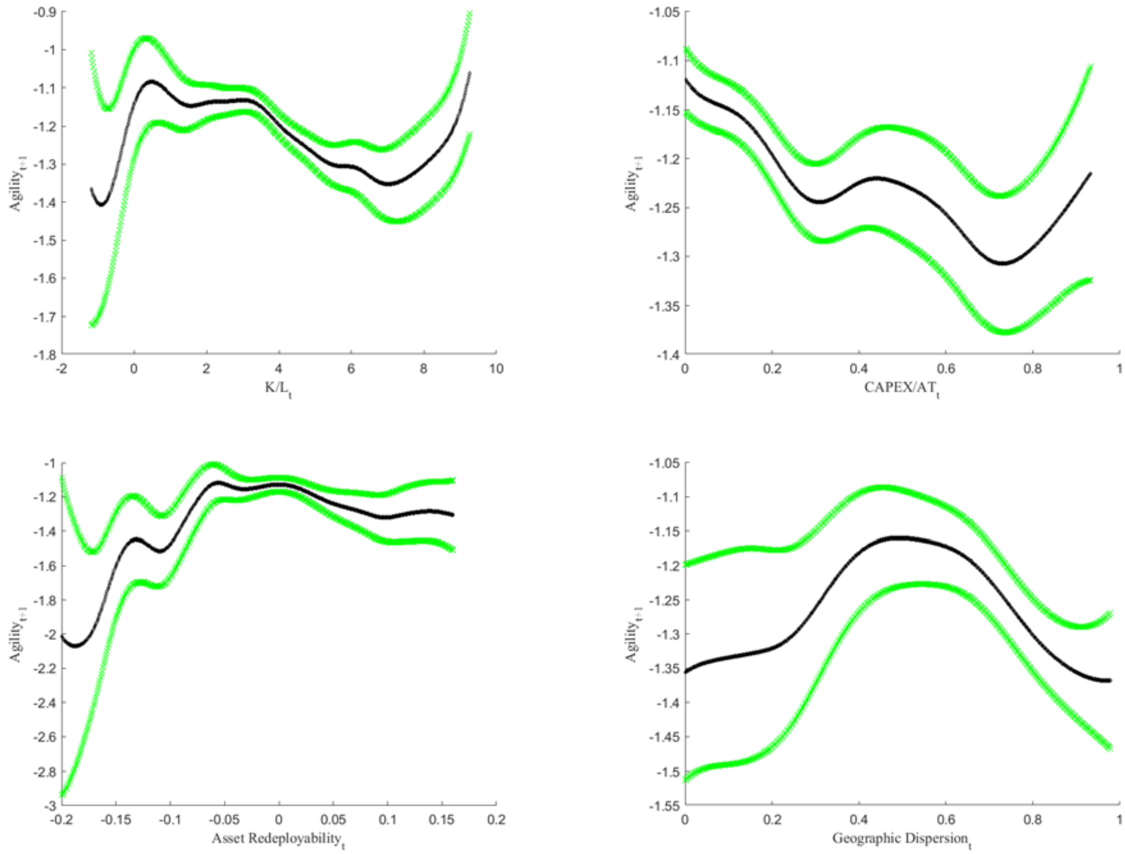
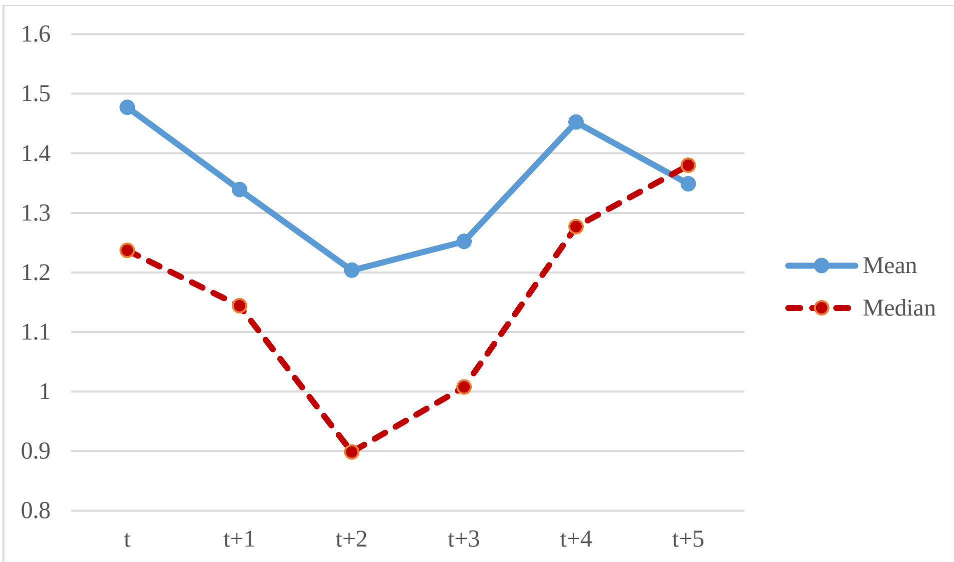


Figure 4: Agility dynamics after acquisitions

This figure exhibits dynamics of the absolute difference between the acquirer's $Agility$ and target's $Agility$ after their acquisition is completed in year t. The absolute deviation of the acquirer's $Agility$ in t, t+1,…, t+5 from the target's $Agility$ in t is observed for each acquirer-target pair. The solid (dotted) line represents the mean (median) of the absolute deviation.



Appendix A : First Essay

Appendix Table A1: Variable definition

Variable	Description
Firm characteristics (CRSP/Compustat/BoardEx/SDC/Thomson Reuters 13F)	
$Acquisition\ Value/AT$	Total transaction values of acquisitions / Total Assets (AT)
$Board\ Independence$	The number of non-executive directors / The number of entire directors
$Board\ Size$	Logarithm of 1 plus the number of directors
$Cash/AT$	Cash and Short-Term Investments (CHE) / Total Assets (AT)
$CEO\ Duality$	1 if a CEO serves as the chairman in the same firm and 0 otherwise.
$Dividend\ Payer$	1 if Dividends Common/Ordinary (DVC) is available and 0 otherwise.
$Firm\ Age$	The number of years a firm a firm appears on the Compustat tapes
$Firm\ Herfindahl\ Index$	Sales concentration of business segments within a firm
$Firm\ Size$	Logarithm of Total Assets (AT)
$Leverage$	[Long-Term Debt (DLTT) + Debt in Current Liabilities (DLC)] / Total Assets (AT)
$Long-term\ Bond\ Rating$	Numerical transformation of long-term bond rating (SPLTICRM)
$Market\ Share\ Growth$	Sales (SALE) growth minus industry (SIC2) average of Sales (SALE) growth in the same year
$MTB\ (Market-to-Book)$	[Total Liabilities (LT) – Deferred Taxes and Investment Tax Credit (TXDITC) + Preferred Stock (defined below) + Common Shares Outstanding (CSHO) * Price Close (PRCC_F)] / Total Assets (AT)
$Net\ Leverage$	[Long-Term Debt (DLTT) + Debt in Current Liabilities (DLC) – Cash and Short-Term Investments (CHE)] / Total Assets (AT)
$Number\ of\ Segments$	The number of business segments in a firm
$Preferred\ Stock$	Liquidating value (PSTKL) if available, else Redemption value (PSTKRV) if available, else Carrying value (PSTK).
$R\&D/AT$	Research and Development Expense (XRD) / Total Assets (AT) if available, else 0.
ROA	Operating Income Before Depreciation (OIBDP) / Total Assets (AT)
$Short-term\ Investors$ (%)	Proportion of shares outstanding held by transient investors
$Tangibility$	Net Property Plant and Equipment (PPENT) / Total Assets (AT)
$Zscore$	[1.2 * Working Capital (WCAP) + 1.4 * Retained Earnings (RE) + 3.3 * Pretax Income (PI) + 0.999 * Sales (SALE)] / Total Assets (AT)
Industry characteristics (Compustat/SDC)	
$HHI\ (Industry\ Herfindahl\ Index)$	Sales (SALE) concentration of firms within an industry
$Industry\ M\&A\ Wave$	Sum of transaction values of acquisitions in an industry / Sum of Total Assets (AT) in an industry
$Industry\ R\&D\ Intensity$	Sum of Research and Development Expense (XRD) in an industry / Sum of Total Assets (AT) in an industry

Appendix Table A2: Persistence test with "fictitious" $Agility$

This table reports the mean persistence of "fictitious" $Agility$ measure. "Fictitious" $Agility$ is simulated 1,000 times using the same parameters but with different values of $Internal\ Fluidity$ and $External\ Fluidity$ for the sample firms in the same period. Each row of Panel A displays the mean proportion of firms in the corresponding "fictitious" $Agility$ quintile in year t, which remain in the same "fictitious" $Agility$ quintile in year t+1, t+2, …, t+5. Each row of Panel B shows the mean migration rates of firms in the corresponding "fictitious" $Agility$ quintile in year t to each of the "fictitious" $Agility$ quintiles in year t+1.

Panel A: 5-year follow-up of "fictitious" $Agility$ quintiles

Quintile (in year t)	Proportion of firms remaining in the same quantile (as of year t) in year				
	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
1	0.404	0.283	0.235	0.212	0.199
2	0.314	0.243	0.220	0.207	0.200
3	0.308	0.229	0.209	0.202	0.200
4	0.356	0.251	0.217	0.204	0.200
5	0.544	0.376	0.284	0.231	0.200

Panel B: Year-to-year follow-up of "fictitious" $Agility$ quintiles

Quintile (in year t)	Proportion of firms migrating in year $t+1$ to Quintile				
	1	2	3	4	5
1	0.404	0.267	0.161	0.102	0.066
2	0.265	0.314	0.217	0.127	0.076
3	0.161	0.217	0.308	0.208	0.105
4	0.101	0.127	0.208	0.356	0.208
5	0.066	0.077	0.105	0.207	0.544

Appendix Table A3: Pairwise correlation matrix

This table reports the pairwise correlation matrix between $Agility$ and firm flexibility measures. Firm flexibility measures are categorized into financial flexibility measures (Cash/AT, Leverage, Net Leverage, Long-term Bond Rating), governance flexibility measures (Board Size, Board Independence, CEO Duality, Short-term Investors (%)), and organizational flexibility measures (Firm Age, Firm Size, Number of Business Segments, Firm Herfindahl Index). Variable definitions are described in Appendix A Table A1. The symbol ***, **, and * denote statistical significance for two-tailed t-tests at the 1%, 5%, and 10% levels, respectively.

Variables	Agility	Cash/AT	Leverage	Net Leverage	Long-term Bond Rating	Board Size	Board Independence	CEO Duality	Short-term Investors (%)	Firm Age	Firm Size	Number of Segments	Firm Herfindahl Index
Agility	1.000												
Cash/AT	0.025***	1.000											
Leverage	-0.023***	-0.440***	1.000										
Net Leverage	-0.029***	-0.877***	0.817***	1.000									
Long-term Bond Rating	0.025*	-0.111***	0.447***	0.387***	1.000								
Board Size	-0.008	-0.219***	0.236***	0.266***	-0.480***	1.000							
Board Independence	0.011	-0.033***	0.105***	0.077***	-0.238***	0.351***	1.000						
CEO Duality	-0.007	-0.093***	0.043***	0.083***	-0.109***	-0.002	-0.089***	1.000					
Short-term Investors (%)	-0.010	0.012	0.035***	0.012	0.182***	0.150***	0.110***	0.024***	1.000				
Firm Age	0.004	-0.079***	0.059***	0.081***	-0.091***	0.067***	0.136***	-0.107***	-0.042***	1.000			
Firm Size	-0.031***	-0.369***	0.406***	0.453***	-0.633***	0.631***	0.287***	0.106***	0.247***	0.211***	1.000		
Number of Segments	-0.015*	-0.217***	0.138***	0.213***	-0.260***	0.257***	0.103***	0.068***	0.005	0.087***	0.320***	1.000	
Firm Herfindahl Index	0.010	0.228***	-0.134***	-0.218***	0.225***	-0.250***	-0.111***	-0.059***	-0.006	-0.085***	-0.278***	-0.867***	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix Table A4: Extended estimation window

This table reports the effect of $Agility$ on product market performance and firm survival likelihood when firm-by-firm regression of (3) is estimated with a 10-year estimation window. The independent variables are measured at year t, and the definitions are described in Appendix A Table A1. The dependent variables of Column 1, 2, and 3 are market share growth in year t+1, t+3, and t+5, respectively. The dependent variables in Column 4, 5, and 6 are indicator variables equal to one if a firm is delisted from CRSP as of year t+1, t+3, and t+5, respectively. The specifications are estimated via OLS with year and industry fixed effects in Column 1, 2, and 3. The specifications are estimated via logit regressions with year and industry fixed effects in Column 4, 5, and 6. I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Market\ Share\ Growth_{t+1}$	$Market\ Share\ Growth_{t+3}$	$Market\ Share\ Growth_{t+5}$	$Delist_{t+1}$	$Delist_{t+3}$	$Delist_{t+5}$
$Agility$	0.064	0.107*	0.175*			
	(0.113)	(0.068)	(0.062)			
$High\ Agility$				-0.256**	-0.128*	-0.044
				(0.023)	(0.072)	(0.536)
$Low\ Agility$				0.068	-0.032	-0.018
				(0.594)	(0.714)	(0.833)
$Cash/AT$	0.067	0.704	2.503**	-0.630**	-0.490**	0.153
	(0.899)	(0.354)	(0.038)	(0.041)	(0.015)	(0.446)
$Leverage$	-0.305	-0.151	-0.918	1.480***	1.793***	1.694***
	(0.546)	(0.842)	(0.468)	(0.000)	(0.000)	(0.000)
$Dividend\ Payer$	0.249	0.427*	0.221	-0.542***	-0.563***	-0.601***
	(0.156)	(0.082)	(0.541)	(0.000)	(0.000)	(0.000)
$Zscore$	0.033*	0.029	-0.128*	-0.006	-0.012**	-0.004
	(0.093)	(0.476)	(0.063)	(0.121)	(0.014)	(0.468)
$Size$	-0.637***	-0.962***	0.474	-0.186***	-0.194***	-0.171***
	(0.000)	(0.000)	(0.238)	(0.000)	(0.000)	(0.000)
Age	-0.132***	-0.206***	-0.397***	-0.004	-0.016	-0.023
	(0.000)	(0.000)	(0.000)	(0.801)	(0.225)	(0.149)
MTB	0.072	-0.100	-0.504***	-0.010	-0.015**	-0.171***
	(0.172)	(0.180)	(0.000)	(0.224)	(0.022)	(0.000)
ROA	-2.990***	-1.481*	5.139***	-0.249	-0.290	-0.448*
	(0.000)	(0.061)	(0.000)	(0.445)	(0.224)	(0.070)
$Tangibility$	-0.490	0.101	-0.010	-0.418	-0.780***	-0.614**
	(0.576)	(0.938)	(0.997)	(0.228)	(0.001)	(0.015)
$R\&D/AT$	-3.917***	-0.398	12.216***	0.255	-0.690	-0.646
	(0.002)	(0.838)	(0.000)	(0.675)	(0.102)	(0.164)
$Constant$	6.648***	9.305***	1.591			
	(0.000)	(0.000)	(0.602)			
Observations	10,141	7,435	4,853	10,084	9,269	7,086
R-squared	0.404	0.433	0.468			
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Appendix Table A5: Magnitude of competitive threats

This table reports the effect of $Agility$ on product market performance and firm survival likelihood when firm-by-firm regression of (3) is estimated after eliminating the observations with $External\ Fluidity$ in the bottom quintile of the same year. The independent variables are measured at year t, and the definitions are described in Appendix A Table A1. The dependent variables of Column 1, 2, and 3 are market share growth in year t+1, t+3, and t+5, respectively. The dependent variables in Column 4, 5, and 6 are indicator variables equal to one if a firm is delisted from CRSP as of year t+1, t+3, and t+5, respectively. The specifications are estimated via OLS with year and industry fixed effects in Column 1, 2, and 3. The specifications are estimated via logit regressions with year and industry fixed effects in Column 4, 5, and 6. I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Market\ Share\ Growth_{t+1}$	$Market\ Share\ Growth_{t+3}$	$Market\ Share\ Growth_{t+5}$	$Delist_{t+1}$	$Delist_{t+3}$	$Delist_{t+5}$
$Agility$	0.036	0.134**	0.162*			
	(0.445)	(0.049)	(0.057)			
$High\ Agility$				-0.265	-0.241**	-0.280***
				(0.108)	(0.020)	(0.005)
$Low\ Agility$				-0.086	0.136	-0.056
				(0.721)	(0.356)	(0.712)
$Cash/AT$	-1.174	0.199	1.327	0.053	0.394	1.029***
	(0.119)	(0.857)	(0.335)	(0.914)	(0.199)	(0.001)
$Leverage$	-0.570	-1.185	0.000	1.251**	1.294***	1.470***
	(0.453)	(0.286)	(1.000)	(0.015)	(0.000)	(0.000)
$Dividend\ Payer$	0.174	-0.005	0.261	-0.264	-0.361***	-0.437***
	(0.500)	(0.990)	(0.550)	(0.163)	(0.002)	(0.000)
$Zscore$	-0.037	0.031	-0.066	0.001	-0.005	-0.006
	(0.213)	(0.672)	(0.458)	(0.866)	(0.638)	(0.610)
$Size$	-0.316	-0.607**	0.417	-0.176***	-0.141***	-0.123***
	(0.110)	(0.037)	(0.291)	(0.000)	(0.000)	(0.000)
Age	-0.086***	-0.068	-0.356***	0.042	0.035	0.034
	(0.005)	(0.119)	(0.000)	(0.255)	(0.193)	(0.277)
MTB	-0.035	0.182*	-0.336**	-0.143**	-0.255***	-0.337***
	(0.657)	(0.098)	(0.012)	(0.046)	(0.000)	(0.000)
ROA	-0.726	-1.931	5.120***	-0.026	-0.185	-0.499
	(0.416)	(0.147)	(0.002)	(0.966)	(0.665)	(0.253)
$Tangibility$	-1.060	-2.747	-1.533	0.240	-0.536	-0.868**
	(0.438)	(0.165)	(0.561)	(0.699)	(0.201)	(0.038)
$R\&D/AT$	-4.848**	2.905	12.670***	1.670	0.697	-0.306
	(0.026)	(0.338)	(0.001)	(0.102)	(0.327)	(0.674)
$Constant$	3.903*	3.692*	0.472			
	(0.066)	(0.091)	(0.863)			
Observations	4,639	3,536	2,492	3,888	3,960	3,276
R-squared	0.453	0.464	0.509			
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Appendix Table A6: Reporting quality

This table reports the effect of $Agility$ on product market performance and firm survival likelihood when firms whose business descriptions are less likely to be informative are excluded. In Column 1 through 6, firms are excluded if they are younger than 5 years old or appear in the sample for the first time. In Column 7 through 12, firms are excluded if their size is in top 20% of the sample. The independent variables are measured at year t, and the definitions are described in Appendix A Table A1. The dependent variables of Column 1, 2, and 3 (Column 7, 8, and 9) are market share growth in year t+1, t+3, and t+5, respectively. The dependent variables in Column 4, 5, and 6 (Column 10, 11, and 12) are indicator variables equal to one if a firm is delisted from CRSP as of year t+1, t+3, and t+5, respectively. The specifications are estimated via OLS with year and industry fixed effects in Column 1, 2, and 3 (Column 7, 8, and 9). The specifications are estimated via logit regressions with year and industry fixed effects in Column 4, 5, and 6 (Column 10, 11, and 12). I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$Market\ Share\ Growth_{t+1}$	$Market\ Share\ Growth_{t+3}$	$Market\ Share\ Growth_{t+5}$	$Delist_{t+1}$	$Delist_{t+3}$	$Delist_{t+5}$	$Market\ Share\ Growth_{t+1}$	$Market\ Share\ Growth_{t+3}$	$Market\ Share\ Growth_{t+5}$	$Delist_{t+1}$	$Delist_{t+3}$	$Delist_{t+5}$
$Agility$	0.088**	0.143***	0.005				0.065*	0.097**	0.056			
	(0.022)	(0.004)	(0.930)				(0.073)	(0.027)	(0.317)			
$High\ Agility$				-0.203*	-0.154**	-0.086				-0.111	-0.115*	-0.115*
				(0.076)	(0.039)	(0.239)				(0.293)	(0.092)	(0.081)
$Low\ Agility$				0.033	0.056	-0.089				-0.025	0.094	-0.053
				(0.825)	(0.570)	(0.378)				(0.862)	(0.311)	(0.571)
Observations	8,700	6,500	4,370	8,574	8,113	6,305	9,549	7,255	5,041	9,461	9,081	7,380
R-squared	0.375	0.446	0.464				0.360	0.439	0.446			
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Appendix Table A7: Product Differentiation vs. Assimilation

This table investigates the effects of $Agility_{+}$ and $Agility_{+}$ on product market performance and firm survival likelihood. The independent variables are measured at year t, and the definitions are described in Appendix A Table A1. The dependent variables of Column 1, 2, and 3 are market share growth in year t+1, t+3, and t+5, respectively. The dependent variables in Column 4, 5, and 6 are indicator variables equal to one if a firm is delisted from CRSP as of year t+1, t+3, and t+5, respectively. The specifications are estimated via OLS with year and industry fixed effects in Column 1, 2, and 3. The specifications are estimated via logit regressions with year and industry fixed effects in Column 4, 5, and 6. I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) $Market\ Share$ $Growth_{t+1}$	(2) $Market\ Share$ $Growth_{t+3}$	(3) $Market\ Share$ $Growth_{t+5}$	(4) $Delist_{t+1}$	(5) $Delist_{t+3}$	(6) $Delist_{t+5}$
$Agility_{+}$	0.064	0.117*	0.054			
	(0.175)	(0.055)	(0.428)			
$Agility_{-}$	0.077	0.074	0.044			
	(0.104)	(0.229)	(0.586)			
$High\ Agility_{+}$				-0.157	-0.213**	-0.203**
				(0.251)	(0.016)	(0.016)
$High\ Agility_{-}$				-0.106	-0.048	-0.050
				(0.398)	(0.548)	(0.514)
$Low\ Agility$				0.121	0.049	-0.105
				(0.333)	(0.555)	(0.204)
Observations	10,886	8,311	5,769	10,971	10,403	8,428
R-squared	0.348	0.429	0.433			
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Appendix Table A8: Quasi-agility

This table reports the effect of $Quasi\text{-}agility$ on product market performance and firm survival likelihood. The estimation process of $Quasi\text{-}agility$ is identical to that of $Agility$ except that it replaces $(W_{it+1} - W_{it}) \cdot D_t$ by $(W_{it+1} - W_{it}) \cdot W_{it}$ in firm-by-firm regression of (3). In Panel A, the dependent variables of Column 1, 2, and 3 (Column 4, 5, and 6) are market share growth in year t+1, t+3, and t+5, respectively. In Panel B, the dependent variables in Column 1, 2, and 3 (Column 4, 5, and 6) are indicator variables equal to one if a firm is delisted from CRSP as of year t+1, t+3, and t+5, respectively. The specifications are estimated via OLS with year and industry fixed effects in Panel A. The specifications are estimated via logit regressions with year and industry fixed effects in Panel B. I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Market share growth

	(1) $Market\ Share\ Growth_{t+1}$	(2) $Market\ Share\ Growth_{t+3}$	(3) $Market\ Share\ Growth_{t+5}$	(4) $Market\ Share\ Growth_{t+1}$	(5) $Market\ Share\ Growth_{t+3}$	(6) $Market\ Share\ Growth_{t+5}$
$Quasi\text{-}agility$	0.054*	0.057	-0.029	0.041	0.043	-0.041
	(0.086)	(0.135)	(0.552)	(0.213)	(0.266)	(0.410)
$Agility$				0.060*	0.083*	0.059
				(0.084)	(0.050)	(0.283)
Observations	10,931	8,349	5,803	10,886	8,311	5,769
R-squared	0.348	0.429	0.433	0.349	0.429	0.433
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Panel B: Survival likelihood

	(1) $Delist_{t+1}$	(2) $Delist_{t+3}$	(3) $Delist_{t+5}$	(4) $Delist_{t+1}$	(5) $Delist_{t+3}$	(6) $Delist_{t+5}$
$High\ Quasi\text{-}agility$	-0.082	-0.027	-0.108*	-0.065	-0.007	-0.112*
	(0.417)	(0.671)	(0.084)	(0.536)	(0.911)	(0.083)
$Low\ Quasi\text{-}agility$	0.149	0.062	0.036	0.136	0.054	0.039
	(0.235)	(0.460)	(0.659)	(0.279)	(0.523)	(0.636)
$High\ Agility$				-0.104	-0.116*	-0.090
				(0.319)	(0.082)	(0.159)
$Low\ Agility$				0.110	0.045	-0.113
				(0.380)	(0.590)	(0.173)
Observations	11,015	10,500	8,518	10,971	10,403	8,428
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Appendix Table A9: Residual agility

This table reports the effect of $Residual\ Agility$ on product market performance and firm survival likelihood. Residual Agility is estimated as the residual from the regression of Agility in t on significant firm flexibility measures from each flexibility category (i.e., Net Leverage, Board Size, Firm Size, CAPEX/AT) in t-1 in each industry. The independent variables are measured at year t, and the definitions are described in Appendix A Table A1. The dependent variables of Column 1, 2, and 3 are market share growth in year t+1, t+3, and t+5, respectively. The dependent variables in Column 4, 5, and 6 are indicator variables equal to one if a firm is delisted from CRSP as of year t+1, t+3, and t+5, respectively. The specifications are estimated via OLS with year and industry fixed effects in Column 1, 2, and 3. The specifications are estimated via logit regressions with year and industry fixed effects in Column 4, 5, and 6. I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Market\ Share\ Growth_{t+1}$	$Market\ Share\ Growth_{t+3}$	$Market\ Share\ Growth_{t+5}$	$Delist_{t+1}$	$Delist_{t+3}$	$Delist_{t+5}$
$Residual\ Agility$	0.049	0.106**	0.053			
	(0.248)	(0.040)	(0.425)			
$High\ Agility$				-0.128	-0.108	-0.123*
				(0.239)	(0.117)	(0.063)
$Low\ Agility$				0.093	0.086	-0.068
				(0.488)	(0.326)	(0.439)
$Cash/AT$	-0.459	1.303	2.500**	-0.425	-0.396**	0.298
	(0.488)	(0.137)	(0.043)	(0.155)	(0.038)	(0.116)
$Leverage$	-0.818	-0.726	0.067	1.534***	1.855***	1.648***
	(0.266)	(0.379)	(0.957)	(0.000)	(0.000)	(0.000)
$Dividend\ Payer$	0.052	0.195	0.256	-0.426***	-0.484***	-0.528***
	(0.792)	(0.342)	(0.343)	(0.000)	(0.000)	(0.000)
$Zscore$	0.030	0.015	-0.061	-0.006	-0.011**	-0.003
	(0.205)	(0.828)	(0.606)	(0.111)	(0.028)	(0.496)
$Size$	-0.304	-0.746***	-0.122	-0.155***	-0.174***	-0.157***
	(0.179)	(0.003)	(0.753)	(0.000)	(0.000)	(0.000)
Age	-0.075**	-0.049	-0.237***	-0.016	-0.011	-0.008
	(0.013)	(0.158)	(0.000)	(0.415)	(0.436)	(0.647)
MTB	-0.004	-0.088	-0.392**	-0.011	-0.014**	-0.246***
	(0.970)	(0.385)	(0.029)	(0.204)	(0.040)	(0.000)
ROA	-2.788***	-1.040	4.334*	-0.378	-0.528**	-0.483*
	(0.001)	(0.341)	(0.067)	(0.259)	(0.029)	(0.057)
$Tangibility$	-1.871*	0.005	-0.194	-0.405	-0.504**	-0.592**
	(0.093)	(0.998)	(0.944)	(0.252)	(0.034)	(0.015)
$R\&D/AT$	-1.969	0.520	9.907**	0.310	-0.464	-0.481
	(0.403)	(0.876)	(0.023)	(0.597)	(0.254)	(0.281)
$Constant$	2.587	3.813**	1.472			
	(0.126)	(0.023)	(0.596)			
Observations	9,969	7,582	5,238	9,687	9,308	7,467
R-squared	0.357	0.430	0.432			
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Appendix Table A10: Manufacturing industry

This table reports the effect of $Agility$ on product market performance and firm survival likelihood using manufacturing industry firms. In Panel A, the regressions only include firms in SIC 2-digit between 20-39. In Panel B, the regressions only include firms in SIC 2-digit of 27, 30, 32, 33, 34, 35, 37, and 38. The independent variables are measured at year t, and the definitions are described in Appendix A Table A1. The dependent variables of Column 1, 2, and 3 are market share growth in year t+1, t+3, and t+5, respectively. The dependent variables in Column 4, 5, and 6 are indicator variables equal to one if a firm is delisted from CRSP as of year t+1, t+3, and t+5, respectively. The specifications are estimated via OLS with year and industry fixed effects in Column 1, 2, and 3. The specifications are estimated via logit regressions with year and industry fixed effects in Column 4, 5, and 6. I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Manufacturing industry (SIC 2-digit 20-39)

	(1)	(2)	(3)	(4)	(5)	(6)
	$Market\ Share\ Growth_{t+1}$	$Market\ Share\ Growth_{t+3}$	$Market\ Share\ Growth_{t+5}$	$Delist_{t+1}$	$Delist_{t+3}$	$Delist_{t+5}$
$Agility$	0.103*	0.161**	0.145			
	(0.063)	(0.022)	(0.122)			
$High\ Agility$				-0.148	-0.139	-0.233***
				(0.302)	(0.125)	(0.007)
$Low\ Agility$				0.130	0.072	-0.158
				(0.433)	(0.509)	(0.150)
Observations	5,906	4,529	3,159	5,998	5,652	4,588
R-squared	0.453	0.503	0.523			
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Panel B: Low-Q manufacturing industry (SIC 2-digit 27, 30, 32, 33, 34, 35, 37, 38)

	(1)	(2)	(3)	(4)	(5)	(6)
	$Market\ Share\ Growth_{t+1}$	$Market\ Share\ Growth_{t+3}$	$Market\ Share\ Growth_{t+5}$	$Delist_{t+1}$	$Delist_{t+3}$	$Delist_{t+5}$
$Agility$	0.028	-0.020	-0.014			
	(0.411)	(0.574)	(0.375)			
$High\ Agility$				-0.431*	-0.128	-0.222
				(0.067)	(0.367)	(0.101)
$Low\ Agility$				-0.051	0.240	0.006
				(0.845)	(0.144)	(0.971)
Observations	2,599	2,026	1,447	2,510	2,420	2,019
R-squared	0.319	0.402	0.404			
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Appendix Table A11: Reasons for delisting

This table compares the unconditional probabilities of delisting between $Low\ Agility$ and $High\ Agility$ firms under different reasons for delisting. Each row displays the cumulative proportion of firms in the corresponding $Agility$ quintile in year t ($Low\ Agility$ and $High\ Agility$), which are delisted in year t+1, t+2, …, t+5 for voluntary (CRSP DLSTCD 570 and 573), involuntary (CRSP DLSTCD 400 or above, excluding 570 and 573), and M&A (CRSP DLSTCD 200 – 399) reasons. Failed delisting aggregates these three types of delisting.

Delisting type	Agility (in t)	Proportion of firms delisted				
		$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
Failed	Low	6.05%	12.70%	17.83%	21.51%	24.80%
	High	4.73%	10.35%	15.22%	19.40%	22.64%
Voluntary	Low	0.20%	0.46%	0.46%	0.66%	0.79%
	High	0.12%	0.35%	0.52%	0.62%	0.80%
Involuntary	Low	1.45%	2.50%	3.88%	4.80%	5.72%
	High	1.12%	2.39%	3.71%	4.70%	5.67%
M&A	Low	4.41%	9.74%	13.49%	16.05%	18.29%
	High	3.48%	7.61%	11.00%	14.08%	16.17%

Appendix Table A12: Homogeneous goods industry

This table reports the effect of $Agility$ on product market performance and firm survival likelihood using manufacturing industry firms. In Panel A, the regressions only include firms in industries producing differentiated goods. In Panel B, the regressions only include firms in industries producing homogeneous goods. The industry-level product homogeneity follows from Rauch (1999). The independent variables are measured at year t, and the definitions are described in Appendix A Table A1. The dependent variables of Column 1, 2, and 3 are market share growth in year t+1, t+3, and t+5, respectively. The dependent variables in Column 4, 5, and 6 are indicator variables equal to one if a firm is delisted from CRSP as of year t+1, t+3, and t+5, respectively. The specifications are estimated via OLS with year and industry fixed effects in Column 1, 2, and 3. The specifications are estimated via logit regressions with year and industry fixed effects in Column 4, 5, and 6. I report p-values in parentheses. The symbol ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Differentiated goods industry

	(1)	(2)	(3)	(4)	(5)	(6)
	$Market\ Share\ Growth_{t+1}$	$Market\ Share\ Growth_{t+3}$	$Market\ Share\ Growth_{t+5}$	$Delist_{t+1}$	$Delist_{t+3}$	$Delist_{t+5}$
$Agility$	0.070*	0.116**	0.033			
	(0.079)	(0.018)	(0.511)			
$High\ Agility$				-0.128	-0.116*	-0.125*
				(0.231)	(0.088)	(0.054)
$Low\ Agility$				0.128	0.089	-0.073
				(0.337)	(0.309)	(0.403)
Observations	9,990	7,644	5,314	10,012	9,502	7,717
R-squared	0.354	0.453	0.468			
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Panel B: Homogeneous goods industry

	(1)	(2)	(3)	(4)	(5)	(6)
	$Market\ Share\ Growth_{t+1}$	$Market\ Share\ Growth_{t+3}$	$Market\ Share\ Growth_{t+5}$	$Delist_{t+1}$	$Delist_{t+3}$	$Delist_{t+5}$
$Agility$	0.227	-0.052	0.064			
	(0.215)	(0.842)	(0.889)			
$High\ Agility$				-0.187	-0.172	-0.008
				(0.619)	(0.491)	(0.974)
$Low\ Agility$				0.158	-0.293	-0.584*
				(0.677)	(0.290)	(0.052)
Observations	896	667	455	874	872	692
R-squared	0.488	0.509	0.567			
Firm Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Appendix Figure A1: Word cloud of PEPSICO INC, COCA-COLA CO, and competitors

These figures present the word cloud changes of PEPSICO INC, COCA-COLA CO, and their competitors based on the word dictionaries created from 10-K business descriptions. Size of each word reflects the frequency of its usage in the document. Words that are infrequently used (i.e., appear less than five times) are excluded from the word cloud for visibility. Panel A shows the word cloud of competitors (MONSTER BEVERAGE CORP, NATIONAL BEVERAGE CORP, COTT CORP, CRYSTAL ROCK HOLDINGS INC, REEDS INC) in year 2003 and 2010. Panel B and C show the word cloud of PEPSICO INC and COCA-COLA CO, respectively, in year 2011 and 2018.

Panel A: Competitors

2003

2010

Panel B: PEPSICO INC

2011

2018

Panel C: COCA-COLA CO

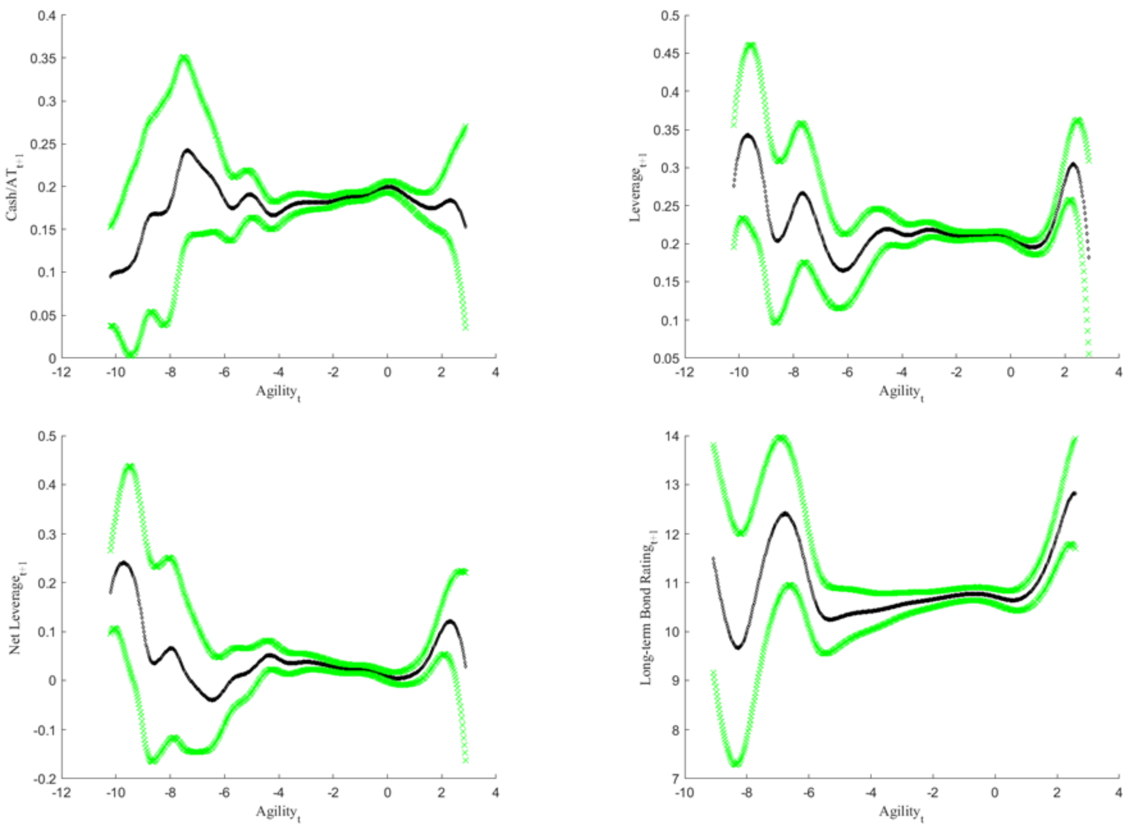
2011

2018

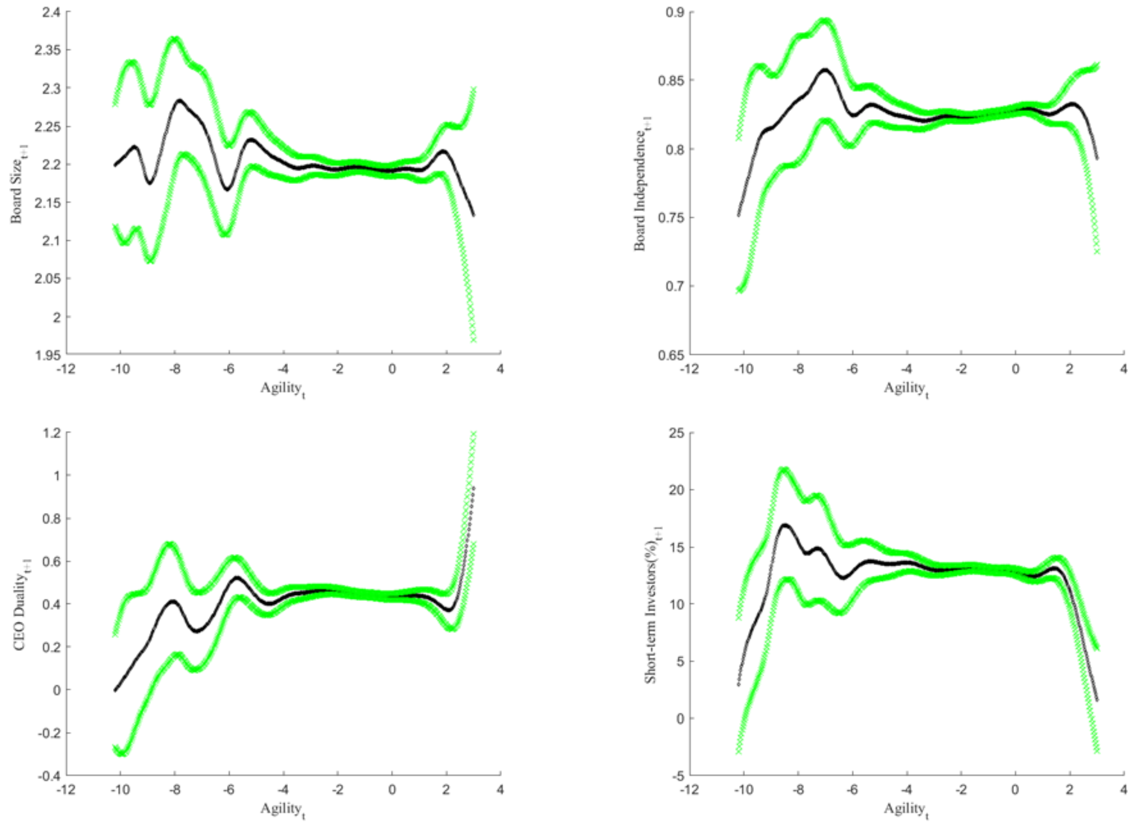
Appendix Figure A2: Local linear regression of firm variables (in year t+1) on agility (in year t)

These figures present how firm flexibility measures (in year t+1) changes with $Agility$ (in year t). Firm flexibility measures are categorized into financial flexibility measures (Cash/AT, Leverage, Net Leverage, Long-term Bond Rating), governance flexibility measures (Board Size, Board Independence, CEO Duality, Short-term Investors (%)), and organizational flexibility measures (Firm Age, Firm Size, Number of Business Segments, Firm Herfindahl Index). I estimate a local linear regression of each firm flexibility measures (in year t+1) on $Agility$ (in year t) with Gaussian kernel function and Silverman's rule-of-thumb bandwidth choice. Vertical and horizontal axes represent firm flexibility variables and $Agility$, respectively. The black (green) line represents the local linear regression estimates (95% confidence interval).

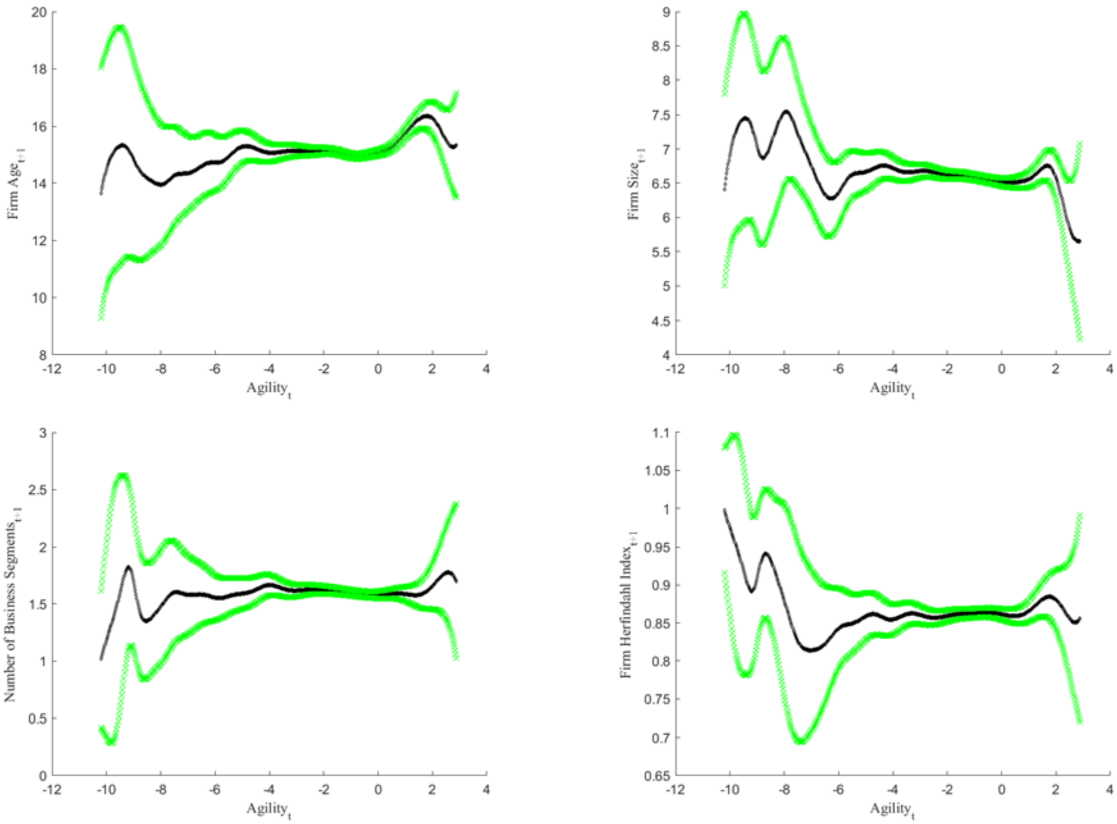
Panel A: Financial flexibility measures



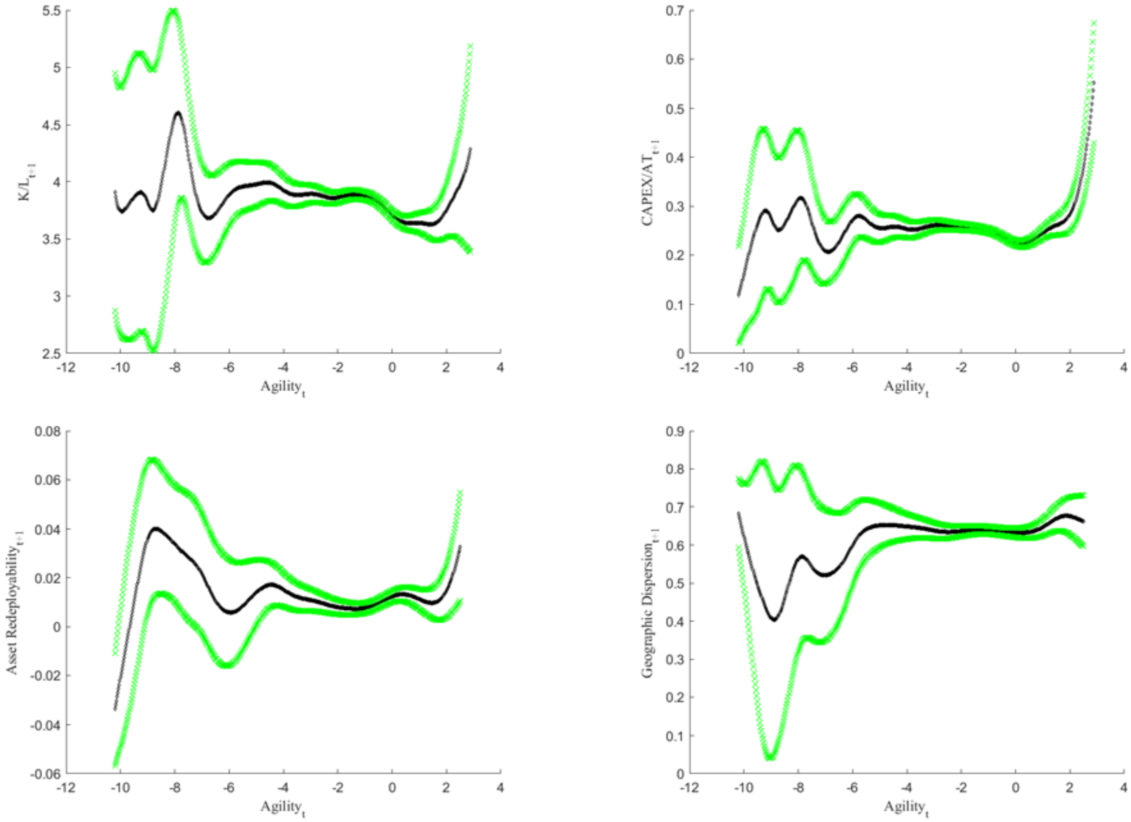
Panel B: Governance flexibility measures



Panel C: Organizational flexibility measures

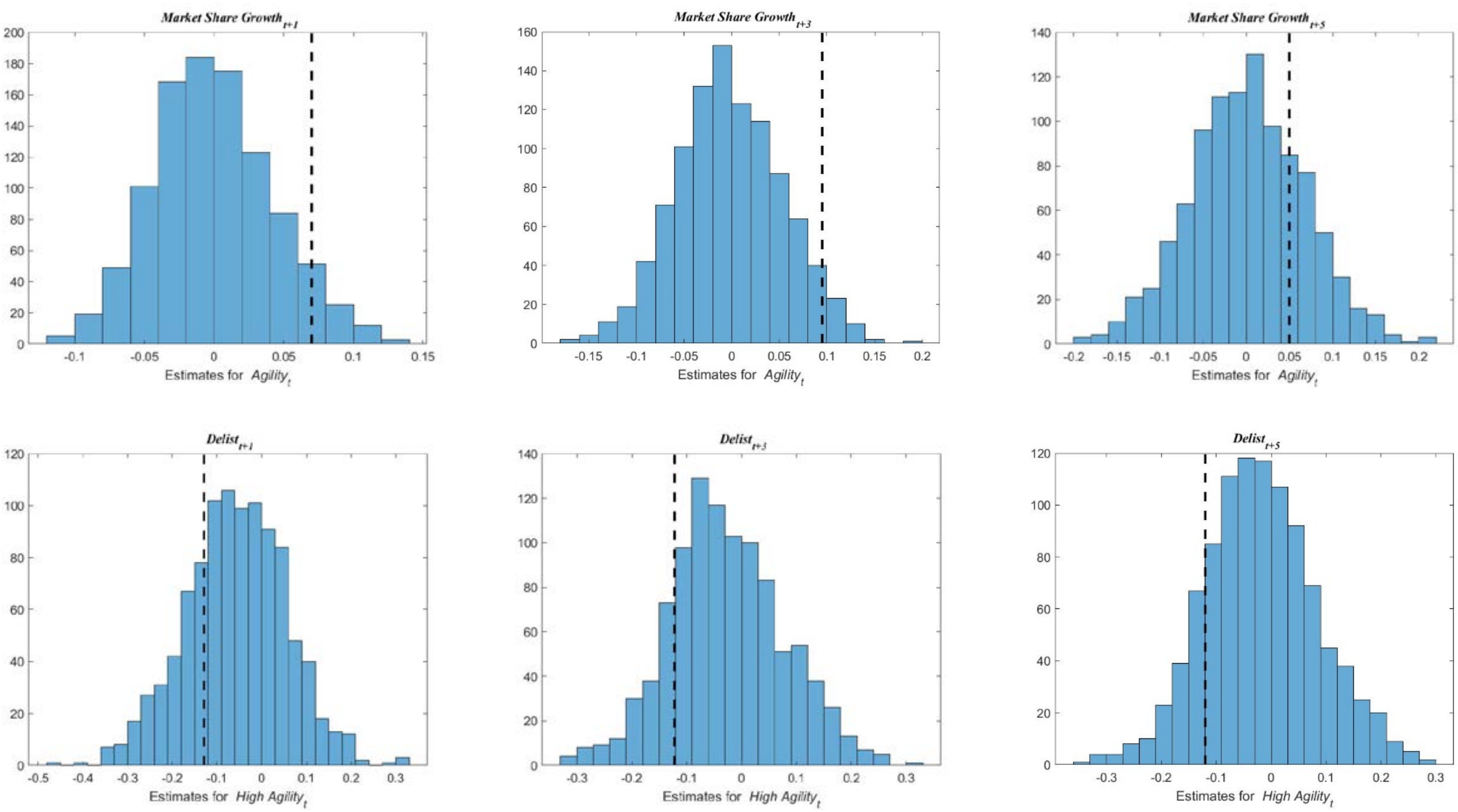


Panel D: Operating flexibility measures



Appendix Figure A3: Falsification test

These figures show falsification tests for the robustness of the main results. "Fictitious" $Agility$ is simulated 1,000 times using the same parameters but with different values of $Internal\ Fluidity$ and $External\ Fluidity$ for the sample firms in the same period. $Agility$ is replaced by "fictitious" $Agility$ in the specifications of Tables 8 and 9. Next, the distribution of 1,000 coefficient estimates of "fictitious" $Agility$ in each specification is plotted as a histogram. The top (bottom) three histograms exhibit the distributions when the dependent variable is market share growth in year t+1, t+3, and t+5 (an indicator variable equal to one if a firm is delisted from CRSP as of year t+1, t+3, and t+5).



Appendix B : Second Essay

Appendix Table B1: Robustness

Panel A: Aggregated trade credit and patent

VARIABLES	(1) $Trade\ Credit_{t+1}$	(2) $Trade\ Credit_{t+2}$	(3) $Trade\ Credit_{t+3}$
$Customer\ Innovation_t$	0.108**	0.130**	0.166***
	(0.041)	(0.020)	(0.004)
Observations	26,192	24,305	22,518
R-squared	0.393	0.369	0.353
Year FE	Y	Y	Y
Industry FE	Y	Y	Y

Panel B: Aggregated trade credit and patent (weighted average)

VARIABLES	(1) $Trade\ Credit_{t+1}$	(2) $Trade\ Credit_{t+2}$	(3) $Trade\ Credit_{t+3}$
$Customer\ Innovation_t$	0.111	0.139*	0.181**
	(0.121)	(0.068)	(0.021)
Observations	26,190	24,304	22,518
R-squared	0.393	0.368	0.353
Year FE	Y	Y	Y
Industry FE	Y	Y	Y

Panel C: Principal Customer as the sole customer

VARIABLES	(1) $Trade\ Credit_{t+1}$	(2) $Trade\ Credit_{t+2}$	(3) $Trade\ Credit_{t+3}$
$Customer\ Innovation_t$	0.124***	0.126***	0.144***
	(0.000)	(0.004)	(0.006)
Observations	11,599	8,374	6,188
R-squared	0.220	0.233	0.255
Year FE	Y	Y	Y
Industry FE	Y	Y	Y

Panel D: Principal Customer with sales portion above 80%

VARIABLES	(1) $Trade\ Credit_{t+1}$	(2) $Trade\ Credit_{t+2}$	(3) $Trade\ Credit_{t+3}$
$Customer\ Innovation_t$	0.426*	0.497	0.809*
	(0.092)	(0.173)	(0.072)

Observations	490	330	222
R-squared	0.595	0.674	0.760
Year FE	Y	Y	Y
Industry FE	Y	Y	Y

Appendix C : Third Essay

Appendix Table C1: Variable descriptions

Variable	Description
Age	Current fiscal year minus year in which a firm first appears in Compustat
Cash/K	Cash and Short-term Investments (CHE) / Beginning-of-period Capital (PPENT)
Δ(Cash/K)	Change of Cash/K (defined above) from last fiscal year
Inv/K	Investment (CAPX) / Beginning-of-period Capital (PPENT)
Δ(Inv/K)	Change of Inv/K (defined above) from last fiscal year
CF/K	Cash Flow (IB+DP) / Beginning-of-period Capital (PPENT)
Payout Ratio	Total Payout (DV+PRSTKC) / Total Assets (AT)
Market-to-book	(Liabilities(LT)-Deferred Taxes and Investment Tax Credit(TXDITC)+Preferred Stock(as defined below)) / (Liabilities(LT)-Deferred Taxes and Investment Tax Credit(TXDITC)+Preferred Stock(as defined below)+ Price Close(PRCC_F)*Common Shares Outstanding(CSHO)).
Leverage	(Long-term Debt (DLTT) + Debt in Current Liabilities (DLC)) / Total Assets (AT)
ROA	Operating Income before Depreciation (OIBDP) / Total Assets (AT)
Sales Growth	Sales (SALE) / Lagged Sales (SALE) - 1
Log(Assets)	Natural logarithm of Total Assets (AT)
Analyst Coverage	Natural logarithm of the number of analysts on I/B/E/S providing earnings forecasts
Long-term Bond Rating	Numerical transformation of long term credit ratings (SPLTICRM) as given in Appendix C
Short-term Bond Rating	Numerical transformation of short term credit ratings (SPSTICRM) as given in Appendix C
$\text{Fraud}_{\text{Within}}$	Indicator variable: 1 if fraud occurs within the same industry, and 0 otherwise during last fiscal year
$\text{Fraud}_{\text{Top}}$	Indicator variable: 1 if fraud occurs in the supplier industry for which the firm is in the Top-customer Industry, and 0 otherwise during last fiscal year
$\text{Fraud}_{\text{Bottom}}$	Indicator variable: 1 if fraud occurs in the customer industry for which the firm is in the Top-supplier Industry, and 0 otherwise during last fiscal year

Appendix Table C2: Numerical transformation of bond rating

Long-term Bond Rating (letter)	Long-term Bond Rating (number)	Short-term Bond Rating (letter)	Short-term Bond Rating (number)
AAA	1	A-1+	1
AA+	2	A-1	2
AA	3	A-2	3
AA-	4	A-3	4
A+	5	B	5
A	6	B-1	6
A-	7	B-3	7
BBB+	8	C	8
BBB	9	D	9
BBB-	10		
BB+	11		
BB	12		
BB-	13		
B+	14		
B	15		
B-	16		
CCC+	17		
CCC	18		
CCC-	19		
CC	20		
C	21		
D	22		
SD	22		

Bibliography

Acharya, V. V., Baghai, R. P., & Subramanian, K. V. (2014). Wrongful discharge laws and innovation. *The Review of Financial Studies*, *27*(1), 301-346.

Aghion, P., & Howitt, P. (1992). A Model of Growth Through Creative Destruction. *Econometrica*, *60*(2), 323-351. doi:10.2307/2951599

Ahern, K. R., & Harford, J. (2014). The importance of industry links in merger waves. *The Journal of Finance*, *69*(2), 527-576.

Akhigbe, A., & Martin, A. D. (2000). Information-signaling and competitive effects of foreign acquisitions in the US. *Journal of Banking & Finance*, *24*(8), 1307-1321.

Alchian, A. A. (1950). Uncertainty, evolution, and economic theory. *Journal of political economy*, *58*(3), 211-221.

Almeida, H., & Campello, M. (2007). Financial constraints, asset tangibility, and corporate investment. *The Review of Financial Studies*, *20*(5), 1429-1460.

Almeida, H., Campello, M., & Weisbach, M. S. (2004). The cash flow sensitivity of cash. *The Journal of Finance*, *59*(4), 1777-1804.

Alti, A. (2003). How sensitive is investment to cash flow when financing is frictionless?. *The Journal of Finance*, *58*(2), 707-722.

Al-Ubaydli, O., & McLaughlin, P. A. (2017). RegData: A numerical database on industry-specific regulations for all United States industries and federal regulations, 1997–2012. *Regulation & Governance*, *11*(1), 109-123.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, *5(1)*, 31-56.

Anderson, R. C., Mansi, S. A., & Reeb, D. M. (2003). Founding family ownership and the agency cost of debt. *Journal of Financial economics*, *68*(2), 263-285.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance*, *61(1)*, 259-299.

Arena, M., & Julio, B. (2011). Litigation risk, cash holdings, and corporate investment. *Marquette University and London Business School Working Paper*.

Argente, D., Lee, M., & Moreira, S. (2020). The Life Cycle of Products: Evidence and Implications. *Available at SSRN 3163195*.

Beatty, A., Liao, S., & Yu, J. J. (2013). The spillover effect of fraudulent financial reporting on peer firms' investments. *Journal of Accounting and Economics, 55*(2), 183-205.

Becker, J. M., & Thomas, S. (2008). The spillover effect of changes in industry concentration. Working Paper.

Bena, J., & Li, K. (2014). Corporate innovations and mergers and acquisitions. *The Journal of Finance*, *69*(5), 1923-1960.

Bena, J., Ortiz-Molina, H., & Simintzi, E. (2020). Shielding firm value: Employment protection and process innovation. *Available at SSRN 3223176*.

Bernard, A. B., Jensen, J. B., & Schott, P. K. (2006). Trade costs, firms and productivity. *Journal of monetary Economics*, 53(5), 917-937.

Bloom, N., Draca, M., & Van Reenen, J. (2016). Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity. *The review of economic studies, 83*(1), 87-117.

Bloom, N., Romer, P. M., Terry, S. J., & Van Reenen, J. (2013). A trapped-factors model of innovation. *American Economic Review*, *103*(3), 208-13.

Blundell, R., Griffith, R., & Van Reenen, J. (1999). Market share, market value and innovation in a panel of British manufacturing firms. *The review of economic studies*, *66*(3), 529-554.

Bolton, P., & Scharfstein, D. S. (1990). A theory of predation based on agency problems in financial contracting. *The American economic review*, 93-106.

Boone, A. L., Floros, I. V., & Johnson, S. A. (2016). Redacting proprietary information at the initial public offering. *Journal of Financial Economics*, 120(1), 102-123.

Bushee, B. J. (1998). The influence of institutional investors on myopic R&D investment behavior. *Accounting review*, 305-333.

Bushee, B. J. (2001). Do institutional investors prefer near-term earnings over long-run value?. *Contemporary Accounting Research, 18(2)*, 207-246.

Bushee, B. J., & Noe, C. F. (2000). Corporate disclosure practices, institutional investors, and stock return volatility. *Journal of accounting research*, 171-202.

Carlin, W., Schaffer, M., & Seabright, P. (2004). A minimum of rivalry: Evidence from transition economies on the importance of competition for innovation and growth. *The B.E. journal of economic analysis & policy*, 3(1), 1-45.

Cen, L., Dasgupta, S., & Sen, R. (2016). Discipline or disruption? Stakeholder relationships and the effect of takeover threat. *Management Science, 62(10)*, 2820-2841.

Chava, S., Agnes Cheng, C. S., Huang, H., & Lobo, G. J. (2010). Implications of securities class actions for cost of equity capital. *International Journal of Law and Management, 52(2),* 144-161.

Choi, J. J., Ju, M., Trigeorgis, L., & Zhang, X. T. (2021). Outsourcing flexibility under financial constraints. *Journal of Corporate Finance*, *67*, 101890.

Choi, S. J., Nelson, K. K., & Pritchard, A. C. (2009). The screening effect of the private securities litigation reform act. *Journal of Empirical Legal Studies*, *6*(1), 35-68.

Christopher, M., & Towill, D. R. (2000). Supply chain migration from lean and functional to agile and customised. *Supply Chain Management: An International Journal*, *5*(4), 206-213.

Cohen, L., & Frazzini, A. (2008). Economic links and predictable returns. *The Journal of Finance*, *63*(4), 1977-2011.

Cohen, L., Diether, K., & Malloy, C. (2013). Misvaluing innovation. *The Review of Financial Studies*, *26*(3), 635-666.

Cohen, W. M., & Klepper, S. (1996). Firm size and the nature of innovation within industries: the case of process and product R&D. *Review of Economics and Statistics*, *78*(2), 232-243.

Cooper, M. J., Gulen, H., & Schill, M. J. (2008). Asset growth and the cross-section of stock returns. *the Journal of Finance, 63(4)*, 1609-1651.

Cunningham, C., Ederer, F., & Ma, S. (2021). Killer acquisitions. *Journal of Political Economy, 129(3)*, 649-702.

Deng, S., Willis, R. H., & Xu, L. (2014). Shareholder litigation, reputational loss, and bank loan contracting. *Journal of Financial and Quantitative Analysis*, *49*(4), 1101-1132.

Denis, D. J., & Sibilkov, V. (2009). Financial constraints, investment, and the value of cash holdings. *The Review of Financial Studies*, *23*(1), 247-269.

Dimitrov, V., Palia, D., & Tang, L. (2015). Impact of the Dodd-Frank act on credit ratings. *Journal of Financial Economics*, *115*(3), 505-520.

Dove, R. (1995). Measuring agility: The toll of turmoil. *Production*, *107*(1), 16-18.

Dove, R. (2002). Response ability: the language, structure, and culture of the agile enterprise. *John Wiley & Sons*.

Duan, R., Larkin, Y., & Ng, L. K. (2019). Short-Term Institutional Investors and the Diffusion of Supply Chain Information. *Available at SSRN 3277201*.

Dyck, A., Morse, A., & Zingales, L. (2010). Who blows the whistle on corporate fraud?. *The Journal of Finance*, *65*(6), 2213-2253.

Erickson, T., & Whited, T. M. (2000). Measurement error and the relationship between investment and q. *Journal of political economy*, *108*(5), 1027-1057.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance, 47(2)*, 427-465.

Fama, E. F., & French, K. R. (2004). New lists: Fundamentals and survival rates. *Journal of financial Economics*, *73*(2), 229-269.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of financial economics*, *116(1)*, 1-22.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of political economy*, *81*(3), 607-636.

Fan, J. P. (2000). Price uncertainty and vertical integration: an examination of petrochemical firms. *Journal of Corporate Finance*, *6*(4), 345-376.

Fazzari, S. M., Hubbard, R. G., Petersen, B. C., Blinder, A. S., & Poterba, J. M. (1988). Financing constraints and corporate investment. *Brookings papers on economic activity*, *1988*(1), 141-206.

Fee, C. E., & Thomas, S. (2004). Sources of gains in horizontal mergers: evidence from customer, supplier, and rival firms. *Journal of Financial Economics*, *74*(3), 423-460.

Feenstra, R. C., Romalis, J., & Schott, P. K. (2002). US imports, exports, and tariff data, 1989-2001 (No. w9387). *National bureau of economic research.*

Firth, M. (1996). Dividend changes, abnormal returns, and intra-lndustry firm valuations. *Journal of financial and Quantitative Analysis*, *31*(2), 189-211.

Freeman, K. (2020). The Economics of Trade Credit: Risk and Power. *Available at SSRN 3235838*.

Frésard, L. (2010). Financial strength and product market behavior: The real effects of corporate cash holdings. *The Journal of finance*, 65(3), 1097-1122.

Frésard, L., & Valta, P. (2016). How does corporate investment respond to increased entry threat?. *The Review of Corporate Finance Studies*, 5(1), 1-35.

Gabay, M. (2018). The Prescription Drug User Fee Act: Cause for Concern?. *Hospital pharmacy*, *53*(2), 88-89.

Gande, A., & Lewis, C. M. (2009). Shareholder-initiated class action lawsuits: Shareholder wealth effects and industry spillovers. *Journal of Financial and Quantitative Analysis*, *44*(4), 823-850.

Garcia, D., & Norli, Ø. (2012). Geographic dispersion and stock returns. *Journal of Financial Economics*, *106*(3), 547-565.

Giannetti, M., & Yu, X. (2020). Adapting to radical change: The benefits of short-horizon investors. Management Science, forthcoming.

Gilchrist, S., & Himmelberg, C. P. (1995). Evidence on the role of cash flow for investment. *Journal of monetary Economics*, *36*(3), 541-572.

Goranson, H. T., & Goranson, T. (1999). *The agile virtual enterprise: cases, metrics, tools*. Greenwood Publishing Group.

Gormley, T. A., & Matsa, D. A. (2009). *Growing out of trouble? managerial responses to risk of corporate liability*. Working Paper.

Gutiérrez, G., & Philippon, T. (2017). *Declining Competition and Investment in the US* (No. w23583). National Bureau of Economic Research.

Harford, J. (2005). What drives merger waves?. *Journal of financial economics*, *77*(3), 529-560.

Hashmi, A. R. (2013). Competition and innovation: The inverted-U relationship revisited. *Review of Economics and Statistics*, *95*(5), 1653-1668.

Haushalter, D., Klasa, S., & Maxwell, W. F. (2007). The influence of product market dynamics on a firm's cash holdings and hedging behavior. *Journal of Financial Economics*, *84*(3), 797-825.

Hay, G. A., & Kelley, D. (1974). An empirical survey of price fixing conspiracies. *The Journal of Law and Economics*, *17*(1), 13-38.

Hertzel, M. G., Li, Z., Officer, M. S., & Rodgers, K. J. (2008). Inter-firm linkages and the wealth effects of financial distress along the supply chain. *Journal of Financial Economics*, *87*(2), 374-387.

Hoberg, G., & Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. *The Review of Financial Studies*, *23*(10), 3773-3811.

Hoberg, G., & Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, *124*(5), 1423-1465.

Hoberg, G., Phillips, G., & Prabhala, N. (2014). Product market threats, payouts, and financial flexibility. *The Journal of Finance*, *69*(1), 293-324.

Hou, K., & Robinson, D. T. (2006). Industry concentration and average stock returns. *The Journal of Finance*, *61*(4), 1927-1956.

Hsu, P. H., Lee, H. H., Liu, A. Z., & Zhang, Z. (2015). Corporate innovation, default risk, and bond pricing. *Journal of Corporate Finance*, *35*, 329-344.

Hsu, Y. (2011). Design innovation and marketing strategy in successful product competition. *Journal of Business & Industrial Marketing*, *26*(4), 223-236.

Itzkowitz, J. (2013). Customers and cash: How relationships affect suppliers' cash holdings. *Journal of Corporate Finance*, *19*, 159-180.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *The Journal of finance*, *45*(3), 881-898.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, *48*(1), 65-91.

Kaplan, S. N., & Zingales, L. (1997). Do investment-cash flow sensitivities provide useful measures of financing constraints?. *The quarterly journal of economics*, *112*(1), 169-215.

Kim, H., & Kung, H. (2017). The asset redeployability channel: How uncertainty affects corporate investment. *The Review of Financial Studies*, *30*(1), 245-280.

Klein, B., Crawford, R. G., & Alchian, A. A. (1978). Vertical integration, appropriable rents, and the competitive contracting process. *The journal of Law and Economics*, *21*(2), 297-326.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, *132*(2), 665-712.

Kumar, P., & Langberg, N. (2009). Corporate fraud and investment distortions in efficient capital markets. *The RAND Journal of Economics*, *40*(1), 144-172.

Lambrecht, B. M., Pawlina, G., & Teixeira, J. C. (2016). Making, buying, and concurrent sourcing: Implications for operating leverage and stock beta. *Review of Finance*, *20*(3), 1013-1043.

Lang, L. H., & Stulz, R. (1992). Contagion and competitive intra-industry effects of bankruptcy announcements: An empirical analysis. *Journal of financial economics*, *32*(1), 45-60.

Lehn, K. (2018). Corporate governance, agility, and survival. *International Journal of the Economics of Business*, *25*(1), 65-72.

Levin, R. C. and P. C. Reiss (1988), Cost–reducing and Demand–creating R&D with Spillover, *RAND Journal of Economics*, 19, 538–556.

Levitt, T. (1965). Exploit the Product Life Cycle. *Harvard Business Review*, 43, 81–94.

Li, K. (2018). Innovation externalities and the customer/supplier link. *Journal of Banking & Finance*, *86*, 101-112.

Lin, C. T., Chiu, H., & Chu, P. Y. (2006). Agility index in the supply chain. *International Journal of production economics*, *100*(2), 285-299.

Lin, P., & Saggi, K. (2002). Timing of entry under externalities. *Journal of Economics*, *75*(3), 211-225.

Lowry, M., & Shu, S. (2002). Litigation risk and IPO underpricing. *Journal of Financial Economics*, *65*(3), 309-335.

MacKay, P., & Phillips, G. M. (2005). How does industry affect firm financial structure?. *The Review of Financial Studies*, *18*(4), 1433-1466.

Maksimovic, V., & Pichler, P. (2001). Technological innovation and initial public offerings. *The Review of Financial Studies*, 14(2), 459-494.

Massa, M., Rehman, Z., & Vermaelen, T. (2007). Mimicking repurchases. *Journal of Financial Economics*, *84*(3), 624-666.

McLaughlin, P. A., & RegData, U. S. (2020). 3.2 Annual (dataset). *QuantGov, Mercatus Center at George Mason University, Arlington, VA.*

Metes, G., Gundry, J., & Bradish, P. (1998). *Agile networking: competing through the Internet and intranet*. Prentice-Hall, Inc..

Nickell, S. J. (1996). Competition and corporate performance. *Journal of political economy*, *104*(4), 724-746.

Phillips, G. M., & Zhdanov, A. (2013). R&D and the Incentives from Merger and Acquisition Activity. *The Review of Financial Studies*, *26*(1), 34-78.

Rauch, J. E. (1999). Networks versus markets in international trade. *Journal of international Economics*, *48*(1), 7-35.

Rauh, J. D. (2006). Investment and financing constraints: Evidence from the funding of corporate pension plans. *The Journal of Finance*, *61*(1), 33-71.

Rhodes-Kropf, M., & Robinson, D. T. (2008). The market for mergers and the boundaries of the firm. *The Journal of Finance*, *63*(3), 1169-1211.

Schlingemann, F. P., Stulz, R. M., & Walkling, R. A. (2002). Divestitures and the liquidity of the market for corporate assets. *Journal of financial Economics*, 64(1), 117-144.

Schmitz Jr, J. A. (2005). What determines productivity? Lessons from the dramatic recovery of the US and Canadian iron ore industries following their early 1980s crisis. *Journal of political Economy*, *113*(3), 582-625.

Schott, P. (2010). US manufacturing exports and imports by SIC or NAICS category and partner country, 1972 to 2005. *Notes.*

Schumpeter, J. (1911). The theory of economic development. Harvard Economic Studies. Vol. XLVI.

Sevilir, M., & Tian, X. (2012, May). Acquiring innovation. In *AFA 2012 Chicago Meetings Paper.*

Sharifi, H., & Zhang, Z. (1999). A methodology for achieving agility in manufacturing organisations: An introduction. *International journal of production economics*, *62*(1-2), 7-22.

Solow, R. M. (1957). Technical change and the aggregate production function. *The review of Economics and Statistics*, 312-320.

Tang, H. (2012). Labor market institutions, firm-specific skills, and trade patterns. *Journal of International Economics*, *87*(2), 337-351.

Uysal, V. B. (2011). Deviation from the target capital structure and acquisition choices. *Journal of Financial Economics*, 102(3), 602-620.

Valta, P. (2012). Competition and the cost of debt. *Journal of Financial Economics*, 105(3), 661-682.

Vernon, J. A., Golec, J. H., Lutter, R., & Nardinelli, C. (2009). An exploratory study of FDA new drug review times, prescription drug user fee acts, and R&D spending. *The Quarterly Review of Economics and Finance*, *49*(4), 1260-1274.

Verrecchia, R. E. (1983). Discretionary disclosure. *Journal of accounting and economics*, 5, 179-194.

Verrecchia, R. E., & Weber, J. (2006). Redacted disclosure. *Journal of Accounting Research*, 44(4), 791-814.

Williamson, O. E. (1979). Transaction-cost economics: the governance of contractual relations. *The journal of Law and Economics*, *22*(2), 233-261.

Xu, J. (2012). Profitability and capital structure: Evidence from import penetration. *Journal of Financial Economics*, 106(2), 427-446.

Yu, X., Zhang, P., & Zheng, Y. (2015). Corporate Governance, Political Connections, and Intra-Industry Effects: Evidence from Corporate Scandals in China. *Financial Management*, *44*(1), 49-80.

Yusuf, Y. Y., Sarhadi, M., & Gunasekaran, A. (1999). Agile manufacturing: The drivers, concepts and attributes. *International Journal of production economics*, *62*(1-2), 33-43.