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Innovation, market valuations, policy uncertainty and trade: Theory and evidence

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DEDICATION

I would like to dedicate this thesis to my wife Jingyun Feng and to my son Feliman Li without whose support I would not have been able to complete this work.

TABLE OF CONTENTS

	Page
LIST OF TABLES	vi
LIST OF FIGURES	viii
ACKNOWLEDGMENTS	ix
ABSTRACT	x
CHAPTER 1. INTRODUCTION	1
CHAPTER 2. INNOVATION, TECHNOLOGY SCOPE AND FIRM PRODUCTIVITY	4
2.1 Introduction	4
2.2 Theoretical Mechanism	8
2.2.1 Final Good Production	8
2.2.2 Innovation	9
2.3 Data	11
2.3.1 Data Sources	11
2.3.2 Variables Construction	14
2.3.3 Descriptive Statistics	19
2.4 Empirics and Results	21
2.4.1 Innovation and Innovation Scope	22
2.4.2 Citation and Citation Scope	24
2.4.3 Originality and Generality	26
2.4.4 Robustness Checks	28
2.5 Conclusion	34
CHAPTER 3. DOES INNOVATION INCREASE STOCK RETURNS? THE ROLE OF INNOVATION EFFICIENCY	35
3.1 Introduction	35
3.2 Data, Variables, and Summary Statistics	43
3.2.1 Patents, Citations, and Innovation Efficiency	43
3.2.2 Financial Variables and Equity Prices	52
3.2.3 Summary Statistics	59
3.3 Empirical Specifications	64
3.3.1 Tobin's q Regression	64
3.3.2 Fama-MacBeth Regression	65
3.3.3 Excess Return Regressions	66
3.4 Empirical Results	67

3.4.1 Tobin's q and Innovation Efficiency . . . 68
3.4.2 Operating Performance and Innovation Efficiency . . . 77
3.4.3 Profitability and Innovation Efficiency . . . 80
3.4.4 Productivity and Innovation Efficiency . . . 84
3.4.5 Excess Return and Innovation Efficiency . . . 87
3.5 Conclusion . . . 90

CHAPTER 4. POLICY UNCERTAINTY, INNOVATION, AND FIRM ENTRY AND EXIT UNDER OPEN ECONOMY – THEORY AND EVIDENCE FROM CHINESE FIRMS . . . 93
4.1 Introduction . . . 93
4.2 Literature Review . . . 102
4.3 Model . . . 105
4.3.1 Preferences . . . 106
4.3.2 Final Good Production . . . 107
4.3.3 Intermediate Good Production . . . 108
4.3.4 Innovation . . . 109
4.3.5 Trade and Trade Policy . . . 113
4.3.6 Equilibrium . . . 114
4.4 Estimation Analysis . . . 131
4.4.1 Empirical Specification . . . 131
4.4.2 Data . . . 135
4.4.3 Estimation Results . . . 141
4.5 Conclusion . . . 155

CHAPTER 5. CONCLUSION . . . 158

BIBLIOGRAPHY . . . 161

APPENDIX A. ADDITIONAL DATA INFORMATION . . . 172
A.1 Industries Classification Based on Technology . . . 172
A.2 Matching with CRSP by Decade . . . 172
A.3 Comparing KPSS Patent Data with NBER Patent Data . . . 173
A.4 Comparing Cumulative Returns . . . 174

APPENDIX B. ROBUSTNESS CHECKS FOR INNOVATION EFFICIENCY . . . 175
B.1 Innovation Efficiency and Tobin's q: different IE quartiles . . . 175
B.2 Alternative Innovation Efficiency Measure . . . 176
B.3 Alternative Productivity Measure . . . 177

APPENDIX C. ROBUSTNESS CHECKS FOR POLICY UNCERTAINTY . . . 179
C.1 Alternative Innovation Measure . . . 179
C.2 Poisson Method for Innovation . . . 180
C.3 Alternative Measure of Policy Uncertainty . . . 181
C.4 Logistic Method for Firm Entry and Exit . . . 182

APPENDIX D. ADDITIONAL DERIVATIONS FOR POLICY UNCERTAINTY 185
D.1 Expected Value of Exporting 185
D.2 Lemma 6 Proof 186
D.3 Expected Waiting Value 186
D.4 Export Waiting Cutoff Condition 187
D.5 Profit Loss Bound 188

LIST OF TABLES

		Page
Table 2.1	Variable Description of Innovation and Productivity	13
Table 2.2	Summary Statistics of Innovation and Productivity	20
Table 2.3	Baseline Results for Innovation and Innovation Scope	23
Table 2.4	Baseline Results for Citation and Citation Scope	25
Table 2.5	Alternative Measures on the Novelty of Innovation	27
Table 2.6	Robustness Check for Poisson Method	29
Table 2.7	Robustness Check for Alternative Technology Classification and Nonself-Citation	31
Table 2.8	Robustness Check for Alternative Productivity Measure	33
Table 3.1	Number of Firms, Granted Patents, Tech Fields and Citations	45
Table 3.2	Variable Description	58
Table 3.3	Summary Statistics for Different Periods	59
Table 3.4	Summary Statistics of Innovation Efficiency for Selected Industries	61
Table 3.5	Summary Statistics for Different Innovation Efficiency Levels	62
Table 3.6	Correlation Coefficients of Innovation Efficiency and Market Valuations	63
Table 3.7	Innovation Efficiency and Tobin's q, 1950-2010	69
Table 3.8	Innovation Efficiency and Tobin's q in Different Periods	72
Table 3.9	Innovation Efficiency and Tobin's q under Different Industrial Technologies, 1950-2010	75
Table 3.10	Innovation Efficiency and Operating Performance, 1950-2010	79
Table 3.11	Innovation Efficiency and Profitability, 1950-2010	81
Table 3.12	Innovation Efficiency, Profit Margin, and Productivity, 1950-2010	82
Table 3.13	Innovation Efficiency and Productivity, 1950-2010	85
Table 3.14	Innovation Efficiency and Excess Return, 1950-2010	86
Table 3.15	Innovation Efficiency and Excess Returns in Different Periods	88
Table 4.1	Main Trade Affairs Since 2017	94
Table 4.2	Countries in Antidumping Database	137
Table 4.3	Descriptive Statistics of Patent Specification	138
Table 4.4	Descriptive Statistics of Firm Entry and Exit Specification	140
Table 4.5	Policy Uncertainty and Innovation, 2000-2006	142
Table 4.6	Policy Uncertainty and Innovation with US Exporter, 2000-2006	144
Table 4.7	Policy Uncertainty and Innovation with Active Dummy, 2000-2006	147
Table 4.8	Policy Uncertainty and Entry, 2000-2006	149
Table 4.9	Policy Uncertainty and Exit, 2000-2006	150
Table 4.10	Policy Uncertainty and Entry with Time-Varying Heterogenous Effects, 2000-2006	152
Table 4.11	Policy Uncertainty and Exit with Time-Varying Heterogenous Effects, 2000-2006	154
Table A.1	Industries Classification Based on Technology	172

Table A.2 Matching with CRSP by Decade 173
Table B.1 Innovation Efficiency and Tobin's q: different IE quartiles, 1950-2010 175
Table B.2 Innovation Efficiency and Tobin's q, Alternative Measures (1950-2010) . . . 176
Table B.3 Innovation Efficiency, Profit Margin, and Productivity (OP Method), 1950-2010 178
Table C.1 Policy Uncertainty and Innovation using R&D, 2000-2006 179
Table C.2 Policy Uncertainty and Innovation using Poisson Method, 2000-2006 180
Table C.3 Policy Uncertainty and Entry using Intensity, 2000-2006 181
Table C.4 Policy Uncertainty and Exit using Intensity, 2000-2006 182
Table C.5 Policy Uncertainty and Entry using Logistic Method, 2000-2006 183
Table C.6 Policy Uncertainty and Exit using Logistic Method, 2000-2006 184

LIST OF FIGURES

		Page
Figure 2.1	Average TFP and Innovation during 1976-2006	18
Figure 2.2	Box Plots for Firm-level Innovation and TFP Percentile Distribution	19
Figure 3.1	Total and Average Firm Patents, Citations, and Tech Fields, 1950-2010	46
Figure 3.2	Average Self Citations, Non-self Citations, and Citation Tech Fields, 1950-2010	48
Figure 3.3	Average Innovation Efficiency, 1950-2010	52
Figure 3.4	Market Size Distribution of All Firms and Firms with Patents in 1995 and 2005	53
Figure 3.5	Average Excess Returns and Tobin's q, 1962-2010	55
Figure 4.1	News-Based Index of Aggregate Trade Policy Uncertainty	95
Figure 4.2	News-Based Index of Aggregate TPU and Average Patent Counts	97
Figure 4.3	Innovation and Changes of Product Lines	112
Figure 4.4	Possible Quality Frontier, Trade Cost, and Trade Flows	119
Figure 4.5	Impact of Policy Uncertainty on Home Imports and Exports	128
Figure 4.6	Patent Applications by Type in China	136
Figure A.1	Number of Patents with Matched Assignees	173
Figure A.2	Benchmarking Cumulative Returns Using the S&P Composite Index	174

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ABSTRACT

This dissertation presents the theoretic and empirical findings on innovation, market returns, and trade, with particular focuses on how firm's innovation activities affects their market returns through the channel of productivity improving, and how policy uncertainty affects firm's trading and innovation decisions.

Chapter 2 examines the relationship between productivity and innovation, using the U.S. manufacturers' patent data from 1976-2006. First, this chapter investigates whether productive firms actively participate in innovation in terms of having more patents, and then examines whether their innovation activities are involved in a wide spectrum of technological categories. The empirical results reveal that: (i) productivity is positively correlated with the number of patents granted and the number of technological categories for these patents; and (ii) productivity is positive correlated with the number of citations per granted patent, and is also positively correlated with the number of technological categories for cited patents per granted patent.

Chapter 3 examines the impact of innovation on firm's operating performance, market valuation, and stock returns, especially the role of Innovation Efficiency in predicting firm's future market valuation. Three different measures of Innovation Efficiency–number of granted patents per patent or citation (backward and forward) technological fields scaled by research and development expenditures–are proposed, which combine the breadth of knowledge used to innovate and R&D investments. The empirical results show that: (i) firm's market valuation and excess returns increases are largely driven by the changing valuation of Innovation Efficiency, while innovation quantity, measured by patent intensity and R&D intensity, has a strong and significant negative effect; (ii) the positive effect of Innovation Efficiency became larger over time from 1950 to 2010 and for high-technology industries; (iii) high efficient innovation firms are able to achieve higher and more persistent profitability and better operating performance through the effect of productivity.

Chapter 4 introduces a dynamic general equilibrium growth model with policy uncertainty where policy uncertainty endogenously affects the dynamics of technical change, market leadership, firm entry and exit selection, and trade flows, in a world with two large open economies at different stages of development. The theoretical investigation illustrates that increase in policy uncertainty has significant negative effect on exports and imports, but has ambiguous effects on innovation and welfare, while dynamically, trade liberalization boosts domestic innovation through induced international competition. In the empirical portion, this chapter studies how policy uncertainty affect innovation and firm decisions to enter into and exit from export markets by estimating the impact of trade policy uncertainty on patents applied by Chines manufacturing firms, as well as firm's entry and exit. Using Chinese patent applications and Chinese customs transactions between 2000-2006, this chapter exploits time-variation in product-level trade policy and the empirical results show that: (i) Chinese firms have less incentive in innovation activities when facing increased trade policy uncertainty; (ii) Chinese firms are less likely to enter new foreign markets when their products are subject to increased trade policy uncertainty; (iii) Chinese firms are more likely to exit from established foreign markets when policy uncertainty increases.

CHAPTER 1. INTRODUCTION

A large body of literature in finance, international trade, and macroeconomics studies firms' innovation activities. As indicated by lots of research, firms' innovation activities play a crucial role in firms' long-term development. Innovation helps firms obtain sustained competitiveness. Overall, the academic research agree that innovation plays a key role in firms' operation. However, far is still unknown referring to innovation efficiency and the impact of policy uncertainty. This dissertation is motivated from emerging issues with respect to innovation, productivity, market returns, and trade.

The first issue is to explain the sources of productivity growth and investigate the relationship between firm-level productivity and innovative activities. Large body of empirical literature suggest a positive correlation between productivity and innovation, but was less conclusive about how firms' productivity is related with the spectrum of the efficiency of innovation, such as technological categories associated with patents, innovation originality, and innovation generality. Chapter 2 examines the empirical relationship between firm-level productivity and innovation from a variety of perspective using the NBER patent data and Compustat financial data of manufacturing firms in the U.S between 1976-2006. The empirical results reveal several interesting findings. First, the consistent and positive correlation between productivity and innovation quantity is confirmed. More productive firms tend to apply for more patents and produce more patentable inventions. Second, a positive correlation between productivity and extensive innovation scope is documented. Productive firms tend to engage in a wide spectrum of technological fields. Lastly, innovation generality and originality are positively correlated with firm productivity- productivity is positively correlated with both average citations per patent and average cited technical fields per patent. Productive firms tend to cite more patents per patented invention and are more capable of learning from cited patents across various technologies fields.

The second issue is what impact do firms' innovative activities have on market value and stock returns. An increasing stream of literature in economics and finance has shown that technological growth can explain major swings in stock market value. Existing studies mainly focus on the effect of innovative activities on operating performance, stock returns, and market valuation from innovation input or output perspective separately. These literature use either the number of patents and citations, or the R&D expenditure as measure of innovation, and analyze the economic and financial effects of innovative activities. However, no study has analyzed the value of innovative activities and the impact of innovation efficiency on market value and stock returns is still unknown. To this end, Chapter 3 investigates what role of Innovation Efficiency in determining firms' market valuation and stock returns. Innovation Efficiency is measured by three different indexes that combining the breadth of knowledge used to innovate and R&D investments: number of granted patents per special technological fields scaled by R&D, number of granted patents per technological categories of non-self patents cited by a firm's patents scaled by R&D, and number of granted patents per technological categories of the citations received in the year before the forecast period by a firm's patents that were granted over the previous 5 years scaled by R&D. This chapter matches the patents and citations data of all the U.S. listed firms with the financial data of public firms between 1950 and 2010. The empirical results show that stock market increases was largely driven the changing valuation of Innovation Efficiency, while innovation quantity has strong and significant negative effect on firm's future market values. Firm with higher Innovation Efficiency can obtain higher return on assets (ROA), return on equity (ROE), and cash flows over the next year after extensive controls. On the contrary, patent counts scaled by market equity reduces firm's future ROA and cash flow and predicts higher future ROE. Comparing to Innovation Efficiency, the effects of patent quantity are all insignificant. High Innovation Efficiency firms are able to achieve higher and more persistent profitability through the effect of innovation efficiency on productivity and profit margin. Comparing to Innovation Efficiency, the quantity effects of innovation are insignificant and negative.

The third issue is how policy uncertainty affects firms' investment in innovation and exporting decisions. Emerging evidence suggests that policy uncertainty plays a key role in firms' decision to invest in innovation and export to new markets because firms must incur sunk costs to start exporting and when uncertainty increases firms do not invest and wait until uncertainty is resolved. Policy uncertainty increased as increasing trade negotiations and proposals result in an increase in uncertainty about the future and the outlook for international trade. Firms' innovation decisions are partially depended on policies because politicians make policy and regulatory decisions that affect the economic environment in which innovative firms operate. Changing policies and regulations causes future economic environment uncertain and reduce innovation investment. Chapter 4 first develops a model of international trade economy with policy uncertainty and innovation. The basic idea of the model is that policy uncertainty causes risk and loss in intermediate goods production and hence affects firms' profit. Firms reduce investment in innovation due to production profit deduction. Entrants observe policy uncertainty and suspend their entry decision till policy is finally announced or withdraw. Policy uncertainty increases firms's option value of waiting. Only firms with high quality goods will choose to enter the foreign market because their option value of waiting is relatively lower than their entry value. Exporting firms exit foreign market as policy uncertainty increases and casing reduction in those firms' innovation. On the contrary, increase number of surviving firms in domestic market stimulates cost-reducing innovation thereby leading to faster productivity growth. Chapter 4 then embodies five major data sources to empirically investigate the impact of policy uncertainty on innovation and trade. For firms' innovation activities, the empirical results show that increased policy uncertainty significantly decreases patent applications. For entry, the empirical results show that increased uncertainty about the future tariff rate in destination country reduces participation in exporting activity. Entry into foreign markets declines as policy uncertainty increases. For firms' exit decisions, estimation results show that increased uncertainty about the future tariff rate in destination country increases exits from existing exporting market. Exit from existing foreign markets increases as policy uncertainty increases.

CHAPTER 2. INNOVATION, TECHNOLOGY SCOPE AND FIRM PRODUCTIVITY

This study examines the relationship between productivity and innovation, using the U.S. manufacturers' patent data from 1976-2006. First, this study investigates whether productive firms actively participate in innovation in terms of having more patents, and then examine whether their innovation activities are involved in a wide spectrum of technological categories. Moreover, this study is interested in, to successfully develop a new patent in a certain technological field, whether productive firms need to cite more or less patents within the field and/or across various related fields. The firm-level productivity is estimated as the total factor productivity (TFP). This study finds that: (i) productivity is positively correlated with the number of patents granted and the number of technological categories for these patents; and (ii) productivity is positive correlated with the number of citations per granted patent, and is also positively correlated with the number of technological categories for cited patents per granted patent. Whereas the former finding indicates that productive firms actively conduct research and their innovation is involved in different technological fields, the latter suggests that, to develop a new patent, productive firms are capable of learning from cited patents in various technologies fields.

2.1 Introduction

The quest to explain the sources of productivity growth has led to a large body of empirical literature that investigates the relationship between firm-level productivity and innovative activities by using patent data. Early work suggested a positive correlation between productivity and innovation, but was less conclusive about how firms' productivity is related with the spectrum of technological categories associated with patents. The process of producing a patentable innovation is similar to the combination of several pieces of familiar and unfamiliar technological components

(Fleming, 2001). Entering in an unfamiliar technological field would incur additional costs to overcome technical barriers. A firm's productivity may be associated with the probability of choosing to bear such costs, and may be important in expanding the spectrum of technological fields and spurring innovation by combining new ideas and inventions.

This study examines the empirical relationship between firm-level productivity and innovation from a variety of perspectives. First, this study investigates whether productive firms actively participate in innovation in terms of patents. Second, this study examines whether firms' patents are involved in a wide spectrum of technological categories (extensive innovation scope), and whether their innovative activities focus on inventing within a narrow set of fields (intensive innovation scope). Third, this study investigates whether, to successfully develop a patentable innovation in a certain technological field, productive firms cite patents across various related fields (extensive citation scope) or whether they only cite more patents from a narrow set of technological categories (intensive citation scope). Lastly, this paper explores how the novelty of invented patents is correlated with firm-level productivity.

The data that this study uses pertain to US public firms in the manufacturing sector over the period 1976-2006. This dataset is compiled from two main sources: the NBER patent database, and Compustat data (Wharton Research Data Services). The former provides comprehensive information for patents granted by the US Patent and Trademark Office, while the latter includes detailed financial information for all firms traded in the US stock market during the study period. Since the main focus of this paper is on the manufacturing sector, this study further restricts sample to industries within this sector, and match the data with the industry-level NBER-CES manufacturing productivity database.

Productivity, a key variable in this analysis, is estimated as total factor productivity (TFP), using the Levinsohn and Petrin (2003)'s method. To link productivity with innovation, the dependent variables include measures of innovation quantity measured by the number of patents. Each patent is classified into technological fields by using the International Patent Classification (IPC) code. This study uses technological categories associated with patents to define extensive and intensive innovation scope, capturing the technology spectrum in which a firm has produced patentable inventions. The extensive innovation scope is simply proxied by the number of different technological fields associated with these patents, while the intensive innovation scope is the number of different technological fields divided by the number of patents. Similarly, this study counts the number of different technological fields for cited patents, and divide it by the number of patents. This measure captures the number of cited technical fields per patent that a firm learns from cited patents. Furthermore, two additional measures on the "generality" and "originality" of patents are used, following Trajtenberg et al. (1997).

The findings in this study are consistent with the empirical literature on the relationship between firm-level productivity and innovation (Hall, 2011; Mohnen and Hall, 2013). First, this study documents a consistent and positive correlation between productivity and innovation quantity – the more productive a firm, the more patentable inventions are produced. Second, there are some novel insights about how productivity is related to extensive and intensive innovation scope at the firm level. A positive correlation between productivity and extensive innovation scope is documented. Productive firms tend to engage in a wide spectrum of technological fields. Moreover, intensive innovation scope is also positively correlated with productivity, indicating that on average productive firms appear to invent relatively less patents in a wide area of technical fields. Lastly, the findings in this study show that productivity is positively correlated with both average citations per patent and average cited technical fields per patent. The former indicates productive firms tend to cite more patents per patented invention, while the latter suggests that these productive firms are more capable of learning from cited patents across various technologies fields. Furthermore, the "generality" and "originality" measures of novel patents are positively correlated with firm productivity.

This paper is related to the growing literature that study innovation using firm-level patent. One strand is the (causal) relationship between productivity and patent innovation. Recent review papers (Nagaoka et al., 2010; Hall, 2011; Mohnen and Hall, 2013) summarize the pioneering work by Griliches (1996, 1998), which attempt to employ patents stock to explain the residual growth in productivity. Most of the followed-up studies that have examined the effects of innovation on labor productivity are based on the well-known CDM (Crepon et al., 1998) model. This model is generally presented as a recursive system of three blocks of equations with endogenous choices of innovation, and hence handles some of the endogeneity problem related to R&D expenditures and product or process innovation. Whereas a few studies document a negative correlation between innovation and productivity (Roper et al., 2008; Van Leeuwen and Klomp, 2006), this strand of work have found the positive relationship between innovation and productivity (Crepon et al., 1998; Janz et al., 2004; Loof and Heshmati, 2006; Castellani and Zanfei, 2007; Hall et al., 2009; Raymond et al., 2013; Hall and Sena, 2014). When the growth rather than the level of productivity is chosen as the dependent variable (Geroski, 1989a; Miguel Benavente, 2006) or human capital is added as a control variable (Crepon et al., 1998; Castellani and Zanfei, 2007; Therrien and Hanel, 2009), the effects of innovation on productivity is weakened.

This paper is also related to existing literature that use the matched data between NBER patent database and firm-level financial information. Among the first wave of practitioners that link NBER patent with firms' innovation expenditure, Bound et al. (1982); Hall et al. (1984) analyze the R&D and patenting behavior of manufacturing firms. Hall et al. (2001b) summarize how NBER patent data are merged and matched with public firms in Compustat. Using this matched firm-level patent data, one of emerging studies by Hall and Helmers (2010) examines the role of patent protection in technical changes, and another work by Hall and Harhoff (2012) investigate whether patent protection encourages technology transfer from dirty to clean. Arora et al. (2015) emphasizes the decline of scientific publications in corporate R&D.

The remainder of the this chapter is organized as follows. The next section introduces a theoretical mechanism that reveals the theoretical relationship between productivity and innovation. Section 2.3 describes data sources, data construction and description. The empirical strategy, results and robustness checks are provided in section 2.4. The last section concludes the paper.

2.2 Theoretical Mechanism

2.2.1 Final Good Production

The production of final goods requires the input of capital, skilled labor and unskilled labor. Final good production follows a Cobb-Douglas technology and the total output at time t is given by

$$y_t = \varphi_t n_t^{1-\theta}(k_t^{1-\alpha-\beta} h_t^{\alpha} l_t^{\beta})^{\theta}, \tag{2.1}$$

where y_t is production, φ_t is productivity, n_t denotes the number of available varieties, k_t is input capital, h_t is skilled labor, l_t is unskilled labor.

Firm's profit can be represented as

$$\pi_t = \varphi_t n_t^{1-\theta}(k_t^{1-\alpha-\beta} h_t^{\alpha} l_t^{\beta})^{\theta} - \omega_h h_t - \omega_l l_t - r k_t - f \tag{2.2}$$

where ω_h is the wage paid to skilled labor, ω_l is the wage paid to unskilled labor, f is the fixed cost.

Firm's profit maximizing problem is to choose optimal inputs of capital, skilled labor and unskilled labor given the prices, which is given by

$$\max_{k_t,h_t,l_t} \left\{\varphi_t n_t^{1-\theta}(k_t^{1-\alpha-\beta} h_t^{\alpha} l_t^{\beta})^{\theta} - \omega_h h_t - \omega_l l_t - r k_t - f\right\} \tag{2.3}$$

Solving the first order conditions, then

$$\begin{aligned} \omega_h &= \alpha\theta \tfrac{y_t}{h_t} \\ \omega_l &= \beta\theta \tfrac{y_t}{l_t} \\ r &= (1-\alpha-\beta)\theta \tfrac{y_t}{k_t} \end{aligned} \tag{2.4}$$

Normalizing the unskilled labor's wage ($\omega_l = 1$), then

$$\omega_h = \frac{\alpha l_t}{\beta h_t}, \quad r = \frac{(1-\alpha-\beta) l_t}{\beta k_t} \tag{2.5}$$

Use the result in equation (2.5) to firm's profit maximizing problem (2.3), then

$$\max_{k_t,h_t,l_t} \left\{\varphi_t n_t^{1-\theta}(k_t^{1-\alpha-\beta} h_t^{\alpha} l_t^{\beta})^{\theta} - \frac{\alpha}{\beta} l_t - l_t - \frac{1-\alpha-\beta}{\beta} l_t - f\right\} \tag{2.6}$$

A representative firm chooses its input of capital, skilled labor and unskilled labor to maximize its production profit. As capital and skilled labor are function of unskilled labor, so firm chooses its optimal unskilled labor first and then determines its input of skilled labor and capital to maximize its profit. As such, the optimal inputs, output, and profit is given by

$$\begin{aligned}
&k_t(\varphi_t) = \tfrac{1-\alpha-\beta}{\beta r}(\theta\beta\varphi_t)^{\frac{1}{1-\theta}}\varepsilon^{\frac{\theta}{1-\theta}}n_t\\
&h_t(\varphi_t) = \tfrac{\alpha}{\beta\omega_h}(\theta\beta\varphi_t)^{\frac{1}{1-\theta}}\varepsilon^{\frac{\theta}{1-\theta}}n_t\\
&l_t(\varphi_t) = (\theta\beta\varphi_t)^{\frac{1}{1-\theta}}\varepsilon^{\frac{\theta}{1-\theta}}n_t\\
&y_t(\varphi_t) = \tfrac{1}{\beta\theta}(\theta\beta\varphi_t)^{\frac{1}{1-\theta}}\varepsilon^{\frac{\theta}{1-\theta}}n_t\\
&\pi_t = (1-\theta)y_t - f = \tfrac{1-\theta}{\beta\theta}(\theta\beta\varphi_t)^{\frac{1}{1-\theta}}\varepsilon^{\frac{\theta}{1-\theta}}n_t - f
\end{aligned} \tag{2.7}$$

where $\varepsilon = (\frac{1-\alpha-\beta}{\beta r})^{1-\alpha-\beta}(\frac{\alpha}{\beta\omega_h})^{\alpha}$.

Claim 1. *If firm's productivity $\varphi_1 > \varphi_2$, then*

$$\begin{aligned}
&y(\varphi_1) > y(\varphi_2),\ \pi(\varphi_1) > \pi(\varphi_2)\\
&k(\varphi_1) > k(\varphi_2),\ h(\varphi_1) > h(\varphi_2),\ l(\varphi_1) > l(\varphi_2)
\end{aligned} \tag{2.8}$$

Claim 1 shows that firms with higher productivity tend to with larger scale (both in input and output), and gain more from the market (profit is larger).

2.2.2 Innovation

Similar to Adams (1990), assume firms innovation depends on current own stocks of knowledge U_t, current stocks of knowledge in other fields I_t, and researchers s_t. The production of ideas satisfies a Cobb-Douglas form, which is

$$\dot{n}_t = X_t = \lambda U_t^{\eta} I_t^{\gamma} s_t^{1-\eta-\gamma} \tag{2.9}$$

where η, γ, $1-\eta-\gamma \in (0,1)$ are the elasticities of own knowledge stock, of knowledge stock in other fields, and of scientists, respectively. $\lambda > 0$ is the scale effect, $\dot{n}_t = X_t$ is new added varieties of goods. Use $x_t = \frac{\dot{n}_t}{s_t} = \lambda U_t^{\eta} I_t^{\gamma} s_t^{-\eta-\gamma} = \lambda u_t^{\eta} i_t^{\gamma}$ to be the intensive innovation of skilled labor or scientist, where $u_t = \frac{U_t}{s_t}$ is the own knowledge stock per scientist, $i_t = \frac{I_t}{s_t}$ is the knowledge stock per scientist in other fields. Total cost of innovation is

$$C_t = \omega_s s_t + f_U U_t + f_I I_t = s_t(\omega_s + f_U u_t + f_I i_t) \tag{2.10}$$

where ω_s is the wage of scientist, f_U and f_I are the fixed costs that need to pay for the use of knowledge. Firm gains $v_t(\varphi_t) = \sum_{t=1}^{\infty} (1-\rho)^t \pi_t(\varphi_t) = \frac{\pi_t(\varphi_t)}{\rho}$ from producing one unit of goods, and gains $\Pi_t^I = X_t v_t - C_t = X_t \frac{\pi_t(\varphi_t)}{\rho} - s_t(\omega_s + f_U u_t + f_I i_t) = s_t(x_t v_t - \omega_s - f_U u_t - f_I i_t)$ from innovation. The maximizing decision in innovation sector is:

$$\max \left\{ \pi_t^I = \frac{\Pi_t^I}{s_t} = x_t v_t - \omega_s - f_U u_t - f_I i_t = \lambda u_t^\eta i_t^\gamma v_t - \omega_s - f_U u_t - f_I i_t \right\} \tag{2.11}$$

Solve the first order condition, then the knowledge stocks per scientist are:

$$\begin{aligned} u_t(\varphi_t) &= \tfrac{\eta\phi}{f_U} v_t^{\frac{1}{1-\eta-\gamma}} = \tfrac{\eta\phi}{f_U} (\tfrac{\pi_t}{\rho})^{\frac{1}{1-\eta-\gamma}} \\ i_t(\varphi_t) &= \tfrac{\gamma\phi}{f_I} v_t^{\frac{1}{1-\eta-\gamma}} = \tfrac{\gamma\phi}{f_I} (\tfrac{\pi_t}{\rho})^{\frac{1}{1-\eta-\gamma}} \end{aligned} \tag{2.12}$$

where $\phi = [\lambda(\frac{f_U}{\eta})^{-\eta}(\frac{f_I}{\gamma})]^{\frac{1}{1-\eta-\gamma}}$, and $\pi_t = \frac{1-\theta}{\beta\theta}(\theta\beta\varphi_t)^{\frac{1}{1-\theta}} \varepsilon^{\frac{\theta}{1-\theta}} n_t - f$. Since π_t is increasing in φ_t, u_t and i_t are also increasing in φ_t, then

Claim 2. *If firm's productivity $\varphi_1 > \varphi_2$, then*

$$u(\varphi_1) > u(\varphi_2),\ i(\varphi_1) > i(\varphi_2) \tag{2.13}$$

Claim 2 shows that firms with higher productivity tend to learn more about advanced science in its own field and other fields. Current knowledge stock is the accumulation of previous advanced science, firms with higher productivity pay relatively less to get and apply the frontier knowledge. From equation (2.12), firm's innovation output per scientist is

$$x_t(\varphi_t) = \phi v_t^{\frac{\eta+\gamma}{1-\eta-\gamma}} = \phi(\frac{\pi_t}{\rho})^{\frac{\eta+\gamma}{1-\eta-\gamma}} \tag{2.14}$$

The profit per scientist that firms can get from innovation is then:

$$\pi_t^I(\varphi_t) = \phi(1-\eta-\gamma) v_t^{\frac{1}{1-\eta-\gamma}} - \omega_s = \phi(1-\eta-\gamma)(\frac{\pi_t}{\rho})^{\frac{1}{1-\eta-\gamma}} - \omega_s \tag{2.15}$$

Equation (2.15) shows that the optimal profit from innovation is a function of optimal profit from producing final goods. As such, similar to u_t and i_t, firm's innovation output x_t and profit π_t^I are also increasing in its productivity φ.

Claim 3. *If firm's productivity $\varphi_1 > \varphi_2$.*

$$\begin{aligned} &x(\varphi_1) > x(\varphi_2),\ X(\varphi_1) > X(\varphi_2) \\ &\pi^I(\varphi_1) > \pi^I(\varphi_2),\ \Pi^I(\varphi_1) > \Pi^I(\varphi_2) \end{aligned} \tag{2.16}$$

Claim 3 shows that firms with higher productivity tend to gain more from innovation, and thus invest and produce more in innovation. Higher profit in innovation spurs firms to invest more, and thus apply more patents.

2.3 Data

2.3.1 Data Sources

The data pertain to the US public firms in the manufacturing sector over the period of 1976 - 2006. This study compiles the data from two main sources: the NBER patent database and the Compustat data. The former provides comprehensive information for patents granted by the US Patent and Trademark Office (USPTO), while the latter maintained by Wharton Research Data Services (WRDS) includes detail financial information for all firms traded in the U.S. stock market during the study period. The industry-level variables that are used to construct variables of interests are obtained from the NBER-CES manufacturing industry database (Becker et al., 2013).

The NBER patent data comprise detail information on US patents granted from 1976 - 2006, and all citations associated with these patents.[1] The patent information file records patent application year, granted year, technological classification in terms of 8-digit IPC code, and the unique assignee identification number. There are about 2.87 million patents associated with 0.20 million firms in this original database. Moreover, for each granted patent, the patent citing file contains information about all citations made to each patent (backward citations) and total cites received by patents

[1] Please see the data from the new NBER data project via link https://sites.google.com/site/patentdataproject/Home.

(forward citations) issued during 1976-2006. There are about 23 million citation observations with 2.8 million citing patents and 2.5 million cited patents.

The US Compustat database provides historical archive of annual financial statement and balance sheet for all firms traded in the US stock market from 1975 to 2007. The firm-level variables include gvkey as an identification code, standard industry classification (SIC), net sales, number of employees, book value of asset value, capital expenditure, wage, R&D expenses, and may others. This study uses this firm-level data to estimate TFP, and construct other firm-level variables of interest, including capital intensity, firm age, size, and R&D expenditure per value of assets. The construction method mainly follows Keller and Yeaple (2009), which will be discussed in details in the following subsection of variable construction.

Bessen (2009) has matched patent data with public firms in Compustat, using an algorithm involved with firm names.[2] As owners of patent change over time, the patent and Compustat matched file provides dynamic match of patent assignee to corporate entity in the Compustat. The matching results uniquely link assignee identification number from patent data with public firms' permanent identification number (i.e., gvkey) in Compustat database. In the matched sample, there are around 1.8 million patents associated with 6,575 unique corporate identities and 132,585 firm-by-year observations.

Since the main focus of this paper is on the manufacturing sector, this study further restrict the sample within this industry, and match with the industry-level NBER-CES manufacturing productivity database. This step of data matching and merging leads to a final sample of 52,055 firm-by-year observations with 3,182 unique firms across the study period from 1976 to 2006. These firms have 528,620 granted patents with over 5 million citations.[3]

[2] For the matching algorithm and matched results, please refer to the new NBER patent project via link https://sites.google.com/site/patentdataproject/Home.

[3] Table **??** in Appendix summarizes changes in sample size due to data merging and matching.

Table 2.1: Variable Description of Innovation and Productivity

Variables	Description
Firm-Level Patent Data from NBER Patent Database	
Patent	Number of patents
Tech Fields	Number of unique technology categories associated with patents under 4-digit IPC
Citation	Number of forward citations for firms' patents
Cited Tech Fields	Number of unique technology categories associated with cited patents under 4-digit IPC
Innovation	$\log(1 + \#\text{ of Patent})$
Extensive Innovation Scope	$\log(1 + \#\text{ of Tech Field})$
Intensive Innovation Scope	$\log(1 + \frac{\#\text{ of Tech Field}}{\#\text{ of Patent}})$
Citation	$\log(1 + \#\text{ of Citation})$
Average Citation	$\log(1 + \frac{\#\text{ of Citation}}{\#\text{ of Patent}})$
Extensive Citation Scope	$\log(1 + \#\text{ of Cited Tech Field})$
Intensive Citation Scope	$\log(1 + \frac{\#\text{ of Cited Tech Field}}{\#\text{ of Patent}})$
Patent Stock	Stock of patents
Technology Stock	Stock of patents' unique technology categories under 4-digit IPC
Firm-Level Financial Statement from Compustat of WRDS	
TFP	Productivity estimated by the Levinsohn and Petrin (2003)'s method
Alt. TFP	Alternative productivity estimated by the Olley and Pakes (1996)'s method
Sales	Value of net sales/turnovers (item 12 at Compustat), deflated by industry-level value of shipment deflator
Capital	Total net value of property, plants and equipment less depreciation (item 8), deflated by industry-level shipment deflator
Labor	Number of employees (item 29)
Wage Expenditure	Total payrolls, calculated labor multiplied by average industry wage
Materials	Costs of goods sold (item 41) plus administrative and selling expenses (item 189) less depreciation (item 14) and wage expenditure, deflated by industry-level material costs deflator
R&D Expenses	Research and development expenses (item 46)
Asset Value	Book value of total assets (item 29)
Investment	Capital expenditures (item 128), deflated by industry-level investment deflator
Revenue	Total revenue
Age	Firm's age (current year - the first year)
Size	Log sales, deflated by industry-level value of shipment deflator
Capital Intensity	Log ratio of capital to labor
Industry-level Data at the 4-Digit SIC from the NBER-CES Manufacturing Data	
Value of Shipment Deflator	Deflator for value of shipment
Investment Deflator	Deflator for investment value
Material Cost Deflator	Deflator for material costs

2.3.2 Variables Construction

Table 2.1 presents the definition and construction of each dependent and independent variables of interests used in this empiric work.

2.3.2.1 Innovation

The main dependent variable is innovation. The existing studies in related literature have employed patents to measure firm-level innovation output (Griliches, 1998; Hall et al., 2001b; Amore and Morten, 2011; Aghion et al., 2013). Following this strand, this study uses the log number of patents granted to proxy firm's innovation quantity,

$$\text{Innovation}_{it} = log(1 + \#\text{ of Patent}_{it})$$

Following Hall et al. (2001b, 2005a), as a robustness check, this study introduces a new variable to count firm-level patents. Hence, the number of patents is weighted by future citations received and adjusted for truncation, that is, Alt. $\text{Innovation}_{it} = log(1 + \#\text{ of Weighted Patents}_{it})$. Following Chemmanur et al. (2015), this study measures innovation quality by patents per R&D expenditure and citations per R&D expenditure, while accounting for dynamic effects of R&D investments from 4 year lags to current period with different discount factors,

$$\text{Patent}/R\&D_{it} = log(1 + \frac{\#\text{ of Patents}_{it}}{R\&D_{it} + 0.8R\&D_{it-1} + 0.6R\&D_{it-2} + 0.4R\&D_{it-3} + 0.2R\&D_{it-4}})$$
$$\text{Citation}/R\&D_{it} = log(1 + \frac{\#\text{ of Citations}_{it}}{R\&D_{it} + 0.8R\&D_{it-1} + 0.6R\&D_{it-2} + 0.4R\&D_{it-3} + 0.2R\&D_{it-4}})$$

Each patent is assigned with a 8-digit IPC code provided by the World Intellectual Property Organization (WIPO). The IPC separates the whole body of technical knowledge using a hierarchical classification system, i.e., section, class, subclass, group and subgroup, in descending order of hierarchy. There are eight sections with each section symbol designated by one of the capital letters A through H. Each section is subdivided into classes which are the second hierarchical level of the IPC. The class symbols consist of the section symbol followed by a 2-digit number. Each class comprises several subclasses with the symbol of the class symbol followed by a capital letter.

Lastly, each subclass is then broken down into groups, either main groups or subgroups. Take one IPC code for example, $H01S3/00$ is the code for "Lasers", where "H" denotes the section of Electricity, "H01" stands for the class of "Basic Electric Elements", while "H01S" references the subclass of "Devices using Stimulated Emission." The IPC has been periodically revised to take account of technical improvement with minor adjustments for the definition of class and subclass technology fields. Using the 2006 edition of the IPC, the whole body of technology spectrum is divided into 129 classes and 633 subclasses.[4] This study uses 4-digit IPC code (i.e., the subclass) to define technological fields. For each year, this study sums up the number of different technological categories in which a firm's patents are classified. Hence, the *extensive innovation scope* is measured by the log number of unique technological fields, capturing the wide spectrum of a firms' technological categories in which it has invented patents.

$$\text{Extensive Innovation Scope}_{it} = log(1 + \#\text{ of TechField}_{it})$$

To further understand the intensiveness of a firms' technological spectrum, this study measures the *intensive innovation scope* by the log number of unique technological fields divided by the number of patent,

$$\text{Intensive Innovation Scope}_{it} = log(1 + \frac{\#\text{ of TechField}_{it}}{\#\text{ of Patent}_{it}})$$

Definition of technology categories is of importance to this study. To check whether results are robust to the alternative IPC code, this study uses the first 3-digit IPC code (i.e., class) to separate technology categories from each other. An alternative measure of extensive innovation scope is the count of different technological fields associated with patents in terms of the first 3-digit IPC code. Thus, Alt. Extensive Innovation $\text{Scope}_{it} = log(1 + \#\text{ of Alt. Tech Field}_{it})$. Similarly, an alternative measure of intensive innovation scope is defined as Alt. Intensive Innovation $\text{Scope}_{it} = log(1 + \frac{\#\text{ of Alt. TechField}_{it}}{\#\text{ of Patent}_{it}})$.

[4] Please refer to the summary statistics table provided by the WIPO http://www.wipo.int/classifications/ipc/en/ITsupport/Version20060101/transformations/stats.html.

Forward citations appear to be correlated with the value of patents (Trajtenberg, 1987), whereas backward citations reflect knowledge spillover of "prior art."[5] For each firm, this study calculates average backward citations per patent, that is,

$$\text{Average Citation}_{it} = log(1 + \frac{\#\text{ of Citation}_{it}}{\#\text{ of Patent}_{it}})$$

Similar to the innovation scope, for each granted patent owned by a firm, this study classifies all patents that were cited by the focal patent into different technological categories in terms of 4-digit IPC code. This study then calculate the number of unique technological fields associated with cited patents for all patents granted by the firm. This measure denotes *extensive citation scope*.

$$\text{Extensive Citation Scope}_{it} = log(1 + \#\text{ of CitedTechField}_{it})$$

Furthermore, the *intensive citation scope*, computed as the number of unique cited technological fields divided by the number of patents granted, captures how many different fields on average a firm must reference to innovate a new patent.

$$\text{Intensive Citation Scope}_{it} = log(1 + \frac{\#\text{ of CitedTechField}_{it}}{\#\text{ of Patent}_{it}})$$

In the section of robustness check, this study broadens the definition of technological fields from 4-digit IPC (i.e., subclass) to 3-digit IPC (i.e., class) code on the one hand, and recalculate measures of citation scope by using the number of nonself-citations, which is the number of backward citations from other firms but itself.

A wide variety of citations-based measures is defined to examine different aspects of patent innovation. Following Trajtenberg et al. (1997), this study further uses "generality" and "originality" measures, computed in the original patent file, to proxy patent quality. The former is computed based upon a patent's forward citations, while the latter is calculated based upon its backward citations. The "generality" measure renders a lower score if a patent's forward citations are concentrated in a few technology fields, while a higher score if its forward citations belong to a wide range

[5]Patent examiners, rather than applicants, are ultimately responsible for for the citations made(Hall et al., 2001b; Nagaoka et al., 2010). Unfortunately, this study could not distinguish citations added by patent examiners with citations referenced by inventors.

of fields. Similarly, the "originality" measure takes a high score if a patent's backward citations in a wide range of fields, but a low score if its backward citations belonging to a narrow set of technologies. This study further calculates the firm-level generality and originality measures by computing the weighted average patents scores of "generality" and "originality," respectively.

2.3.2.2 Other Firm-Level Controls

The main variable of interest is the estimated firm-level productivity, denoted by TFP_{it}. The estimation of productivity is full of challenges. Olley and Pakes (1996) (the OP method for short) solves the simultaneity of output and capital stock when estimating the TFP. In addition, this method corrects the selection bias problem that only firms with high productivity can survive and be continually observed in panel data sample. Based on the OP method, Levinsohn and Petrin (2003) (the LP method for short) propose a similar method by introducing intermediate inputs to the estimation to solve the simultaneity problem. Compared with OLS and fixed effects, both the OP and LP methods use investment or intermediate inputs to control for correlation between input and unobserved productivity. Because of their special advantages, the OP method and the LP method are widely used in applied researches relative to firm's productivity (Keller and Yeaple, 2009; Smarzynska Javorcik, 2004; Fernandes, 2007; Kasahara and Rodrigue, 2008; Petrin and Levinsohn, 2012). This study uses the TFP estimated from the LP method in the baseline, and choose the TFP estimated from the OP method as a robustness check.

With a handful of firm-level variables including sales, labor, materials, and capital from Compustat, this study follows the instruction from Keller and Yeaple (2009) to estimate TFP, using the OP method.[6]

$$TFP_{it} = y_{it} - \beta_k^{op} k_{it} - \beta_l^{op} l_{it} - \beta_m^{op} m_{it}$$

where β_k^{op}, β_l^{op} and β_m^{op} are the Olley-Pakes estimated coefficients for the capital, labor, and materials elasticities in production function, respectively. Let y_{it} be the logarithm of output of firm i at year t. Denote l_{it}, m_{it} and k_{it} as the firms' log labor, materials, and capital inputs, respec-

[6] For detailed estimation of TFP from the OP method, please refer to the appendix in Keller and Yeaple (2009).

tively. Following Keller and Yeaple (2009), the output y_{it} is net sales (from Compustat) deflated by industry-level value of shipment index (from the NBER-CES). Labor, l_{it}, is measured by the number of employees from Compustat. Capital, k_{it}, is sum of value of property, plant, and equipment, and net depreciation (from Compustat), and further deflated by industry-level investment deflator (from the NBER-CES). Materials, m_{it}, are defined as costs of goods sold (from Compustat) plus administrative and selling expenses (from Compustat) less depreciation (from Compustat) and wage expenditures. Wage expenditures are calculated by labor multiplied by average industry wage rate from the NBER-CES database.

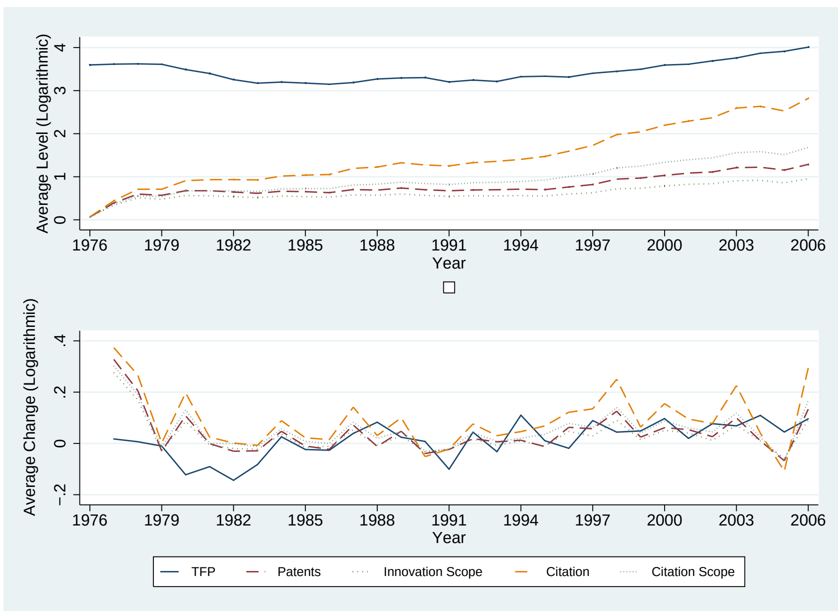


Figure 2.1: Average TFP and Innovation during 1976-2006

As noted in the growing literature (Konar and Cohen, 2001; Bloom et al., 2010; Carrion-Flores and Innes, 2010; Amore and Morten, 2011; Kock et al., 2012), other firm-level characteristics play important roles in explaining firms innovation activities. Specifically, this study uses firm's (log) deflated net sales to measure firm size. Capital intensity is calculated as the ratio of deflated capital to employment. Moreover, this study also controls for firm's age, which is the difference between the current year and its beginning year reported in Compustat. R&D expense is generally regarded as a driving force for firm's innovation. This study employs R&D expense per asset value as a control variable. Last, but not least, patent stock and technology stock represent firms' knowledge stock. Firms tend to create ideas and invent new patents if they have accumulated knowledge in certain technological fields that they are familiar with. Thus, the stock of patents and technologies have expected positive impacts on firms' innovative behavior. For each firm, this study sums up all patents and unique technological categories occurred in previous years, and use these variables to measure the spillover effects of knowledge stock on innovation.

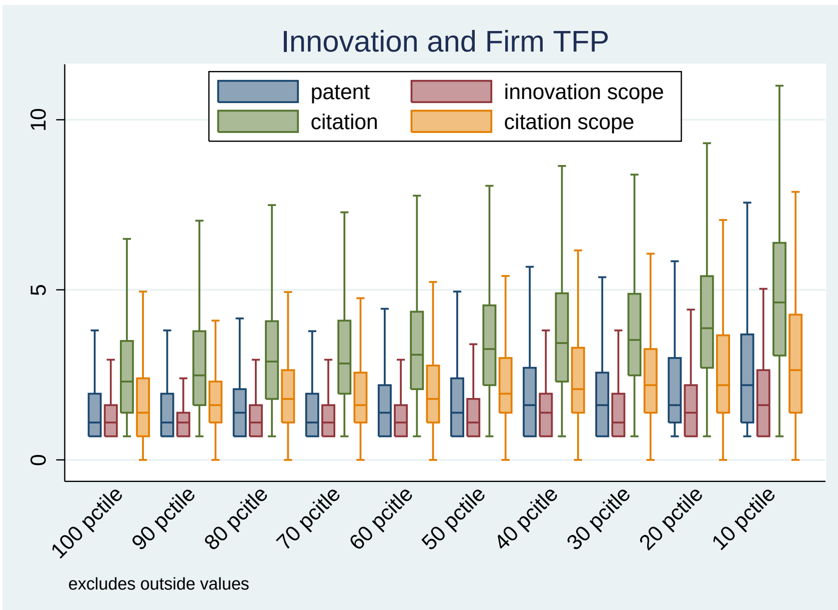


Figure 2.2: Box Plots for Firm-level Innovation and TFP Percentile Distribution

2.3.3 Descriptive Statistics

The upper panel of Figure 2.1 depicts average TFP and innovation across year during the study period of 1976 - 2006, while the lower panel of Figure 2.1 captures annual changes in average TFP and innovation measures. For each year, this study takes average of firm-level TFP, innovation, innovation scope, citation, and citation scope. This figure shows that innovation activities are positively correlated with TFP across years. I further take a close look at the correlation between TFP and innovation at firm level. Figure 2.2 provides box plots for firm-level innovation and TFP.

This study ranks firms by their estimated TFP, and divide the TFP distribution by 10 deciles. For each decile of the productivity distribution, a series of box plot for firm-level innovation, innovation scope, citation, and citation scope are plotted. As shown in Figure 2.2, the horizontal line is the 10 deciles of TFP distribution. From left to right, the TFP increases from the lowest 10 percentile to the top 10 percentile. Clearly, there is a positive correlation between productivity and innovation activities.

Table 2.2: Summary Statistics of Innovation and Productivity

Variables	N	Mean	Std. Dev.	Min	Max
Patent	37340	12.22	71.80	0	2344
Extensive Innovation Scope	37340	3.241	9.854	0	152
Intensive Innovation Scope	37340	0.344	0.422	0	5
Citation	37340	127.9	931.1	0	60010
Average Citation	37340	5.415	13.14	0	505.8
Extensive Citation Scope	37340	9.261	25.89	0	359
Intensive Citation Scope	37340	1.094	1.856	0	44
Originality (ln)	37340	1.398	1.956	0	10.38
Generality (ln)	37340	1.148	1.763	0	9.356
Patent Stock	37340	117.8	759.5	1	30937
Technology Stock	37340	11.37	28.92	1	397
TFP	36663	3.521	1.536	-6.844	11.22
Alt. TFP	33485	37.53	26.22	-1.375	113.3
Capital (ln)	37216	3.112	2.754	-6.908	11.64
Employment (ln)	36849	-0.116	2.240	-6.908	6.776
Capital Intensity (ln)	36815	3.235	1.073	-2.977	8.352
RD Expenditure per Asset Value (ln)	30899	-2.804	1.983	-10.23	9.435
Sale (ln)	37239	4.753	2.419	-0.0192	12.72
Age	37340	11.22	7.083	1	31

Note: TFP is the estimated productivity, using the LP method, while Alt. TFP is the estimated productivity with the OP method. All variables of interests presented in the above table are not implemented in log fashions unless noted.

Table 2.2 presents summary statistics for variables of interests at firm level. On average, each firm has around 12 patents granted per year, covering roughly 3 different technological fields in terms of 4-digit IPC code. The total backward citations for all patents granted by each firm reach more than 120 and are involved in 9 different technological fields. To develop a new patent, each firm on average needs to cite around 5 patents across two different technological fields.

2.4 Empirics and Results

This study is interested in investigating how firm-level productivity is correlated with innovation activities in terms of the number of patents granted and the number of technological fields associated with these patents. Moreover, to successfully develop a new patent in a certain technological field, I explore how firm-level productivity is associated with the number of citations per patent and the number of technological fields associated with these cited patents. Furthermore, this study includes a handful of firm-level controls while estimating the correlation between productivity and innovation activities at firm-level. To this end, the following specification with a set of fixed effects for industry, year, and firm is presented:

$$Y_{it} = \beta_0 + \beta_1 TFP_{it-1} + \alpha \mathbf{X}_{it-1} + \theta_{jt} + \delta_t + \mu_i + \varepsilon_{ijt} \tag{2.17}$$

where i indexes a firm, j indicates an industry, and t references a year. In (2.17), θ_{jt} is a vector of industry variables that remove the time-variant shocks common to all manufacturers in the same industry, δ_t is year fixed effect, μ_i is firm-level fixed effect controlling for unobservable firm heterogeneity, and ε_{ijt} is the stochastic error term.

The outcome variable Y_{it} includes a series of measures on firm-level innovation, innovation scope, citation, and citation scope. TFP_{it-1}, which is critical to this study, denotes the estimated one-year lagged firm-level productivity using the LP method. Other one-year lagged firm-level controls that are related to innovation activities are absorbed in a vector of $\mathbf{X}_{it-1}$. The parameter of interest, denoted by β_1, captures how firm-level productivity is correlated with firms innovation activities.

Based upon the baseline specification (2.17), this study first seeks to explore how productivity and firms characteristics are correlated with innovation, extensive innovation scope, and intensive innovation scope. I then test how firm-level productivity is related with citations and citation scope in both extensive and intensive fashions.

2.4.1 Innovation and Innovation Scope

Table 2.3 presents the OLS estimation results for innovation and innovation scope. In each column, a set of fixed effects for year, industry, and firm as well as industry year trend is added in specification (2.17) as noted in the bottom of the table. Industry fixed effects are measured at 4-digit SIC level. Standard errors presented in the parenthesis are clustered at firm level.

Columns (1) - (3) in Table 2.3 provide the estimated results for the correlation between TFP and innovation, controlling for firms' characteristics that are related to innovation choices. The estimated coefficients for TFP are positive and statistically significant at 1% level in all columns, capturing the positive correlation between firm-level productivity and innovation in terms of the number of patents granted. Productive firms tend to be more actively engaged in innovation. One percent increase in productivity is associated with roughly 10 percent increase in the number of patents granted as noted in column (3). Firms characteristics other than productivity also plays an important role in innovative activities. The effect of firm size on innovation is positive and statistically significant for 1% level. Firms with bigger size in terms of larger value of sales are more likely to bear sunk costs of investment in innovation. In addition, there is a positive estimate of capital intensity, which is statistically significant at 1% level. Firms with intensive capital relative to labor appear to have more patents granted. In column (1), the estimated coefficient for firms age is negative and statistically significant at 1% level, suggesting that younger firms are more actively involved in innovation. With firm fixed effects added in columns (2)-(3), the negative estimates of firm age lose statistical significance at any conventional level, suggesting little evidence on the negative effects of firm age on innovation. When it comes to R&D expenses per value of asset, the estimated coefficient is positive and statistically significant at 1% level. As one of driving forces for innovation, the more expenses in R&D per value of asset, the more patents a firm would have. Lastly, the estimated coefficients for patent stock and technology stock are positive. These positive estimates with statistical significance at 1% level lend support to the strong evidence that knowledge stock has a positive and statistically significant spillover effects on innovation.

Table 2.3: Baseline Results for Innovation and Innovation Scope

VARIABLES	Innovation $log(1 + \#\text{ of Patent}_{it})$			Extensive Innovation Scope $log(1 + \#\text{ of TechField}_{it})$			Intensive Innovation Scope $log(1 + \frac{\#\text{ of TechField}_{it}}{\#\text{ of Patent}_{it}})$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TFP	0.124***	0.174***	0.096***	0.081***	0.113***	0.068***	0.017***	0.018***	0.021***
	(0.015)	(0.023)	(0.022)	(0.011)	(0.017)	(0.016)	(0.005)	(0.006)	(0.007)
Size	0.054***	0.122***	0.169***	0.050***	0.098***	0.125***	0.005	0.037***	0.036***
	(0.010)	(0.022)	(0.023)	(0.007)	(0.016)	(0.017)	(0.003)	(0.006)	(0.006)
Capital Intensity	0.071***	0.085***	0.059***	0.039***	0.057***	0.041***	0.007*	0.009*	0.008*
	(0.012)	(0.016)	(0.015)	(0.009)	(0.012)	(0.011)	(0.004)	(0.005)	(0.005)
Age	-0.029***	0.019	-0.000	-0.021***	0.012	-0.004	-0.004***	-0.008**	-0.010***
	(0.002)	(0.022)	(0.020)	(0.001)	(0.014)	(0.012)	(0.001)	(0.003)	(0.003)
R&D Expenditure	0.115***	0.138***	0.126***	0.090***	0.098***	0.090***	0.025***	0.026***	0.026***
	(0.009)	(0.013)	(0.012)	(0.006)	(0.010)	(0.009)	(0.003)	(0.004)	(0.004)
Patent Stock	0.457***	0.257***	0.271***	0.268***	0.121***	0.133***	-0.005	-0.067***	-0.065***
	(0.023)	(0.028)	(0.026)	(0.015)	(0.020)	(0.019)	(0.004)	(0.005)	(0.005)
Tech Stock	0.248***	0.284***	0.255***	0.267***	0.240***	0.217***	0.055***	0.034***	0.032***
	(0.035)	(0.039)	(0.033)	(0.024)	(0.030)	(0.025)	(0.005)	(0.007)	(0.007)
Observations	31,066	31,066	31,066	31,066	31,066	31,066	31,066	31,066	31,066
Adjusted R^2	0.705	0.290	0.314	0.681	0.232	0.256	0.079	0.033	0.038
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y			Y			Y		
Firm FE		Y	Y		Y	Y		Y	Y
Industry Year Trend			Y			Y			Y

Note: All independent variables are in one-year lagged fashion. TFP is the estimated productivity, using the LP method. Size is log deflated value of sales. Capital intensity is the log ratio of capital to the number of employment. Age is firm's age. R&D expenditure is the log R&D expenses per deflated value of asset. Patent Stock is the stock of a firm's patent in past years. Tech Stock is the stock of unique technological categories associated with a firm's patents in past years. Standard errors presented in the parenthesis are clustered at plant level. Industry dummies are measured at the 4-digit SIC level. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Columns (4)-(6) in Table 2.3 show the estimated results for extensive innovation scope, which is measured by the log number of unique technological categories for patents granted at the firm level. First of all, positive estimates of TFP are documented. These estimates are statistically significant at 1% level, reflecting the positive correlation between productivity and extensive innovation scope. Productive firms tend to develop patents in a wide spectrum of technological categories. The point estimate of β_1 coefficient is 0.068 in column (8), indicating that one percent increase in TFP is associated with 6.8 percent increase in the number of unique technological fields. Secondly, firms attributes including size and capital intensity are found to have positive and statistically significant effects on extensive innovation scope. The estimated effect of R&D expenses on innovation is positive and statistically significant at 1% level. Lastly, knowledge stock, either in a form of patent stock or technology stock, appears to have significantly positive spillover effects on broadening firms' technology spectrum.

Last three columns of Table 2.3 present the corresponding results for intensive innovation scope. The estimated coefficients for TFP are positive and statistically significant at 1% level. These positive estimates suggest that productive firms have less patents per technological field. Other firms' attributes including capital intensity, R&D expenses, and knowledge stock appear to facilitate innovating firms to focus on certain technological fields, as shown by negative and statistically significant coefficients in columns (9)-(12) of Table 2.3.

Together with strong evidence on the positive correlation between productivity and innovation or innovation scope, this study finds that productive firms have more patents, and their innovative activities cover a wide area of technological fields.

2.4.2 Citation and Citation Scope

This study is interested in, to develop a new patent, how many citations are needed for patentable inventions, and how many different technological fields associated with these cited patents the firm must reference. Moreover, I seek to examine how firms attributes are related with citation, average citation, and measures of citation scope. Table 2.4 presents the OLS estima-

Table 2.4: Baseline Results for Citation and Citation Scope

VARIABLES	Citations $log(1+\#\text{ of Citation}_{it})$			Average Citation $log(1+\frac{\#\text{ of Citation}_{it}}{\#\text{ of Patent}_{it}})$			Extensive Citation Scope $log(1+\#\text{ of CitedTechField}_{it})$			Intensive Citation Scope $log(1+\frac{\#\text{ of CitedTechField}_{it}}{\#\text{ of Patent}_{it}})$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TFP	0.213***	0.229***	0.153***	0.102***	0.076***	0.077***	0.115***	0.138***	0.091***	0.009***	0.017***	0.014***
	(0.025)	(0.037)	(0.038)	(0.017)	(0.023)	(0.025)	(0.015)	(0.023)	(0.024)	(0.003)	(0.004)	(0.004)
Size	0.038**	0.265***	0.317***	-0.012	0.169***	0.175***	0.047***	0.163***	0.198***	0.006***	0.017***	0.019***
	(0.017)	(0.037)	(0.040)	(0.011)	(0.021)	(0.023)	(0.010)	(0.023)	(0.025)	(0.002)	(0.003)	(0.003)
Capital Intensity	0.142***	0.139***	0.111***	0.074***	0.059***	0.056***	0.074***	0.086***	0.069***	0.002	0.006*	0.004
	(0.020)	(0.027)	(0.028)	(0.014)	(0.018)	(0.019)	(0.012)	(0.017)	(0.017)	(0.002)	(0.003)	(0.003)
Age	-0.054***	-0.012	-0.039	-0.028***	-0.038***	-0.046***	-0.032***	-0.002	-0.021	-0.001***	-0.002	-0.004
	(0.004)	(0.031)	(0.029)	(0.002)	(0.014)	(0.014)	(0.002)	(0.020)	(0.017)	(0.000)	(0.002)	(0.002)
R&D Expenditure	0.198***	0.232***	0.225***	0.102***	0.117***	0.120***	0.121***	0.143***	0.139***	0.013***	0.017***	0.015***
	(0.015)	(0.023)	(0.022)	(0.010)	(0.015)	(0.015)	(0.009)	(0.015)	(0.014)	(0.002)	(0.002)	(0.002)
Patent Stock	0.720***	0.439***	0.454***	0.251***	0.097***	0.100***	0.393***	0.210***	0.224***	-0.010***	-0.057***	-0.055***
	(0.038)	(0.039)	(0.037)	(0.020)	(0.019)	(0.019)	(0.022)	(0.026)	(0.025)	(0.002)	(0.003)	(0.003)
Tech Stock	0.321***	0.414***	0.377***	0.104***	0.148***	0.138***	0.305***	0.308***	0.280***	0.028***	0.015***	0.014***
	(0.057)	(0.058)	(0.052)	(0.028)	(0.027)	(0.027)	(0.034)	(0.039)	(0.035)	(0.003)	(0.004)	(0.004)
Observations	31,066	31,066	31,066	31,066	31,066	31,066	31,066	31,066	31,066	31,066	31,066	31,066
Adjusted R^2	0.619	0.288	0.299	0.344	0.164	0.169	0.622	0.255	0.269	0.060	0.038	0.044
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y			Y			Y			Y		
Firm FE		Y	Y		Y	Y		Y	Y		Y	Y
Industry Year Trend			Y			Y			Y			Y

Note: All independent variables are in one-year lagged fashion. TFP is the estimated productivity, using the LP method. Size is log deflated value of sales. Capital intensity is the log ratio of capital to the number of employment. Age is firm's age. R&D expenditure is the log R&D expenses per deflated value of asset. Patent Stock is the stock of a firm's patent in past years. Tech Stock is the stock of unique technological categories associated with a firm's patents in past years. Standard errors presented in the parenthesis are clustered at plant level. Industry dummies are measured at the 4-digit SIC level. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

tion results for specification (2.17) with dependent variables constructed based upon citation and citation scope.

So far as the effect of productivity on citation is concerned, this study finds consistently positive coefficients of β_1 for the estimated TFP in columns (1)-(3) of Table 2.4. These estimated coefficients are statistically significant at 1% level, lending a strong support on the positive correlation between productivity and citation. Together with the positive correlation between patents and productivity, the more productive a firm, the more patents it has been granted, and the more citations associated with granted patents the firm references. As moving on to the average citation, shown in columns (4)-(6), this study documents positive and statistical significant estimates on the productivity. To develop a new patent, firms with higher productivity on average cite more patents than those with lower productivity. Put it differently, productive firms are more capable of learning from a relatively large number of other patents to develop a new one.

When it comes to citation scope, this study first looks at the extensive citation scope, which is the number of unique technological fields associated with cited patents. As reported in columns (7)-(9) of Table 2.4, the estimated coefficients for TFP are positive and statistically significant at 1% levels. These positive estimates suggest that the more productive a firm, the more the number of technological fields associated with cited patents the firm references. The remaining columns of Table 2.4 show the results for intensive citation scope. A consistently positive estimate for TFP is documented with statistical significance at 1% level, suggesting productive firms on average cite patents from a wider spectrum of technological fields than their competing counterparts.

2.4.3 Originality and Generality

Table 2.5 presents the OLS results for measures regarding novelty of invented patents. Two additional firm-level measures of originality and generality are examined as dependent variables. The measure of originality captures a firm's ability of inventing a new patent by combining pieces of knowledge from different technological fields, whereas the measure of generality reflects how popular patents of a firm are widely used (hence cited) in other future invention of patents.

Table 2.5: Alternative Measures on the Novelty of Innovation

VARIABLES	Originality			Generality		
	(1)	(2)	(3)	(4)	(5)	(6)
TFP	0.192***	0.187***	0.131***	0.184***	0.224***	0.158***
	(0.022)	(0.033)	(0.033)	(0.020)	(0.030)	(0.030)
Size	0.017	0.199***	0.239***	0.027*	0.167***	0.203***
	(0.015)	(0.032)	(0.035)	(0.014)	(0.029)	(0.032)
Capital Intensity	0.138***	0.126***	0.106***	0.093***	0.114***	0.094***
	(0.018)	(0.023)	(0.024)	(0.017)	(0.022)	(0.022)
Age	-0.046***	-0.013	-0.037	-0.034***	-0.016	-0.034
	(0.003)	(0.026)	(0.025)	(0.003)	(0.028)	(0.025)
R&D Expenditure	0.168***	0.191***	0.186***	0.165***	0.203***	0.192***
	(0.013)	(0.020)	(0.019)	(0.012)	(0.019)	(0.018)
Patent Stock	0.660***	0.515***	0.529***	0.536***	0.229***	0.245***
	(0.034)	(0.034)	(0.032)	(0.028)	(0.032)	(0.031)
Tech Stock	0.283***	0.360***	0.327***	0.305***	0.358***	0.329***
	(0.050)	(0.050)	(0.045)	(0.041)	(0.043)	(0.039)
Observations	31,066	31,066	31,066	31,066	31,066	31,066
Adjusted R^2	0.623	0.331	0.341	0.570	0.254	0.264
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y			Y		
Firm FE		Y	Y		Y	Y
Industry Year Trend			Y			Y

Note: All independent variables are in one-year lagged fashion. TFP is the estimated productivity, using the LP method. Size is log deflated value of sales. Capital intensity is the log ratio of capital to the number of employment. Age is firm's age. R&D expenditure is the log R&D expenses per deflated value of asset. Patent Stock is the stock of a firm's patent in past years. Tech Stock is the stock of unique technological categories associated with a firm's patents in past years. Standard errors presented in the parenthesis are clustered at plant level. Industry dummies are measured at the 4-digit SIC level. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

In the first three columns of Table 2.5, estimates of TFP are positive and statistically significant at 1% level, lending a strong support on the positive correlation between productivity and the novelty of invented patents. The higher productivity, the more novel the invented patents owned the firm are. Moreover, consistently positive estimates of TFP are documented in the last three columns of Table 2.5. These statistically significant estimates imply that productive firms tend to invent patents which are generally cited by future inventors.

In addition, firm-level characteristics other than productivity significantly contribute to the novelty of innovation. Size, capital intensity and R&D expenditure per value of asset have positive and statistically significant impacts on both originality and generality of innovation. Age of firms, however, still is negatively correlated with the novelty of innovation. The negative estimates of firm age are statistically significant at 1% level with year and industry fixed effects added, while the significance loses at any conventional level when firm fixed effects are controlled to absorb unobservable firm-level heterogeneity. Lastly, knowledge stock, in a form of patent stock or technology stock, is positively correlated with the novelty of innovation, as suggested by the positive estimates with statistical significance at 1% level in all columns.

2.4.4 Robustness Checks

This study conducts a series of robustness checks on alternative model specification, technological classification, nonself-citations, and productivity measure.

2.4.4.1 Poisson Method

Because the number of patents and the number of unique technological fields associated with patents are count data, the Poisson model is an alternative specification suitable to dealt with this type of data. Instead of taking logarithm, I use the number of patents and the number of unique technological fields served as alternative measures for innovation and extensive innovation scope, respectively. Moreover, the number of citations and the number of unique technological fields associated with cited patents are adopted for dependent variables. The alternative specification is given by,

$$Y_{it} = exp(\beta_1 TFP_{it-1} + \alpha X_{it-1})\eta_{it} + \varepsilon_{it} \tag{2.18}$$

where $Y_{it} \in \{0, 1, 2, 3, \cdots\}$ is the count data of interests. TFP_{it-1} is the estimated one-year lagged productivity using the LP method, and X_{it-1} is a vector of one-year lagged firm attributes including size, age, capital intensity, R&D expenses per value of asset, and knowledge stock in a form of patent and technology stock. η_{it} captures all unobservable, time-varying attributes of firm i and may be correlated with some of variables X_{it-1}. ε_{it} is an error term satisfying $E(\varepsilon_{it}|X_{it-1}, \eta_{it}) = 0$.

Table 2.6: Robustness Check for Poisson Method

VARIABLES	Innovation # of Patent$_{it}$		Extensive Innovation Scope # of TechField$_{it}$		Citation # of Citation$_{it}$		Extensive Citation Scope # of CitedTechField$_{it}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TFP	0.377***	0.338***	0.216***	0.224***	0.208***	0.170	0.158***	0.194***
	(0.025)	(0.078)	(0.013)	(0.049)	(0.047)	(0.128)	(0.013)	(0.044)
Size	0.079***	0.161***	0.108***	0.178***	0.058*	0.127	0.102***	0.175***
	(0.014)	(0.050)	(0.008)	(0.036)	(0.031)	(0.094)	(0.008)	(0.034)
Capital Intensity	0.217***	0.176***	0.072***	0.132***	0.121***	0.274***	0.051***	0.144***
	(0.020)	(0.055)	(0.011)	(0.041)	(0.036)	(0.065)	(0.011)	(0.035)
Age	-0.030***	0.051**	-0.028***	0.026	-0.033***	0.036	-0.028***	0.019
	(0.003)	(0.022)	(0.002)	(0.017)	(0.003)	(0.023)	(0.002)	(0.017)
R&D Expenditure	0.333***	0.238***	0.243***	0.208***	0.277***	0.162*	0.200***	0.213***
	(0.020)	(0.070)	(0.009)	(0.040)	(0.038)	(0.097)	(0.010)	(0.036)
Patent Stock	0.537***	0.300***	0.264***	0.096***	0.640***	0.391***	0.290***	0.137***
	(0.019)	(0.046)	(0.012)	(0.031)	(0.038)	(0.082)	(0.012)	(0.028)
Tech Stock	0.334***	0.440***	0.480***	0.412***	0.241***	0.401***	0.399***	0.373***
	(0.021)	(0.044)	(0.015)	(0.036)	(0.029)	(0.058)	(0.016)	(0.033)
Observations	31,066	30,133	31,066	30,133	31,066	30,133	31,066	30,133
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y		Y		Y		Y	
Firm FE		Y		Y		Y		Y

Note: All independent variables are in one-year lagged fashion. TFP is the estimated productivity, using the LP method. Size is log deflated value of sales. Capital intensity is the log ratio of capital to the number of employment. Age is firm's age. R&D expenditure is the log R&D expenses per deflated value of asset. Patent Stock is the stock of a firm's patent in past years. Tech Stock is the stock of unique technological categories associated with a firm's patents in past years. Standard errors presented in the parenthesis are clustered at plant level. Industry dummies are measured at the 4-digit SIC level. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 2.6 presents the corresponding estimation results for the Poisson specification that employs the count data. Columns differ in the choice of fixed effects (i.e., year, industry, and firm level) as noted in the bottom of the table. Standard errors presented in the parenthesis are clustered at firm level. The first four columns of Table 2.6 show how firms attributes are related with innovation and extensive innovation scope, while the remaining columns present how firms attributes are correlated with citations and extensive citation scope. The positive coefficients for productivity are statistically significant at 1% level in all columns, but column (7), providing the corroborating evidence that TFP is positively correlated with innovation, extensive innovation scope, citation, and extensive citation scope when the count data are employed.

The results for firms other attributes are also robust to the alternative specification of Poisson model. There are consistently positive and statistically significant correlation between firms size and innovation or innovation scope. Similarly, the positive correlations are documented for other firm-level characteristics including capital intensity, R&D expenses and knowledge stock (either in a form of patent or technology stock). One exception is firm age. The estimated coefficients for firm age are negative and statistically significant without firm-level fixed effects. When firm fixed effects are controlled to absorb unobservable firm heterogeneity, firm age has no statistically significant effects on extensive innovation scope, citation and extensive citation scope.

2.4.4.2 Alternative Technology Classification

To test the robustness of our empirical results, this study further relaxes patents' technological classification from the primary 4-digit IPC code to 3-digit IPC code. Hence, technological categories are broadened from subclass to class in the ascending IPC hierarchy. With this alternative definition of technology categories, associated dependent variables of innovation scope and citation scope in forms of both extensive and intensive fashions are recalculated. In addition, an alternative measure for technology stock is computed when the 3-digit IPC code is used to define technology fields.

Columns (1)-(4) in Table 2.7 present the corresponding OLS estimation for specification (2.17) with the implementation of the alternative technology classification. The main results regarding

Table 2.7: Robustness Check for Alternative Technology Classification and Nonself-Citation

VARIABLES	Atl. Tech Class				Nonself Citation			Both	
	Extensive Innovation Scope	Intensive Innovation Scope	Extensive Citation Scope	Intensive Citation Scope	Extensive Citation Scope	Average Citation	Intensive Citation Scope	Extensive Citation Scope	Intensive Citation Scope
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TFP	0.055***	0.019***	0.070***	0.012***	0.088***	0.074***	0.034**	0.069***	0.027**
	(0.014)	(0.007)	(0.020)	(0.003)	(0.024)	(0.025)	(0.014)	(0.020)	(0.011)
Size	0.118***	0.031***	0.176***	0.015***	0.199***	0.173***	0.076***	0.171***	0.059***
	(0.015)	(0.006)	(0.022)	(0.003)	(0.025)	(0.023)	(0.012)	(0.021)	(0.010)
Capital Intensity	0.033***	0.007	0.055***	0.003	0.068***	0.055***	0.025**	0.055***	0.018**
	(0.011)	(0.005)	(0.015)	(0.003)	(0.017)	(0.018)	(0.010)	(0.015)	(0.009)
Age	-0.004	-0.010***	-0.018	-0.003	-0.022	-0.046***	-0.025***	-0.019	-0.020***
	(0.009)	(0.003)	(0.014)	(0.002)	(0.017)	(0.013)	(0.008)	(0.014)	(0.006)
R&D Expenditure	0.079***	0.022***	0.118***	0.013***	0.139***	0.120***	0.053***	0.117***	0.041***
	(0.008)	(0.004)	(0.012)	(0.002)	(0.014)	(0.015)	(0.008)	(0.012)	(0.007)
Patent Stock	0.130***	-0.066***	0.215***	-0.048***	0.279***	0.110***	-0.061***	0.211***	-0.076***
	(0.016)	(0.005)	(0.020)	(0.003)	(0.023)	(0.017)	(0.010)	(0.020)	(0.008)
Alt. Tech Stock	0.143***	0.022***	0.178***	0.005	0.198***	0.099***	0.062***	0.172***	0.045***
	(0.024)	(0.006)	(0.032)	(0.003)	(0.036)	(0.026)	(0.014)	(0.031)	(0.011)
Observations	31,066	31,066	31,066	31,066	31,066	31,066	31,066	31,066	31,066
Adjusted R^2	0.213	0.035	0.241	0.048	0.261	0.161	0.070	0.239	0.053
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry Year Trend	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: All independent variables are in one-year lagged fashion. TFP is the estimated productivity, using the LP method. Size is log deflated value of sales. Capital intensity is the log ratio of capital to the number of employment. Age is firm's age. R&D expenditure is the log R&D expenses per deflated value of asset. Patent Stock is the stock of a firm's patent in past years. Alt. Tech Stock is the stock of unique technological categories by 3-digit IPC associated with a firm's patents in past years. Standard errors presented in the parenthesis are clustered at plant level. Industry dummies are measured at the 4-digit SIC level. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

the positive correlation between productivity and dependent variables of interests are robust to this alternative measure. Productive firms are involved in a wide spectrum of technology categories, and have less patents per technology field. To develop a new patent, productive firms cite patents from a wide area of technological fields.

2.4.4.3 Nonself-Citation

In this robustness check, this study subtracts citations made by firms themselves when counting the number of citations, and the number of unique technological fields associated with citations. Hence measures for average citation, extensive and intensive citation scope are recalculated without accounting for self-citations. Columns (5)-(7) in Table 2.7 present the corresponding results for the relevant dependent variables. In the last two columns of Table 2.7, both the alternative technology classification and nonself-citation are taken into consideration for the relevant dependent variables. This study still finds consistent evidence on the positive and significant correlation between productivity and dependent variables of interests.

2.4.4.4 Alternative Productivity Measure

Lastly, but not least, this study uses the OP method to estimate firm's productivity. Under a series of assumptions, the OP method can get consistent estimations, using the firm-level product function. One of these assumptions is the monotonic relationship between investment and output. However, not every firm in every year conducts investment, thereby having zero investment in some years. Under the OP method, many observations with zero investment have to be deleted.

Table 2.8 shows the estimated results for the baseline specification with an alternative productivity measure estimated from the OP method. A set of fixed effects on year and firm is controlled as noted in the bottom of the table. Compared with the baseline results in Table 2.3 and 2.4, the estimates for the alternative productivity measure remain the same sign with smaller magnitude, but lose statistical significance in any conventional level when it comes to intensive innovation s-

Table 2.8: Robustness Check for Alternative Productivity Measure

VARIABLES	Innovation	Extensive Innovation Scope	Intensive Innovation Scope	Citation	Average Citation	Extensive Citation Scope	Intensive Citation Scope	Originality	Generality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Alt. TFP	0.115***	0.071***	0.002	0.114**	0.004	0.060*	0.008	0.089**	0.111***
	(0.032)	(0.023)	(0.008)	(0.050)	(0.030)	(0.032)	(0.005)	(0.044)	(0.039)
Size	0.223***	0.164***	0.047***	0.398***	0.213***	0.247***	0.028***	0.307***	0.301***
	(0.020)	(0.015)	(0.005)	(0.032)	(0.018)	(0.021)	(0.003)	(0.028)	(0.026)
Capital Intensity	0.051***	0.033***	0.003	0.082***	0.030	0.051***	0.001	0.080***	0.070***
	(0.017)	(0.012)	(0.005)	(0.028)	(0.018)	(0.018)	(0.003)	(0.024)	(0.023)
Age	-0.405***	-0.246***	-0.015	-0.438**	-0.057	-0.226*	-0.029*	-0.347**	-0.437***
	(0.121)	(0.088)	(0.030)	(0.188)	(0.111)	(0.120)	(0.017)	(0.166)	(0.147)
R&D Expenditure	0.087***	0.066***	0.020***	0.162***	0.089***	0.099***	0.011***	0.134***	0.135***
	(0.015)	(0.011)	(0.004)	(0.026)	(0.016)	(0.017)	(0.003)	(0.022)	(0.021)
Patent Stock	0.259***	0.123***	-0.069***	0.450***	0.103***	0.218***	-0.059***	0.531***	0.256***
	(0.030)	(0.022)	(0.006)	(0.042)	(0.020)	(0.028)	(0.004)	(0.037)	(0.035)
Tech Stock	0.293***	0.246***	0.037***	0.426***	0.154***	0.318***	0.018***	0.369***	0.356***
	(0.040)	(0.031)	(0.007)	(0.061)	(0.029)	(0.041)	(0.004)	(0.052)	(0.046)
Observations	27,848	27,848	27,848	27,848	27,848	27,848	27,848	27,848	27,848
Adjusted R^2	0.295	0.238	0.035	0.298	0.170	0.265	0.040	0.345	0.264
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: All independent variables are in one-year lagged fashion. Alt. TFP is the calculated productivity, using the alternative OP method. Size is log deflated value of sales. Capital Intensity is the log ratio of capital to the number of employment. Age is firm's age. R&D Expenditure is the log R&D expenses per deflated asset value. Patent Stock is the stock of a firm's patents in past years. Tech Stock is the stock of unique technological categories associated with a firm's patents in past years. Standard errors presented in the parenthesis are clustered at plant level. Industry dummies are measured at the 4-digit SIC level. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

cope and intensive citation scope. For the remaining firm-level characteristics, the main results are robust to the alternative productivity measure.

2.5 Conclusion

This paper employs firm-level patent data from the US manufacturing public firms over the period of 1976-2006. This study documents several interesting and novel results regarding firm-level productivity and innovation. First, there is a positive correlation between productivity measured by the TFP estimates and innovation proxied by the number of patents. Unsurprisingly, productive firms tend to have more patents. Second, when taking closer look at technological fields associated with these patents, there is strong evidence on the positive correlation between productivity and extensive innovation scope. Productive firms are more actively engaged in innovation not only by having more patents, but also being involved in a wide spectrum of technological fields. Third, a positive correlation between productivity and intensive innovation scope, measured by innovation scope per patent, is documented. Productive firms appear to conduct innovation intensively across a wide spectrum of technological fields. Lastly, when it comes to developing a new patent, this study finds consistently evidence supporting a positive correlation between productivity and extensive citation scope, and a positive correlation between TFP and intensive citation scope. The more productive a firm, the more patents it must cite to develop a new one, the wide spectrum of technological filed associated with cited patents the firms must reference.

CHAPTER 3. DOES INNOVATION INCREASE STOCK RETURNS? THE ROLE OF INNOVATION EFFICIENCY

This study examines the impact of innovation on firm's operating performance, market valuation, and stock returns, especially the role of Innovation Efficiency in predicting firm's future market valuation. Three different measures of Innovation Efficiency–number of patents per patent or citation (backward and forward) technological fields scaled by research and development expenditures–are proposed, which combine the breadth of knowledge used to innovate and R&D investments. The empirical results show that: (i) firm's market valuation and excess returns increases are largely driven by the changing valuation of Innovation Efficiency, while innovation quantity, measured by patent intensity and R&D intensity, has a strong and significant negative effect; (ii) the positive effect of Innovation Efficiency became larger over time from 1950 to 2010 and for high-technology industries; (iii) efficient innovation firms are able to achieve higher and more persistent profitability and better operating performance through the effect of productivity. This evidence suggests that Innovation Efficiency increases firm's productivity competitive advantage and is undervalued by the market.

3.1 Introduction

What impact do firm's inventive activities have on its market valuations and stock returns? This question has grown greatly in significance with the rapid increase of firms' investments in research and development activities in recent years, and the great technological breakthroughes happened over the past 30 years. An increasing stream of literature in economics and finance has shown that technological growth can explain major swings in stock market value. When the assembly line ushered in the age of mass production during the second industrial revolution in the early 20th century, innovation and labor productivity increased drastically, and the stock market run up a lot. Stock market runups have been linked to the increases of productivity, which is caused by the arrival of new technologies and the accumulation of intangible capital by firms (Hall et al., 2001a; Hall, 2011; Chudnovsky et al., 2006). Innovation is a key driver of productivity and investments in R&D lead to improvement of goods and more innovation output (patents), which leads to further productivity increases.

From a macroeconomic perspective, there is a substantial literature evaluating the impact of technology growth or innovation increases on such outcomes as rising productivity (Hall, 2011; Aghion et al., 2009; Geroski, 1989b; Chudnovsky et al., 2006), economic growth (Teal, 1999; Gordon, 2012; Segerstrom, 1991), industry employment (Dachs and Peters, 2014; Harrison et al., 2014; Griffith and Macartney, 2014), worker income (Aghion et al., 2015; Krugman, 1979; Taskin and Zaim, 1997), international trade (Impullitti and Licandro, 2017; Santacreu, 2015; Long et al., 2011; Rubini, 2014), and social welfare (Mukherjee and Sinha, 2013; Chang et al., 2013; Sinha, 2006; Attanasio et al., 2002; Elul, 1995), respectively. While from the finance (or corporate finance) perspective, a lot of literature have shown the importance of firm's innovative activities on its operating performance (Li, 2011; Eberhart et al., 2004; Chan et al., 2001, 1990; Chauvin and Hirschey, 1993; Hall, 1993) and market valuations, such as excess returns and abnormal returns (Pakes, 1985; Jaffe, 1986; Szewczyk et al., 1996; Chambers et al., 2002; Nicholas, 2008; Ciftci et al., 2011; Donelson and Resutek, 2012),

Existing studies mainly focus on the effect of innovative activities on operating performance, stock returns, and market valuation from input or output perspective separately. On the input side, R&D expenditure is most widely used to measure firm's innovation input. A famous study by Griliches (1981) reveals that a firm's past R&D expenditures is significantly related with its market value, measured as the natural logarithm of the firm's Tobin's q, based on a time-series cross-section analysis of data for large U.S. firms. Following this idea, Lev and Sougiannis (1996) use data for a large sample of public companies and find that R&D expenditures are value-relevant to investors and firm's R&D expenditures are significantly associated with its market equity and subsequent stock returns.

Although R&D expenditures have been proved to be a good indicator of a firm's innovative input, its significant association with firm's size and its massive missing values are widely criticized. To deal with the scale effect, R&D intensity is then introduced, it has been shown that higher R&D intensity predicts higher level and volatility of future operating performance and stock returns (Chan et al., 2001; Al-Horani et al., 2003; Eberhart et al., 2004; Chambers et al., 2002; Saad and Zantout, 2014). For example, Eberhart et al. (2004) use R&D/Sales and R&D/Assets to measure firm's R&D intensity, and find that firms with R&D intensity increases consistently experience significantly positive abnormal operating performance, which suggests that R&D intensity has a positive effect on the firm's investments, and the market is slow to recognize the full extent of this benefit. Besides these two indexes, R&D growth has also prove to have predicting power on future stock returns. The benefit of R&D increase reflects intangible information, and investors mis-react to this type of information. Hence, there is an increase abnormal operating performance and abnormal stock returns following increases in R&D (Lev et al., 2005; Eberhart et al., 2004; Hirshleifer et al., 2013).

On the output side, firm's patent and citation information are widely used in measuring firm's innovative benefits. For example, Nicholas (2008) use firm's number of granted patents and historical citation counts to measure patentable assets and find that the 1920s stock market runup was largely driven by the changing valuation of corporate knowledge assets. This method is similar to Pakes (1985), who investigates the dynamic relationships among firm's investment in inventive activities, measured by the number of successful patent applications of the firm, and the stock market value of the firm. Similarly, Hall et al. (2005b) explore the role of patent citations in determining firm's future stock market valuations. They estimate the Tobin's q equations on the ratios of R&D to assets stocks, patents to R&D, and citations to patents and find that each ratio significantly affects market value. Hirshleifer et al. (2013) use a firm's patent counts and historic citation counts scaled by its research and development investment to measure its innovative efficiency. They find that patents/R&D is a strong positive predictor of future returns after controlling for firm characteristics and risk. Similarly, a most recent research by Hirshleifer et al. (2018) measures firm's innovative originality as the number of unique technological classes assigned to the patents cited by the focal patent. They find that firms with greater innovative originality predicts higher abnormal stock returns and less volatile profitability.

However, all of these literature use either the number of patents and citations, or the R&D expenditure to measure innovation, and analyze the economic and financial effects of innovative activities. No study, till now, has analyzed the value of innovative activities and far less is known about the impact of Innovation Efficiency on stock returns in the short and long run at the firm level. Though the lots of studies indicate an important role of innovations in explaining operating performance, market valuation, and stock returns, several literature have shown that the larger quantity of inventive inputs or outputs actually does not necessarily indicates higher profitability and stock returns. For example, Kung and Schmid (2015) and Kogan and Papanikolaou (2014) theoretically show that R&D endogenously drives a small component in productivity that generates long-run uncertainty about economic growth and lead to low asset valuations.

Similarly, Garleanu et al. (2009) show that inventive activities increase the competitive pressure on existing firms and workers, thereby reducing the profits of existing firms and eroding the human capital of older workers. Inventive activity creates a risk factor and reduces market valuations and stock returns, and further reduces real wages and consumption shares of the older agents (Garleanu et al., 2012; Ai et al., 2013). On the empirical side, Hirshleifer et al. (2013) find that R&D-to-market equity actually has insignificant effect on firm's operating performance such as ROA and cash flow, while patent counts-to-market equity even has strong negative effect on firm's future cash flow and market-to-book equity. Hirshleifer et al. (2018) find more evidence on the insignificant effect of R&D-to-market equity and patent counts-to-market equity on firm's operating performance and abnormal stock returns. R&D-to-market equity has significant effect on firm's future ROE and ROA, and increases the volatility of its future ROE and ROA.

How important are technologically related assets in driving firm's operating performance, such as future ROA, ROE, cash flow and profit margin, increase and in predicting future stock returns? How do investors respond to innovation information? Do they care only the quantity of inventive inputs or outputs, or do they value more about the quality of new innovations? This paper attempts to answer these questions by looking at the change of operating performances and market valuations affected by the changing value of corporate patentable assets measured by innovation quantity and efficiency.

Empirically, this paper measures Innovation Efficiency by three different indexes that combining the breadth of knowledge used to innovate and R&D investments. For the first Innovation Efficiency index, I use the number of granted patents in the U.S PER special technological fields scaled by R&D. Intuitively, firms can apply and be granted a lot of patents each year, but some of the patents belong to the same technological field. Patent counts sometimes can not reflect the true quality of the patentable assets because firms tend to apply plenty of patents in order to protect their product lines and gain higher market powers but not all of these patents are valuable (Hall, 2011). Technological fields, in other words technological categories which is specified by the International Patent Classification (IPC) code, capture the range of knowledge the new innovations build (Hall, 2011; Lerner, 1994; Lanjouw and Schankerman, 2004). Based on the 3-digit IPC code, this calculate the total number of technological categories associated with patents of each firm in each year and month.

Similar to Hirshleifer et al. (2018), this paper uses the average range of knowledge, in other words the number of granted patents per technological categories of non-self patents cited by a firm's patents,then scaled by firm's R&D expenditures as the second measure of Innovation Efficiency. Intuitively, a patent that draws knowledge from a wide range of technology is more valuable because it tends to deviate from current technology scopes to a greater extent (Balsmeier et al., 2017). If a firm's patents cite previous patents belonging to a wide set of technologies, it means the firm can combine different technologies in an original way to create a sustainable competitive advantage. The last measure of Innovation Efficiency is based on the research by Trajtenberg (1990) and Hall et al. (2001a), both of which show that the number of citations made to a firm's patents can better reflect those patents' technological or economic significance. Following the literature, this paper uses the number of granted patents per technological categories of the citations received in the year before the forecast period by a firm's patents that were granted over the previous 5 years scaled by R&D expenditure.

To construct firm-level data on patents, operating performance, and stock returns, the paper matches the patents and citations data of all the U.S. listed firms from Kogan et al. (2012) (henceforth KPSS) with the financial data of publicly-held firms listed in the Compustat database, and with the stock prices data on the Center for Research in Security Prices (CRSP) between 1950 and 2010. Although patents are an imperfect measure of innovation, and intangible capital covers a broader set of assets than patented inventions, the measures used in this paper provide important information about how technological change influenced firm's future profitability and market valuations.

This paper first runs q regression, which is based on a conventional q-theory setting as used by Griliches (1981), for the whole period and 3 subperiods to estimate the effect of changes in the value of Innovation Efficiency and quantity on firm's future Tobin's q. In a second approach, this paper examines the changing market value of patentable assets for different Innovation Efficiency levels and industrial technology levels. The q regressions strongly support the view that stock market increases was largely driven by the changing valuation of Innovation Efficiency, while innovation quantity has strong and significant negative effect on firm's future market values. The negative effect of innovation quantity is opposite to most of previous literature, which all support the idea that patent counts or patent counts per R&D is positively related with firm's future market values (Griliches, 1981; Hall et al., 2005b; Nicholas, 2008). The positive effect of Innovation Efficiency becomes larger and larger as time changes from 1950 to 2010 and as industry moves from low technological level to high technological level.

The paper then examines the effect of firm's Innovation Efficiency and quantity on its future operating performance measured by the return on assets (ROA), return on equity (ROE), and cash flow based on the annual Fama-MacBeth regressions (Fama and MacBeth, 1973). The estimation results show that a firm with higher Innovation Efficiency can obtain higher return on assets (ROA), return on equity (ROE), and cash flows over the next year after extensive controls. On the contrary, patent counts scaled by market equity reduces firm's future ROA and cash flow and predicts higher future ROE. Comparing to Innovation Efficiency, the effects of patent quantity are all insignificant.

To explore why firms gain better operating performance over the next period if they have have higher Innovation Efficiency, this paper further examine the relation between Innovation Efficiency and future profitabilities, measured by profit margin, gross margin and abnormal earnings. The estimation results indicate that Innovation Efficiency has insignificant positive effect on firm's future profitability. The effects of patent counts to market equity on future profitability varies as different measures introduced. For profit margin, the quantity effect is significant and positive. These effects may be caused by the productivity effect, which is the main determinant of firm's future profitability, and the productivity effect is confirmed by the Fama-MacBeth regressions. The effect of patent counts to market equity on profit margin becomes negative and significant even at the 1% level, while the significance of Innovation Efficiency effect also increases a lot after controlling productivity (measured by TFP, using the LP method introduced by Levinsohn and Petrin (2003)). According the dominant literature, firm's investments in inventive activities push future productivity increases (Hall, 2011). This paper also find some evidences on this innovation investment effect that firms with higher Innovation Efficiency gains higher productivity increases over the next year. However, patent counts have a insignificant negative effect on future productivity growth. Overall, these results suggest that high Innovation Efficiency firms are able to achieve higher and more persistent profitability through the effect of Innovation Efficiency on productivity and profit margin. Comparing to Innovation Efficiency, the quantity effects are insignificant and negative (at least in part).

Whereas the q regressions and Fama-MacBeth regression rely on end-of-year balance sheet data, this paper matches monthly return data from CRSP with monthly patent data on the firms in the sample to run excess return regression. The estimation results provide a strong economically and statistically significant positive effect of Innovation Efficiency on excess returns over the whole period from January, 1962 to December, 2010. The results also confirm that innovation quantity (patent counts to market equity) has significant negative effect on excess returns. Furthermore, the results show that in the early period of 1962-1985, Innovation Efficiency seems to have some effect as the whole period that promotes the increase of excess returns. However, this positive effect turns to be very significant and negative during the period 1986-2000, and then becomes positive again but insignificant after 2001. These results are inconsistent with any previous literature and may shed some lights on the research between innovation and stock returns. Comparing the effect of Innovation Efficiency on excess return for different industrial technological level, the effect changes from negative to positive as technological level increases, while the effect of innovation quantity decreases from positive to negative. In the low technological level industry, Innovation Efficiency actually reduces future excess returns while quantity effect is positive though it is very small and insignificant.

This study contributes to the previous and current research on innovation and stock returns on the following aspects. First, this paper offers a new innovation-related measure, Innovation Efficiency, which is contemporaneously associated with market valuation, future operating performance, profit and gross margin, and stock returns. Previous literature mostly focus on the effects of either innovative input or output separately. They provide grand evidences on the positive role of innovations in predicting firm's operating performance, market valuation, and stock returns. However, no study investigates the role of Innovation Efficiency. This paper explores the relevance for firm value of Innovation Efficiency which combines innovative input and output. Second, this paper investigate the effect of Innovation Efficiency on market valuation and stock returns from various perspectives such as different periods and different industrial technological levels. The estimation results of this paper show that the Innovation Efficiency effect varies in different periods and within different industries of different technological levels. Third, this paper finds solid evidence that patent counts to market equity does not increase firm's future market valuation or operating performance, and even has negative effect on market valuations when controlling patent efficiency and other financial variables. These results are different with the idea that firms with more patent counts predict higher market valuations in most literature. Finally, this paper extends the sample size and empirical periods to 1950-2010 and uses a new and more complete patent dataset that created by Kogan et al. (2012). Most research on innovation output use the NBER patent data created by Hall et al. (2001a) that only provides patent information within 1976-2006. This paper extends NBER patent data and includes more valuable information.

The remainder of the paper is organized as follows. Section 3.2 describes the matched dataset of company financials, patents, and citations, and provides some descriptive statistics. Section 3.3 outlines the empirical specifications of the Tobin's q regressions, Fama-MacBeth regressions, and monthly excess return regressions, Section 3.4 presents the results, and Section 3.5 concludes.

3.2 Data, Variables, and Summary Statistics

To explore the effect of Innovation Efficiency and quantity on firm's market valuations, operating performance, and stock returns, I use granted patent and citation data from Kogan et al. (2012). I use financial data from the Compustat database, and monthly share price data from the CRSP. I merge these three main data using a matching approach introduced by Kogan et al. (2012).

3.2.1 Patents, Citations, and Innovation Efficiency

3.2.1.1 Patents

The patent data created by Kogan et al. (2012) (henceforth KPSS) provides detailed information regarding all patents that were granted by the United States Patent and Trademark office (USPTO) over the period 1926-2010, including patent number, backward citations of the patent, forward citations of the patent, firm's assignee number and standard name that applied the patents, the value of each patent based on its forward citations, and the technology class categories under 3-digit International Patent Classification (IPC) code and subclass categories under 7-digit IPC code. It also provide the patent-Compustat matched company ID *'permno'* which is the key Patent-Comppustat data merging variable. Besides the KPSS patent data, the NBER patent project created by Hall et al. (2001a) is a widely used patent database, which contains comprehensive information for patents granted by the US Patent and Trademark Office (USPTO) from 1976 through 2006. This database contains all citations associated with these patents, and detailed information of the technological categories of the patents.

This paper uses the KPSS patent data rather than the NBER patent data, because KPSS patent data contains more valuable information of firm's patents and historic citations. The NBER patent data only contains patent information from the period 1976-2006 whereas the KPSS patent data contains patent information from the period 1926-2010, a much greater time period [1]. Furthermore, the KPSS patent data match much better with the Compustat database than NBER patent data[2].

Kogan et al. (2012) has matched patent data with public firms in Compustat, using an algorithm involving firm names[3]. As owners of patents change over time, the Compustat matched file provides a dynamic match of patent assignee to corporate entity in the Compustat data. The matching results uniquely link the assignee identification number from the patent data with public firms' permanent identification number (i.e., gvkey) in Compustat. In the matched sample, there are around 1.8 million patents associated with 6,349 unique corporate identities during the period 1950-2010.

I exclude all firm-years that have the following characteristics: (i) financial firms which have four-digit standard industrial classification (SIC) codes between 6000 and 6999, including finance, insurance, and real estate sectors; (ii) utility firms which have two-digit SIC codes of 49; (iii) firms categorized as public service, international affairs, or non-operating establishments (9000+); (iv) patent granted year is before 1950. This is because the financial variables from the Compustat database only have data after 1950.

After excluding these data and matching with financial variables from the Compustat database, the data contains 1,621,280 granted patents associated with 5,989 unique corporate identities, in other words each firm has around 266 granted patents. Table 3.1 shows the characteristics of number of firms, granted patents, tech fields and citations in the whole period and three subperiods. Total

[1]The KPSS patent database adds an average of 2,187 patents to the NBER patent data per year (Kogan et al., 2012).

[2]The KPSS patent data matches 66% of all patents with Compustat data, or 31% of all granted patents. By comparison, the NBER patent project provides a match for 32% of all patents from 1976- 2006 (Kogan et al., 2012).

[3]For the matching algorithm and matched results, please refer to the KPSS patent project via link https://iu.app.box.com/v/patents.

Table 3.1: Number of Firms, Granted Patents, Tech Fields and Citations

Variables	1950-2010	1950-1969	1970-1989	1990-2010
Total number of firms	20,063	3,500	11,353	14,670
Firms with zero granted patents	14,074	2,607	8,513	10,305
Firms with granted patents	5,989	893	2,840	4,365
Number of firms per year	4,713	1,537	6,421	8,861
Firms with zero granted patents per year	2,717	888	4,657	5,460
Firms with granted patents per year	1,996	649	1,764	3,401
Total number of granted patents	1,621,280	210,457	434,818	976,005
Number of granted patents per year	26,578	10,523	21,741	46,476
Number of patent tech fields per year	7,485	4,398	8,284	9,662
Number of nonself citations per year	99,253	8,155	36,613	24,5671
Number of nonself tech fields per year	9,697	2,962	8,070	17,660
Number of citations received in the past 5 years per year	123,581	9,256	56,885	295,984
Number of citations tech fields received in the past 5 years per year	8,974	2,080	7,310	17,124

Notes: Firms with zero granted patents represent the firms have no granted patents within the whole fiscal year. Granted patents include only the patents granted during 1950-2010. Patent tech fields represent the number of technological categories of granted patents measured by the 3-digit IPC code. Nonself citation is defined as the citation one granted patent cite while the cited patent and citing patent are not belonged to the same assignee. Citations received in the past 5 years represent the citations received by a firm's patents in a specific year that were granted over the previous 5 years. Similarly, citation tech fields received in the past 5 years is defined as the technological categories of the citations received by a firm's patents in a specific year that were granted over the previous 5 years.

number of firms, including firms have and have no granted patents over their fiscal years, in my sample is 20,063. Number of firms with granted patents is 5,989 which is much smaller than the number of firms with zero granted patents, which is defined as firms that have no granted patents within the whole fiscal year. This indicates that around 70% of all firms that do not actually have any patents during 1950-2010. Though number of firms with granted patents in the sample increased a lot during 1990-2010, its proportion did not change much over time. The majority of firms remains zero innovation output in different period.

However, number of granted patents increased a lot from 1950 to 2010 comparing to the change of granted firms counts. The average number of granted patents per year increased from 10,523 in the period 1950-1969 to 46,476 of period 1990-2010. It indicates that firms were granted much more patents in recent period. Number of granted patent tech fields, which is represented by the number of technological categories of granted patents measured by the 3-digit IPC code, increased slightly over the sample period and the number is much smaller than the patent counts. The average number of granted patent tech fields is 7,485 over the whole period, which indicates that the average tech field per granted patent is around 0.28 and almost 4 patents are belonging to a same technological category. Both the total number of patent tech fields and the average number of tech fields per year increased from period 1950-1969 to 1990-2010.

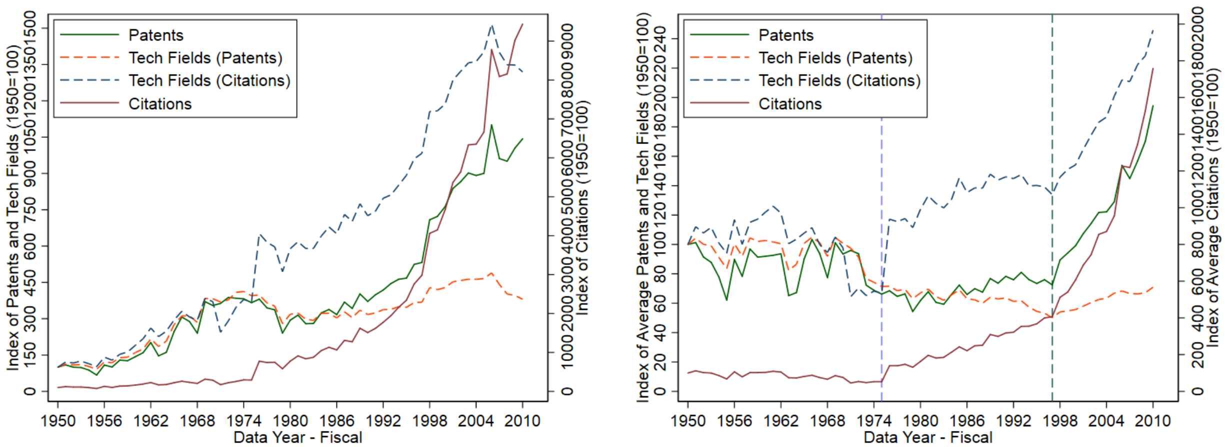


Figure 3.1: Total and Average Firm Patents, Citations, and Tech Fields, 1950-2010

Figure 3.1 shows the increasing trends of total number of granted patents and patent tech fields. An important feature of Figure 3.1 is that the number of average granted patents and technological fields did not change much before 1975, then start to increase gradually within the period 1975-1997, and it increased drastically after 1997. Furthermore, granted patents accumulated much faster than patent tech fields after 1990s, and the gap became larger and larger. This trend can also be observed from the time lines of average patent counts and tech field counts as is show in the left figure of Figure 3.1. Before 1997, both average patent counts and patent tech field counts changed slightly and the average number of tech fields even decreased by around 50% from 1950 to 1997. After 1997, the average patent counts increased drastically while the average tech fields increased very slightly. This provides some contradictions on the positive effect of patent counts on stock market in most literature because the stock market plummeted after the housing bubble of the 2000s burst. The drastic increasing of average patent counts cannot explain this huge jump in stock prices.

3.2.1.2 Citations

Patent counts provide a useful but narrow measure of firm's inventive activity outputs. Although lots of literature have shown broadly consistent results in the positive effect of patents and independent measures of innovation on market valuations (Nicholas, 2008; Hall et al., 2005b), the literature is unanimous in its verdict that raw patent counts need to be adjusted before they can reveal enough information about the process of innovation. To address this problem I use historical patent citations and the technological categories of patent citations as a measure of a patent's technological importance.The patenting process requires inventors to make reference to all prior art relating to an invention. The intuition behind the historical citations measure follows Trajtenberg (1990) and Hirshleifer et al. (2018) that if a granted patent has large citations it must be that the innovation originating in the cited patent had indeed proven to be valuable. Similarly, if a firm's patents cite previous patents belonging to a wide set of technologies, its originality is also high and the patents are more valuable.

Figure 3.1 illustrates the rapid growth of citations and their technological fields between 1950 and 2010. Historical citations come at a much faster rate than patents, and also at a faster rate after 1990s. The same pattern is observed for the tech fields of citations and for the average level. Different from the growth of average patent counts, average historical citations keep increasing over the period 1950-1997 and the growth rate is much smaller than the growth rate between 1998 and 2010, while for patent counts and patent tech fields there is no obvious increasing trend before 1990s.

One of the interesting issues about patent citations is to what extent patents cite previous inventions patented by the same assignee, in other ward self citations, rather than patents of other unrelated assignees. This is important because self citations are related to novelty of the innovative activities, if patents cite lot of patents that belong to the same assignee then it represents that the innovation is only a transfer of knowledge that are mostly internalized, whereas if patents cite more patents that belong to other assignees then it means a wide range of fields are needed to generate the new patents and henceforth the patents are relatively novel (Trajtenberg, 1990; Hall et al., 2001a). Figure 3.2 shows how average self citations , non-self citations, and citation technological fields made has varied over time. Before 1975 there are some movements up and down of the average citation counts, both self and non-self citation counts, and a slightly decline trend. There were gradual increases of the average self and non-self citation counts and citation technological fields in the period 1975-1997. The numbers surged after 1997 except for the technological fields of self citations.

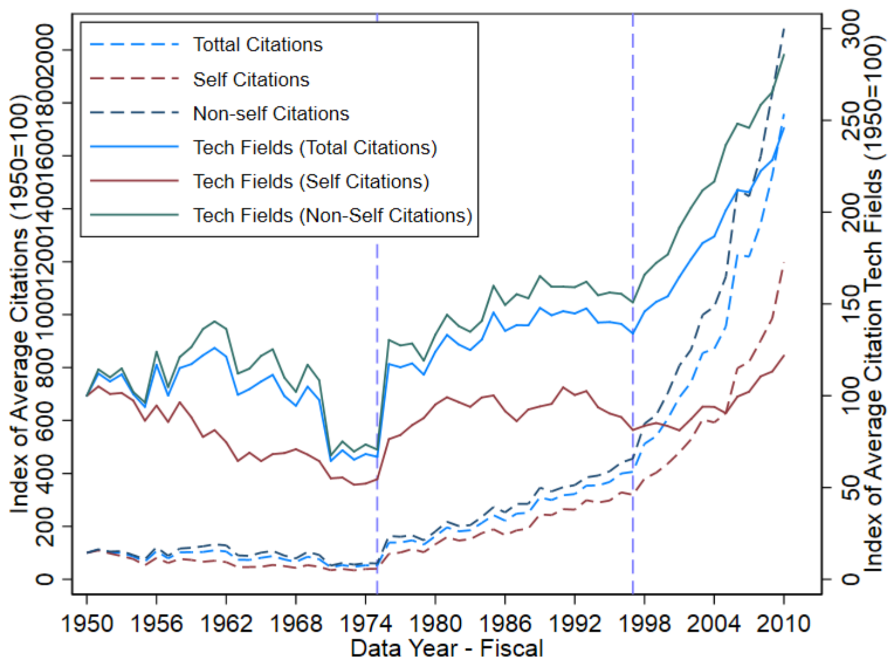


Figure 3.2: Average Self Citations, Non-self Citations, and Citation Tech Fields, 1950-2010

3.2.1.3 Innovation Efficiency

Based on the analysis above and following Hall et al. (2001a) and Hirshleifer et al. (2013), this paper uses three measures to represent firm's Innovation Efficiency: number of granted patents per technological fields scaled by R&D capital ($Ptechs/RD$), number of granted patents per non-self citation technological fields scaled R&D capital ($Nselftechs/RD$), and number of granted patents per technological fields of citations received (forward citations) scaled by R&D capital ($FCtechs/RD$). For the first measure $Ptechs/RD$, it is defined as the ratio of firm $i's$ number of granted patents ($Pcounts_{i,t}$) scaled by its technological fields of its all granted patents in year t ($Ptechfields_{i,t}$) and R&D capital ($RD_{i,t-2}$). For R&D capital, following Chan et al. (2001); Lev et al. (2005), and Hirshleifer et al. (2013), I use the 5-year cumulative R&D expenses adjusted by an annual depreciation rate of 0.2 in fiscal year ending in year t-2, which is $R\&D_{i,t-2} + 0.8 * R\&D_{i,t-3} + 0.8^2 * R\&D_{i,t-4} + 0.8^3 * R\&D_{i,t-5} + 0.8^4 * R\&D_{i,t-6}$. Following the literature, I set missing R&D expenditure to zero in computing the cumulative R&D expenditures. The first measure of Innovation Efficiency ($Ptechs/RD$) then is given by:

$$\frac{Pcounts_{i,t}/Ptechfields_{i,t}}{R\&D_{i,t-2} + 0.8 * R\&D_{i,t-3} + 0.8^2 * R\&D_{i,t-4} + 0.8^3 * R\&D_{i,t-5} + 0.8^4 * R\&D_{i,t-6}}, \tag{3.1}$$

where $R\&D_{i,t-2}$ denotes firm $i's$ R&D expenditures in fiscal year ending in year $t-2$. The reason why I start from $t-2$, in other ward a 2-year gap between R&D capital and granted patents, is from the evidence that it takes 2 years on average for a patent to be granted by USPTO after is is applied (Hall et al., 2001a). The 5-year cumulated R&D expenses indicates that R&D expenses over the previous five years help to generate new patents in year $t-2$ (Hirshleifer et al., 2013). This index actually measures the efficiency of innovation inputs (R&D expenditure), the higher of the index means firm's unit dollar R&D expenses generates more average technological fields.

The $Ptechs/RD$ index is similar to Hirshleifer et al. (2013) that it reflects efficiency of R&D in terms of patents, while here I use the number of granted patents per technological fields instead of just patent counts. The reason is because the scope of patents is more associated with the technological and economic value of inventive activities. Lerner (1994) shows that the technological fields of patents of a firm significantly affect its market valuation, and that broad patents are more valuable when many possible substitutes in the same product class are available.

The second measure of Innovation Efficiency is related the novelty and originality of the innovation seeking patent protection. The index is denoted as the ratio of firm's number of granted patents to its non-self citation technological fields and scaled by its R&D capital ($Nselftechs/RD$). Specifically, the index $Nselftechs/RD$ in year t is defined as firm i's number of granted patents ($Pcounts_{i,t}$) scaled by its technological fields of its non-self citations the granted patents cited in year t ($Nselftechs_{i,t}$) and R&D capital ($RD_{i,t-2}$):

$$\frac{Pcounts_{i,t}/Nselftechs_{i,t}}{R\&D_{i,t-2} + 0.8 * R\&D_{i,t-3} + 0.8^2 * R\&D_{i,t-4} + 0.8^3 * R\&D_{i,t-5} + 0.8^4 * R\&D_{i,t-6}}, \tag{3.2}$$

This measure of Innovation Efficiency follows Hall et al. (2005b) and Hirshleifer et al. (2018) while they focus only on the number of citations made in granted patents (backward citations). My measures here combines the input of inventive activities (R&D expenditures) and the output of these activities (both technological scope of citations made in granted patents and patent counts). My measures henceforth are better proxy of the originality of firm's inventive activities. The intuition is that granted patents are asked to disclose the prior knowledge on which they have relied, including the possible patents, scientific work and other sources of knowledge at the basis of the invention. The larger of the number of citations made in a patent, the higher degree of the novelty of an invention and investigate knowledge transfers in terms of citations networks (Hall et al., 2005b, 2001a). In addition, controlling for non-self citations allows assessing the extent to which new inventions rely on other firms' prior innovative activities and represents the originality of the new technologies.

Because the number of citations a given patent receives (forward citations) reflects the technological importance of the patent for the development of subsequent technologies and the economic value of inventions (Trajtenberg, 1990; Hall et al., 2005b), I use number of granted patents scaled by technological fields of citations received (forward citations) and R&D capital ($FCtechs/RD$) as the third proxy of Innovation Efficiency. Following the literature, I define $FCtechs/RD$ in year t as the number of granted patents scaled by technological fields of the citations received by a firm's granted patents over the previous 5 years and R&D expenditures over the period year t-3 to year t-7:

$$\frac{\sum_{s=1}^{5} Pcounts_{i,t-s}/FCtechs_{i,t-s}}{R\&D_{i,t-3} + 0.8 * R\&D_{i,t-4} + 0.8^2 * R\&D_{i,t-5} + 0.8^3 * R\&D_{i,t-6} + 0.8^4 * R\&D_{i,t-7}}, \tag{3.3}$$

where $FCtechs_{i,t-s}$ is the number of technological fields of the citations received by firm i's granted patents in year $t-s$ ($s \in [1,5]$) and $Pcounts_{i,t-s}$ is the number of granted patents by firm i in year $t-s$. Following the dominated literature, I use 5-year periods to compute firm's number of technological fields of the citations received (Hirshleifer et al., 2013; Hall et al., 2005b, 2001a; Trajtenberg, 1990). This is based on the fact that technology cycles measured by the duration of the benefits of R&D spending are approximately 5 years in most industries (Lev and Sougiannis, 1996).

This forward citations-based Innovation Efficiency measure is similar to Hirshleifer et al. (2013) while they only use the number of citations a given patent receives. I extend their method by including the number of technological fields of forward citations and granted patent counts. This proxy also follows the widely used *Generality* index created by Bresnahan and Trajtenberg (1995) that forward patent citations can be used to assess the rage of later generations of inventions that have benefitted from a patent by means of measuring the range of technology fields. The patent generality index is based on a modification of the Hirschman-Herfindahl Index (HHI) and relies on information concerning the number and distribution of citations received and the technology classes of the patents these citations come from.

Differently from the *Generality* index and other ways in which generality has been calculated in previous studies (e.g. Hall et al. (2001a)) I combine both the input side of inventive activities (cumulative R&D expenditures in previous 5 years) and the output side of innovation. For technological fields used in this paper I refer to the 3-digit technology classes (IPC) of the patents and citations. I construct these three Innovation Efficiency measures for each year from 1950 to 2010. The sample period starts in 1950 to match the financial variables from the Computstat. Since the KPSS Patent database (Kogan et al., 2012) including granted patents and citations from 1926 to 2010, there is no concern about the quality of patent data.

Figure 3.3 shows the change of the three proxies of Innovation Efficiency on average level over the period 1950-2010. Before 1970, the three Innovation Efficiency proxies varied slightly and the values are relatively very low. The Innovation Efficiency then surged during the period 1970-1980 and reached the historical peak around 1979. It suddenly jumped around 1979, one year before the 1980 financial crisis broke out (known as early 1980s recession). During the recession, the Innovation Efficiency moved up and down but remained on a relatively low level. It reached a new periodic peak around 1999 before the Dot-com Bubble crashed in 2000 and then jumped and remained on a very low level. These facts provide some evidence that Innovation Efficiency is a good indicator of the market valuation changes.

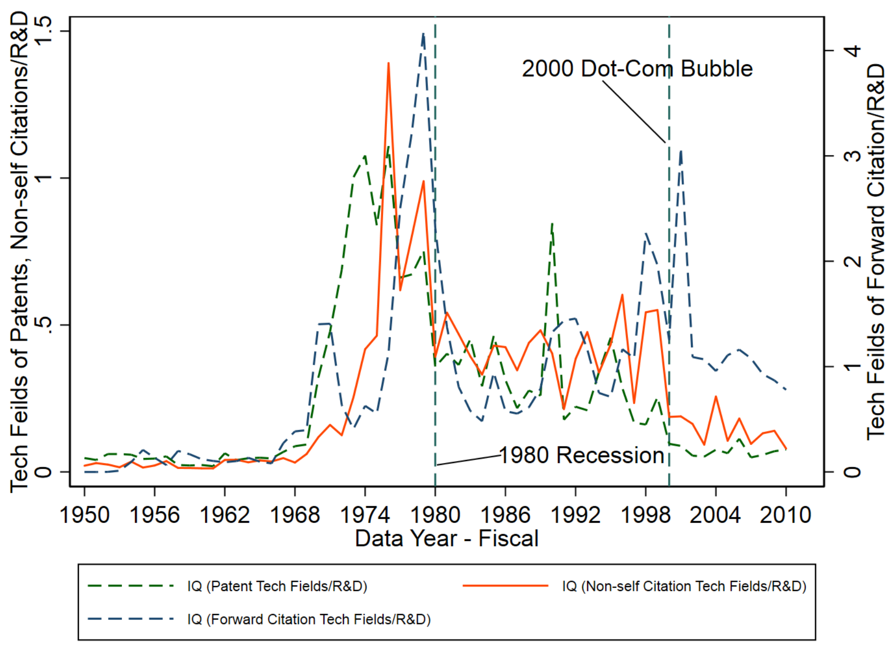


Figure 3.3: Average Innovation Efficiency, 1950-2010

3.2.2 Financial Variables and Equity Prices

The U.S. Compustat database provides a historical archive of annual financial statements and balance sheets for all firms traded in the U.S. stock market from 1950 to 2016. The firm-level variables include gvkey as an identification code, standard industry classification (SIC), net sales, number of employees, book value of asset value, capital expenditure, wage, R&D expenses, and many others. We uses this firm-level data to construct main operating performance proxies such as return on assets (ROA), return on equity (ROE), and cash flow (CF), to estimate total factor productivity (TFP), and to construct other firm-level control variables of interest, including market-to-book ratio, capital intensity, firm size, and R&D intensity. As with the patent data, I exclude the following industries: financial firms (SIC 6000-6999), utility firms (SIC 4900-4999), public service, international affairs, or non-operating establishments (9000+). I also exclude firm-year data if the firm has fewer than four years of continuous records starting in 2010 and moving backward in time to 1950. Four years of continuous data gave a reasonable span over the time series dimension to check the long-run effect of R&D investments. After excluding all the data above, I merge the financial data with patent data using CRSP company id $'permno'$. The basic information of firms is shown in Table 3.1.

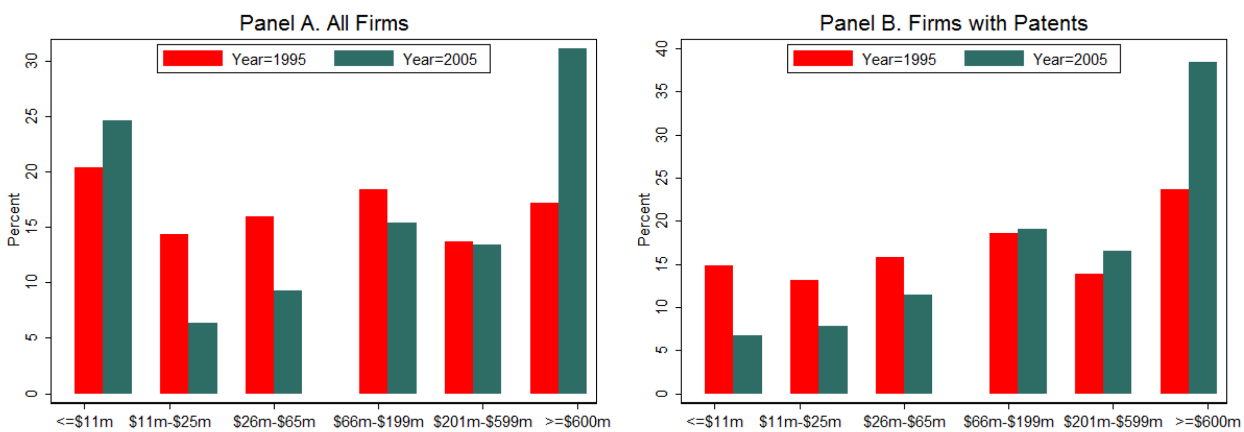


Figure 3.4: Market Size Distribution of All Firms and Firms with Patents in 1995 and 2005

Panel A and B of Figure 3.4 compare the market size distribution of all sample firms and the firms that have patents in 1995 and 2005. Figure 3.4 reflects the fact that firms in the sample were almost evenly distributed according to the market size in 1995, regardless of whether we exclude the firms that do not have any granted patent in their fiscal years or not. But when it came to 2005, the firm size distribution changed. Firms that had more than 600 million dollars of total assets constitute of the majority of the sample. Panel B of Figure 3.4 also shows that large firms are the main source of innovation because they tend to be more active in inventive activities comparing to small market size firms.

3.2.2.1 Tobin's q

To perform the q regression, I follow the procedure of Peters and Taylor (2017). I measure firm i's Tobin's q by scaling its market value by the sum of physical and intangible capital:

$$q_{it} = \frac{V_{it}}{K_{it}^{phy} + K_{it}^{int}} \tag{3.4}$$

The firm's market value V is measured as the market value of outstanding equity plus the book value of debt, minus the firm's current assets, which include cash, inventory, and marketable securities. The replacement cost of physical capital, K^{phy}, is measured as the book value of property, plant, and equipment (Compustat item ppegt). For intangible capital, K^{int}, it is defined as the sum of the firm's eternally purchased (Compustat item intan) and internally created intangible capital (sum of knowledge capital and organization capital). The knowledge capital is estimated using the perpetual inventory method:

$$G_{it} = (1 - \delta_{R\&D})G_{i,t-1} + R\&D_{it} \tag{3.5}$$

where G_{it} is the year-end stock of knowledge capital, $\delta_{R\&D}$ is the depreciation rate of $R\&D$ with value of 0.2. The initial value of knowledge capital G_{i0} is simplified to 0. Similarly, the stock of organization capital is measured by the accumulating 30% of past selling, general, and administrative ($SG\&A$) spending using the perpetual inventory method with the depreciation rate of $\delta_{SG\&A} = 0.2$, as in Equation (3.5).

3.2.2.2 Excess Return

Excess stock return is another key dependent variable. To compute the excess stock return, I collect monthly share price data and risk-free return data from two different databases. Share price data are from the CRSP database, which only provides monthly stock close prices. I use the U.S. one-month Treasury bill rate from the Federal Reserve Bank as the risk free rate, and calculate the excess of the monthly return given in CRSP over the risk free rate.

Figure 3.5 reflects annual average Tobin's q and excess return. Over the sample period, average Tobin's q and excess return exhibit similar pattern. Tobin's q showed a higher value and higher

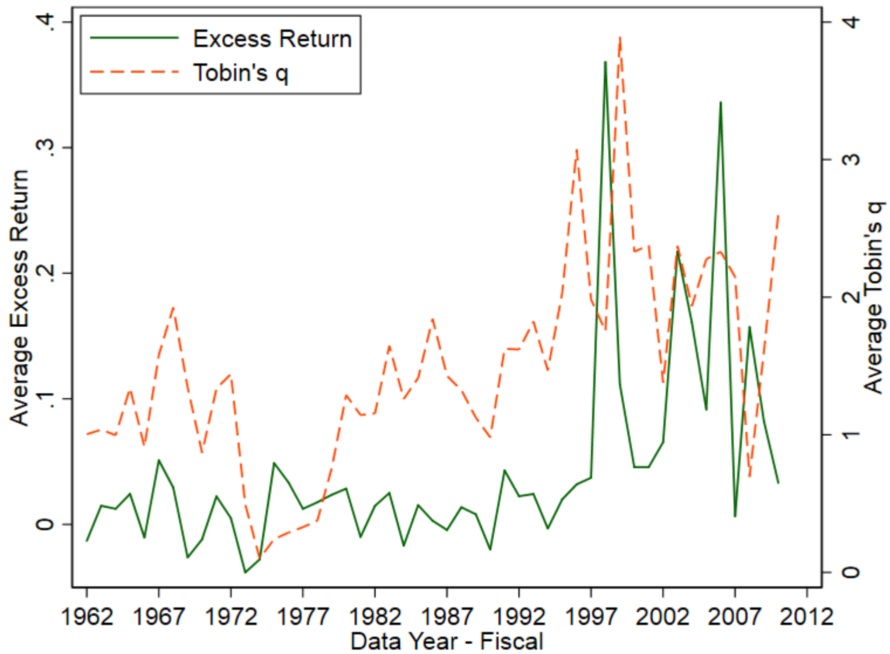


Figure 3.5: Average Excess Returns and Tobin's q, 1962-2010

volatility than excess return. Volatilities of the two time series increased after 1997, which were caused by economic bubbles. The first surge and jump of excess return and Tobin's q happened in the 1990s, and is well known as the Dot-Com Bubble, triggering a US recession after 2002. Excess return and Tobin's q experienced a second surge and jump during the US Housing Bubble occurred from 2003 to 2007, resulted in global economic contraction that has come to be known as the "Great Recession".

3.2.2.3 Operating Performance

Following Core et al. (2006); Hirshleifer et al. (2013), and Hirshleifer et al. (2018) we use return on assets (ROA), return on equity (ROE), and cash flow (CF) as three proxies for firm's operating performance. Return on assets (ROA) is denoted as net income scaled by lagged assets:

$$ROA_{it} = \frac{IB_{it} + IE_{it}}{K_{i,t-1}} \tag{3.6}$$

where IB_{it} is income before extraordinary items, IE_{it} is interest expenses, and $K_{i,t-1}$ is lagged total assets. Return on equity (ROE) is defined as net income scaled by lagged book value of equity:

$$ROE_{it} = \frac{IB_{it} + IE_{it}}{BE_{i,t-1}} \tag{3.7}$$

where book value of equity (BE_{it}) is book value of stock holders' equity plus deferred tax and investment tax credit minus book value of preferred stocks. Following Erickson and Whited (2012) and Almeida and Campello (2007), cash flow (CF) is measured as

$$CF_{it} = \frac{IB_{it} + DP_{it}}{K_{i,t-1}} \tag{3.8}$$

where DP_{it} is depreciation expense.

3.2.2.4 Profitability

Inventive activities may help create unique and superior products, which allow firms to charge higher price premium and gain higher profits from the sustainable competitive productivity advantage. To examine the effect of firm's Innovation Efficiency on its profitability, I use abnormal earning, gross margin, and profit margin to measure firm's profitability. Following Hirshleifer et al. (2013), abnormal earning is defined as

$$AE_{it} = \frac{ER_{it}(1 - \tau_{it}) - r_t BE_{it}}{BE_{it}} \tag{3.9}$$

where ER_{it} is earnings after extraordinary items plus R&D expenses minus preferred dividends for firm i in year t, τ_{it} is tax rate measured by total tax expenses divided by pre-tax book income, r_t is the one-year Treasury bill rate in year t, and BE_{it} is book value of equity. Gross margin is measured by gross sales scaled by total sales:

$$GM_{it} = \frac{S_{it} - SC_{it}}{S_{it}} \tag{3.10}$$

where S_{it} is total sales and SC_{it} is cost of goods sold. To exclude extreme value, I set GM to 1 if it exceeds 1 and -1 if exceeds -1 (Hirshleifer et al., 2018). The last proxy of profitability is profit margin, which is calculated as

$$PM_{it} = \frac{IB_{it} + IE_{it} + T_{it}}{S_{it}} \tag{3.11}$$

whereS_{it} is total sales, IB_{it} is income before extraordinary items, IE_{it} is interest expenses, and T_{it} is total income taxes.

3.2.2.5 Control Variables

As noted in a growing literature (Pastor and Veronesi, 2009; Hsu, 2009; Massimiliano Croce, 2014), other firm-level characteristics play important roles in explaining changes in firms' market valuation and stock returns. Following these studies, this paper also controls some other firm-level characteristic variables.

For the purpose of this paper, I use R&D expenditure and patent counts to denote innovation quantity. Specifically, I use R&D intensity (defined as $R\&D_{it}/BE_{it}$) to measure the amount of innovation inputs and patent counts scaled by the book value of equity ($Patents_{it}/BE_{it}$) to measure the amount of innovation outputs. These two measures are widely used in applied researches relative to firm's innovation or $R\&D$ (Saad and Zantout, 2014; Chan et al., 2001; Eberhart et al., 2004; Nicholas, 2008).

Productivity is a key variable that affects firm's production, future profitability, and market valuation. For this reason, the first control variable is the estimated firm-level productivity, denoted by TFP. My procedure of firm's productivity, or TFP, follow Levinsohn and Petrin (2003) (the LP method for short), who introduce intermediate inputs to the estimation to solve the simultaneity problem. The LP method uses investment or intermediate inputs to control for correlation between input and unobserved productivity. The LP method is widely used in applied research regarding firm productivity (Keller and Yeaple, 2009). This paper uses the TFP estimated from the LP method in the basic estimations and then uses TFP generated by the OP method developed by Olley and Pakes (1996) to perform the robustness check [4].

[4]The estimation of productivity is full of challenges, Olley and Pakes (1996) (the OP method for short) solves the simultaneity of output and capital stock when estimating the TFP. Their method corrects the selection bias problem that only firms with high productivity can survive and be continually observed in panel data sample. The LP method is based on OP method, but it introduces intermediate inputs to the estimation to solve the simultaneity problem and can get more precise results. Because of the special advantages of the LP method, I use this method as the baseline. The LP method is widely used in applied researches relative to firm's productivity (Keller and Yeaple, 2009; Fernandes, 2007; Kasahara and Rodrigue, 2008; Petrin and Levinsohn, 2012) For more details about the difference between OP method and LP method, one can refer to the research by Ackerberg et al. (2015).

Table 3.2: Variable Description

Variable	Description	Data Source
	Innovation Efficiency	
Ptechs/RD	(Patent Counts/Patent Tech Fields)/$R\&D_{t-2,t-6}$	KPSS
Nselftechs/RD	(Patent Counts/Citation Tech Fields)/$R\&D_{t-2,t-6}$	KPSS
FCtechs/RD	(Patent Counts/Citation Tech Fields Received)/$R\&D_{t-3,t-7}$	KPSS
	Market Valuation	
Tobin's q	$V_{it}/(K_{it}^{phy}+K_{it}^{int})$	Compustat
Excess Return	Monthly return minus risk free rate	CRSP
ROA	Net income scaled by lagged assets	Compustat
ROE	Net income scaled by lagged book value	Compustat
CF	Total income scaled by lagged assets	Compustat
	Profitability	
AE	$(ER_{it}(1-\tau_{it})-r_t BE_{it})/BE_{it}$	Compustat
GM	Gross sales scaled by total sales	Compustat
PM	$(IB_{it}+IE_{it}+T_{it})/S_{it}$	Compustat
	Control Variables	
PAT/ME	Patent counts scaled by the book value of equity	KPSS
R&D/ME	R&D expenditure scaled by the book value of equity	Compustat
TFP	TFP generated by LP method	Compustat
Size	Price per share times the outstanding shares	Compustat
AD	Advertising expenditure scaled by market value	Compustat
CapEx	Capital expenditure scaled by market value	Compustat
BTM	The ratio of book value to market value	Compustat

Notes: Patent (citation) tech fields represent the number of technological categories of patents (citations made by granted patents) measured by the 3-digit IPC code. Citation tech fields received is defined as the technological categories of the citations received by a firm's patents in a specific year that were granted over the previous 5 years. $R\&D_{t-2,t-6} = R\&D_{i,t-2}+0.8*R\&D_{i,t-3}+0.8^2*R\&D_{i,t-4}+0.8^3*R\&D_{i,t-5}+0.8^4*R\&D_{i,t-6}$ and $R\&D_{t-3,t-7} = R\&D_{i,t-3}+0.8*R\&D_{i,t-4}+0.8^2*R\&D_{i,t-5}+0.8^3*R\&D_{i,t-6}+0.8^4*R\&D_{i,t-7}$. V_{it} is market value of equity, BE_{it} is book value of equity, IB_{it} is income before extraordinary items, IE_{it} is interest expenses, and T_{it} is total income taxes. KPSS patent data is from Kogan et al. (2012).

Market size is an important factor in predicting excess returns, I use price per share times the number of shares outstanding to measure firm's market size. Advertising expenditure, capital expenditure, and book-to-market value have been proved to have great predicting power on firm's operating performance and market valuation (Peters and Taylor, 2017; Lev et al., 2005; Erickson and Whited, 2012). The value of advertising expenditure and capital expenditure can be obtained directly from the Compustat database, I scale these two variables with firm's market value of equity. Book-to-market value is commonly denoted as the ratio of firm's book value to its market value of equity. Table 3.2 shows the descriptions and data sources of the variables that are used in this paper. It presents the descriptive statistics for the whole sample period and also for different sub-sample periods. Only mean value and standard deviation (represented by $St.D$) are presented.

Table 3.3: Summary Statistics for Different Periods

Periods	1950-2010		1950-1969		1970-1989		1990-2010	
Statistics	Mean	St.D	Mean	St.D	Mean	St.D	Mean	St.D
Panel A: Innovation Efficiency								
Ptechs/RD	0.083	2.299	0.024	0.302	0.147	2.457	0.049	2.411
Nselftechs/RD	0.058	1.247	0.030	0.398	0.113	1.792	0.024	0.804
FCtechs/RD	0.146	6.271	0.386	12.09	0.235	7.840	0.032	1.185
Panel B: Market Valuation								
Tobin's q	1.917	30.250	1.423	4.134	1.254	19.380	2.362	36.26
ROA	-0.092	0.700	0.064	0.076	-0.011	0.374	-0.182	0.907
ROE	0.001	1.440	0.112	0.384	0.044	1.176	-0.042	1.662
CF	-0.130	0.538	0.061	0.071	-0.060	0.320	-0.220	0.681
Panel C: Profitability								
AE	0.206	43.070	0.131	1.748	0.036	14.620	0.335	56.74
GM	-0.956	3.462	-0.609	1.643	-0.760	2.501	-1.164	4.221
PM	-0.953	7.577	0.093	0.339	-0.300	4.033	-1.631	9.870
Panel D: Control Variables								
R&D	53.930	365.3	8.930	19.240	19.15	135.70	77.21	456.6
R&D/ME	0.080	0.185	0.037	0.047	0.060	0.123	0.092	0.212
PAT/ME	7.168	3245	0.047	0.153	0.292	52.440	12.080	4246
TFP	4.605	1.221	4.008	0.614	4.417	0.983	4.894	1.398
Size	1429	9999	332	1511	344	1799	2202	12942
AD	0.773	0.404	0.992	0.084	0.717	0.430	0.768	0.410
CapEx	0.921	1.295	2.069	1.355	0.989	1.296	0.637	1.135
BTM	0.835	0.992	0.654	0.481	1.051	1.022	0.714	0.975

Note: This table reports the pooled mean and standard deviation for different periods. The whole sample period is from 1950 to 2010, I divide it evenly into three different periods: 1950-1969, 1970-1989, and 1990-2010. Each period contains 20 years of data except for the period 1990-2010 (21 years included). Variables are well defined in Table 3.2. R&D expenses and market size are in million dollars. Panel A reports the average level of Innovation Efficiency measures in different periods. Panel B and C reports the average level of market valuation and operating performance in different periods, respectively. Panel D reports the average level of control variables in different periods.

3.2.3 Summary Statistics

Table 3.3 presents summary statistics for variables of interest at the firm level for different periods. The whole sample period is from 1950 to 2010, I divide it evenly into three different periods: 1950-1969, 1970-1989, and 1990-2010. These three periods are consistent with the facts that Innovation Efficiency behaved differently within different periods as is shown in Figure 3.1 - 3.3. Comparing the mean value of Innovation Efficiency proxies in Panel A of Table 3.3, average $Ftechs/RD$ seems to be larger than average $Ptechs/RD$ and $Nselftechs/RD$, and it decreases over time. Average $Ptechs/RD$ and $Nselftechs/RD$ are much larger in the period 1970-1989 than in the other two periods. These differences may be because the number of firms that had no granted patents in these two periods are very large. The mean value then became very small as we scaled by a lot of no-patent firms.

For market valuation and operating performance, the mean and standard deviation of the variables are given in Panel A. Average firm ROA is -0.0492 with the average ROE at 0.001. In the long run, there is no benefit to invest in the stock market. For a firm's productivity, we can observe that TFP increased gradually over time, but the volatility increased even larger. Average market size in the period 1990-2010 is much larger than the other two periods. This is consistent with Figure 3.4 that market size distribution is with high skewness, lots of firms had large market size in the sample. These results suggest that it is important to examine the relation between Innovation Efficiency and operating quality, market valuation, and stock returns within different periods.

Table 3.4 reports the summary statistics of the three Innovation Efficiency measures for selected industries from 1950 to 2010. Industries are classified by the two-digit Standard Industrial Classification (SIC). It's easy to observe that Innovation Efficiency varies among industries no matter which measure is used. Medical and scientific instruments industry (SIC 38) outperforms all the other industries. The average $Ptechs/RD$, $Nselftechs/RD$, and $Ftechs/RD$ for this industry are 0.563, 0.380, and 0.882, respectively. We can also observe that biotech and pharmaceuticals industry (SIC 28) has the lowest Innovation Efficiency performance. The average $Ptechs/RD$, $Nselftechs/RD$, and $Ftechs/RD$ for this industry are 0.178, 0.134, and 0.593, respectively. These results suggest that industrial heterogeneity (or industry fixed effect) should be introduced in examining the effect of Innovation Efficiency on future operating performance and stock returns.

Table 3.4: Summary Statistics of Innovation Efficiency for Selected Industries

Industries	Mean	Standard Deviation	25th percentile	Median	75th percentile
Panel A: $Ptechs/RD$					
Biotech and pharmaceuticals (28)	0.178	0.713	0.007	0.029	0.097
Computers and machinery (35)	0.433	2.312	0.005	0.041	0.201
Electrical and electronics (36)	0.521	5.457	0.007	0.044	0.198
Transportation equipment (37)	0.294	2.067	0.000	0.008	0.098
Medical and scientific instruments (38)	0.563	3.221	0.021	0.091	0.317
Other	0.498	7.423	0.000	0.010	0.107
Total	0.441	5.286	0.000	0.028	0.152
Panel B: $Nselftechs/RD$					
Biotech and pharmaceuticals (28)	0.134	0.890	0.001	0.013	0.061
Computers and machinery (35)	0.351	2.185	0.001	0.013	0.101
Electrical and electronics (36)	0.339	3.229	0.001	0.015	0.085
Transportation equipment (37)	0.293	2.426	0.000	0.002	0.044
Medical and scientific instruments (38)	0.380	2.862	0.003	0.031	0.164
Other	0.331	3.424	0.000	0.001	0.042
Total	0.310	2.861	0.000	0.008	0.072
Panel C: $FCtechs/RD$					
Biotech and pharmaceuticals (28)	0.593	9.684	0.000	0.008	0.077
Computers and machinery (35)	1.073	22.370	0.000	0.009	0.119
Electrical and electronics (36)	0.473	3.552	0.000	0.008	0.097
Transportation equipment (37)	1.714	29.620	0.000	0.004	0.097
Medical and scientific instruments (38)	0.882	9.451	0.000	0.014	0.124
Other	0.669	12.500	0.000	0.000	0.035
Total	0.773	14.440	0.000	0.004	0.075

Note: This table reports the pooled mean, standard deviation, 25th percentile, median, and 75th percentile of the three Innovation Efficiency measures for selected two-digit Standard Industrial Classification (SIC) industries from 1950 to 2010. $Ptechs/RD$, $Nselftechs/RD$, and $FCtechs/RD$ are well defined in Table 3.2. Panel A reports the statistics of Innovation Efficiency measured by $Ptechs/RD$. Panel B reports the statistics of Innovation Efficiency measured by $Nselftechs/RD$. Panel C reports the statistics of Innovation Efficiency measured by $FCtechs/RD$.

Table 3.5 reports the pooled mean of all variables under different Innovation Efficiency levels from 1950 to 2010. Firms are sorted into three groups (low, middle, and high) based on the third and two-thirds percentiles of the Innovation Efficiency measures, $Ptechs/RD$, $Nselftechs/RD$, and $FCtechs/RD$. The average number of firms with zero granted patents in the sample period is 6,001, which constitutes the majority of all firms. This is an economically meaningful set of firms to study, and it is important to introduce no-patent dummy variable in examining the effect of Innovation Efficiency on future stock returns. The average number of firms in the low Innovation

Efficiency portfolio is around 5,300-5,600, and is much larger than the average number of firms in the middle and high Innovation Efficiency portfolios. This reflects that lots of firms actually have low Innovation Efficiency.

Table 3.5: Summary Statistics for Different Innovation Efficiency Levels

			Ptechs/RD			Nselftechs/RD			FCtechs/RD		
Variables	No	All	Low	Middle	High	Low	Middle	High	Low	Middle	High
# of Firms	6001	20063	5379	2070	2294	5411	2004	2117	5509	1803	1832
Panel A: Innovation Efficiency											
Ptechs/RD	0.000	0.056	0.002	0.072	1.675	0.075	0.080	1.275	0.144	0.099	0.793
Nselftechs/RD	0.000	0.06	0.005	0.063	1.134	0.001	0.039	1.328	0.088	0.057	0.700
FCtechs/RD	0.000	0.146	0.009	0.377	2.648	0.057	0.193	2.784	0.001	0.059	3.950
Panel B: Market Valuation											
Tobin's q	2.302	1.917	1.528	1.385	1.413	1.537	1.409	1.302	1.612	1.080	0.976
ROA	-0.125	-0.092	-0.040	-0.073	-0.059	-0.042	-0.071	-0.051	-0.051	-0.037	-0.008
ROE	0.006	0.001	0.009	-0.071	-0.047	0.004	-0.049	-0.048	-0.007	-0.012	-0.004
CF	-0.153	-0.13	-0.091	-0.136	-0.117	-0.093	-0.137	-0.106	-0.102	-0.106	-0.064
AE	0.216	0.206	0.110	0.823	0.080	0.129	0.761	0.077	0.190	0.293	0.116
GM	-0.977	-0.956	-0.931	-1.029	-0.809	-0.939	-1.041	-0.731	-0.947	-0.926	-0.744
PM	-1.016	-0.953	-0.815	-1.206	-0.906	-0.829	-1.221	-0.828	-0.932	-0.671	-0.453
Panel C: Control Variables											
R&D	21.61	53.93	112.30	26.94	4.00	107.50	24.20	4.64	92.83	59.59	17.96
R&D/ME	0.067	0.08	0.090	0.100	0.070	0.090	0.098	0.069	0.092	0.086	0.070
PAT/ME	0.000	7.168	0.324	0.287	117.500	19.550	1.354	0.303	18.720	0.425	1.774
TFP	4.381	4.605	5.071	4.488	3.773	4.891	4.617	3.910	4.630	4.882	4.256
Size	653.7	1429	2931.0	788.3	141.3	2805.0	1025.0	199.4	2525.0	2036.0	701.2
AD	0.803	0.773	0.753	0.686	0.633	0.748	0.681	0.653	0.748	0.651	0.656
CapEx	1.125	0.921	0.757	0.190	0.305	0.744	0.173	0.311	0.729	0.161	0.297
BTM	0.891	0.835	0.770	0.689	0.869	0.775	0.673	0.857	0.765	0.693	0.912

Note: This table reports the pooled mean of all variables under different Innovation Efficiency levels from 1950 to 2010. All variables are well defined in Table 3.2. "No" denotes firms with zero patents within the sample period. "All" denotes all firms are included within the sample period. Firms are sorted into three groups (low, middle, and high) based on the third and two-thirds percentiles of the Innovation Efficiency measures, $Ptechs/RD$, $Nselftechs/RD$, and $FCtechs/RD$. Panel A reports the average level of Innovation Efficiency measures under different situations. Panel B reports the average level of market valuation and operating performance in different Innovation Efficiency levels. Panel C reports the average level of control variables in each case. R&D and Size are in million dollars.

Furthermore, the average market size of low Innovation Efficiency portfolio is around 2,500-3,000 million dollars, which is much larger than the average market size of middle and high portfolios. The average patent intensity (PAT/ME) of low Innovation Efficiency portfolio is around 20, while the average patent intensity of middle and high portfolios are all less than 0.5. These facts indicate that large market size firms actually have low Innovation Efficiency, although they have larger innovation quantity (denoted by PAT/ME). Similar result can be observed if we check R&D and R&D intensity (denoted by $R\&D/ME$). High Innovation Efficiency firms do not spend most on R&D or have the highest R&D intensity. This suggests that large market size firms have greater R&D spending does not necessarily lead to higher Innovation Efficiency.

Table 3.6: Correlation Coefficients of Innovation Efficiency and Market Valuations

	Ptechs/RD	Nselftechs/RD	Fctechs/RD	Tobin's q	ROA	ROE	CF	AE	GM	PM
Ptechs/RD	1.000	0.497	0.099	0.007	-0.008	-0.007	-0.005	-0.002	0.007	0.003
Nselftechs/RD	0.497	1.000	0.141	0.004	0.001	0.000	0.006	-0.001	0.016	0.009
Fctechs/RD	0.099	0.141	1.000	-0.007	0.008	0.002	0.010	-0.001	0.009	0.006
Tobin's q	0.007	0.004	-0.007	1.000	-0.004	-0.003	0.005	-0.002	-0.112	-0.043
ROA	-0.008	0.001	0.008	-0.004	1.000	0.246	0.950	-0.037	-0.036	0.364
ROE	-0.007	0.000	0.002	-0.003	0.246	1.000	0.267	0.091	-0.010	0.101
CF	-0.005	0.006	0.010	0.005	0.950	0.267	1.000	-0.043	-0.035	0.365
AE	-0.002	-0.001	-0.001	-0.002	-0.037	0.091	-0.043	1.000	-0.004	-0.001
GM	0.007	0.016	0.009	-0.112	-0.036	-0.010	-0.035	-0.004	1.000	-0.057
PM	0.003	0.009	0.006	-0.043	0.364	0.101	0.365	-0.001	-0.057	1.000
R&D/ME	-0.027	-0.033	-0.011	-0.117	-0.391	-0.109	-0.415	0.025	0.012	-0.144
R&D	-0.023	-0.029	-0.013	0.004	0.053	0.031	0.055	0.004	-0.046	0.027
PAT/ME	0.000	0.000	0.001	-0.004	-0.001	0.002	-0.001	0.000	0.002	0.001
TFP	-0.099	-0.108	-0.040	-0.097	0.372	0.161	0.378	0.003	-0.032	0.468
Size	-0.022	-0.027	-0.012	0.102	0.077	0.044	0.087	0.002	-0.051	0.032
AD	-0.014	-0.012	0.002	-0.005	-0.075	-0.035	-0.071	0.002	0.075	-0.076
CapEx	0.020	0.029	0.007	-0.128	-0.010	0.020	-0.004	0.001	0.069	0.048
BTM	0.055	0.055	0.031	-0.231	0.082	0.006	0.097	-0.008	0.095	0.072

Note: This table reports the pairwise Pearson correlation coefficients of the three Innovation Efficiency measures with market valuation, operating performance, profitability, and other financial variables from 1950 to 2010. Variables are defined in Table 3.2. The correlation coefficients of profitability and control variables are not reported in the table.

To further check the relevance of Innovation Efficiency, operating performance, market valuation, and stock returns, I also compute the correlation coefficients between firm's Innovation Efficiency and other characteristics. Table 3.6 reports the pairwise Pearson correlations. As is shown in the table, the three Innovation Efficiency measures are positively correlated. The correlation coefficient between $Ptechs/RD$ and $Nselftechs/RD$ is 0.497, while the correlation between $Ptechs/RD$ and $FCtechs/RD$ is 0.099. The correlation between Innovation Efficiency and profitability are also positive though the coefficients are not very large. The positive correlations suggest that Innovation Efficiency is potential predictors of future profitability. In addition, the three Innovation Efficiency measures are negatively correlated with R&D and R&D intensity (R&D/ME), and not correlated with patent intensity (PAT/ME), consistent with the the results above.

3.3 Empirical Specifications

Innovation Efficiency is particular useful for analyzing the changing market value of patentable assets, because they provide tools to examine whether investors were sufficiently sophisticated to respond to the quality of technological inventions. Following the literature, I use three approaches to examine whether Innovation Efficiency can be correlated with changes in operating performance and stock returns. The first approach uses the method pioneered by Griliches (1981) and investigates whether Innovation Efficiency predicts changing in Tobin's q. The second approach follows Fama-MacBeth (Fama and MacBeth, 1973) and examines the predicting power of Innovation Efficiency on operating performance and profitability. The last approach uses the Innovation Efficiency in monthly excess return regression to examine the stock market's changing value of Innovation Efficiency based on Nicholas (2008).

3.3.1 Tobin's q Regression

The model proposed by Griliches (1981) is the standard method for estimating the role of patents and R&D assets in affecting stock market valuations. Firm i's market value is equal to the sum of its physical assets and applied knowledge assets and can be denoted as:

$$V_{it} = q_t(\phi_t K_{it} + \eta_t G_{it})^{\psi} \tag{3.12}$$

where V_{it} is firm i's market value in year t, K_{it} is physical capital, G_{it} is knowledge assets, q_t is productivity, and ϕ and η are the shadow price of capital and knowledge assets. Hall et al. (2005a) extend the basic model and get the following estimating equation of the form:

$$log\ \ Q_{it} = log\ \ (\frac{V_{it}}{G_{it}}) = log\ \ q_t + \sigma log\ \ (1 + \phi_t \frac{K_{it}}{G_{it}}) + \varepsilon_{it} \tag{3.13}$$

where Q_{it} denotes firm i's Tobin's q in year t. The last term $log\ \ (1+\phi_t \frac{K_{it}}{G_{it}})$ is typically approximated by $\phi_t \frac{K_{it}}{G_{it}}$, because the approximation $log(1 + x) \approx x$ is often used to yield a semi-logarithmic equation. ϕ_t measures the shadow value of knowledge assets relative to the tangible assets of the firm. The knowledge assets is a combination of R&D, patents, and citations, which involves the sequential revelation of information about the value to the firm. R&D reveals the input of a firm's resource to innovation, patents catalog the output of such investment, citations indicate the extent to which those innovations refer to, while Innovation Efficiency (defined as output per input of knowledge assets) indicates the success in generating new knowledge that the firm can in principle appropriate. Therefore, the information value of innovation once patents have been invested can be extended to the following equation

$$log\ Q_{it} = log\ q_t + \sigma_1 \frac{Patents_{it-1}}{TechFields_{it-1} \times R\&D_{it-1}} + \sigma_2 \frac{R\&D_{it-1}}{K_{it-1}} + \sigma_3 \frac{TechFields_{it-1}}{K_{it-1}} + \sigma_4 K_{it-1} + \varepsilon_{it} \tag{3.14}$$

where $TechFields$ stands for the number of technological fields (lagged) of patents (non-self citations or citations received), $Patents$ is patent counts (lagged), and $R\&D$ is the stocks of R&D (lagged). Furthermore, $\frac{Patents_{it}}{TechFields_{it} \times R\&D_{it}}$ is defined as Innovation Efficiency (IE, in other words $Ptechs/RD$, $Nselftechs/RD$, $FCtechs/RD$). Specifically, after introducing a set of fixed effects for industry, year, and firms, together with a set of control variables, the estimation model is denoted as:

$$log\ Q_{it} = \sigma_0 + \sigma_1 IE_{i,t-1} + \sigma_2 \frac{R\&D_{i,t-1}}{K_{i,t-1}} + \sigma_3 \frac{TechFields_{it-1}}{K_{i,t-1}} + \alpha \mathbf{X}_{i,t-1} + \theta_{jt} + \delta_t + \mu_i + \varepsilon_{it} \tag{3.15}$$

where i indexes a firm, j indicates an industry, and t references a year. IE stands for Innovation Efficiency, θ_{jt} is a vector of industry variables that remove the time-variant shocks common to all manufacturers in the same industry, δ_t is year fixed effect, μ_i is firm-level fixed effect controlling for unobservable firm heterogeneity, and ε_{it} is the stochastic error term. $\mathbf{X}_{i,t-1}$ is a vector of control variables, including advertising intensity (advertising expense scaled by market value), capital expense intensity (capital expense scaled by market value), book-to-market ratio, non-patent firm dummy (value is 1 if the firm had no granted patent within its whole fiscal years).

3.3.2 Fama-MacBeth Regression

The Fama-MacBeth regression proposed by Fama and MacBeth (1973) is widely used to test the changing value of operating performance and profitability. To examine the relation of Innovation

Efficiency with operating performance and profitability, I follow Fama and French (2000) and conduct the following fixed effect regressions based on the Fama-MacBeth:

$$\begin{aligned}\Delta OP_{i,t} = \beta_0 + \beta_1 log(1 + IE_{i,t-1}) + \beta_2 log(1 + \tfrac{R\&D_{i,t-1}}{K_{i,t-1}}) + \beta_3 log(1 + \tfrac{TechFields_{it-1}}{K_{i,t-1}}) \\ + \beta_4 (G = 0)_{i,t-1} + \alpha log(1 + \mathbf{X}_{i,t-1}) + \theta_{jt} + \delta_t + \mu_i + \varepsilon_{it}\end{aligned} \quad (3.16)$$

where ΔOP_{it} stands for next year's change in firm i's operating performance (profitability) in year t, which includes ROA, ROE, and cash flow (abnormal earning, gross margin, and profit margin, respectively), $log(1 + IE_{i,t-1})$ is the natural log of one plus Innovation Efficiency ($Ptechs/RD$, $Nselftechs/RD$, or $FCtechs/RD$) in year t-1. The reason why I plus one is because the distributions of Innovation Efficiency measures are highly skewed and lots of firms have no patents within the sample periods, which means Innovation Efficiency measures are zero. Similarly, because R&D intensity and patent intensity are sometimes zero as well, I plus one when calculate the natural log. $\mathbf{X}_{i,t-1}$ is a vector of control variables in year t-1, including advertising intensity (advertising expense scaled by market value), capital expense intensity (capital expense scaled by market value), and book-to-market ratio. The non-patent firm dummy variable $G = 0$ is valued 1 if the firm had no granted patent within its whole fiscal years, and zero otherwise.

3.3.3 Excess Return Regressions

Tobin's q regressions and Fama-MacBeth regressions have been proved to be the most tractable methods for recovering estimates of the impact of knowledge assets on equity values and operating performance. However, those regression approaches have potential aggregation bias. Annual financial data and year-end market price may be only a weak proxy for within-year changes in stock market value.

To explore the changing market value of patentable assets, excess return regressions are performed using monthly sample data. The estimating equation for excess returns is based on Nicholas (2008) but is extended to include Innovation Efficiency, innovation intensity, and also R&D intensity. Different from Tobin's q and Fama-MacBeth regression, I also include the size effect in the excess return estimation as scale effect affects firms' returns. As indicated by lots of literature, large firms tend to have lower excess returns comparing to small companies. In addition, momentum effect is also introduced in the excess return estimation. Specifically, the estimation specification for monthly excess return takes the following form of

$$\begin{aligned} R_{it} - R_{ft} = \gamma_0 + \gamma_1 log(1 + IE_{i,t-1}) + \gamma_2 log(1 + \tfrac{R\&D_{i,t-1}}{K_{i,t-1}}) + \gamma_3 log(1 + \tfrac{TechFields_{it-1}}{K_{i,t-1}}) \\ + \gamma_4 log(SIZE_{i,t-1}) + \gamma_5 R_{it-1,t-12} + \gamma_6 (G = 0)_{i,t-1} + \alpha log(1 + \mathbf{X}_{i,t-1}) \\ + \theta_{jt} + \delta_t + \mu_i + \varepsilon_{it} \end{aligned} \tag{3.17}$$

where i indexes a firm, j indicates an industry, and t references a month. $R_{it} - R_{ft}$ is the excess of the monthly return over the one-month Treasury bill rate. $SIZE$ stands for firm's market size, while $R_{it-1,t-12}$ stands for the cumulative return over the prior 12 months. $\mathbf{X}_{i,t-1}$ is a vector of control variables in month t-1, including advertising intensity (advertising expense scaled by market value), capital expense intensity (capital expense scaled by market value), market size, and book-to-market ratio. The non-patent firm dummy variable $G = 0$ is valued 1 if the firm had no granted patent within its whole fiscal years, and zero otherwise.

3.4 Empirical Results

This paper is interested in investigating how firm-level Innovation Efficiency is correlated with operating performance, profitability, and stock returns. To this end, I perform Tobin's q regression, Fama-MacBeth regression, and monthly excess return regression based on the estimation models discussed in Section 3.3. For the Tobin's q regressions, I first estimate the effect of the three Innovation Efficiency measures on Tobin's q and then split the data into three panels by different periods, and different industrial technological level. Estimation results are shown in Section 3.4.1. For the Fama-MacBeth regressions, I examine the effect of Innovation Efficiency on operating performance denoted by return on assets, return on equity, and cash flow using the whole sample data and three subset data. Section 3.4.2 provides the main estimation results for this part. To further investigate why Innovation Efficiency affects firm's operating performance, I examine how future profitability can be predicted by Innovation Efficiency. In order to investigate the role of productivity in determine firm's profitability and operating, I also introduce productivity into the model and examine the effect of Innovation Efficiency on productivity. Estimation results are shown in Section 3.4.3. For the excess return regressions, similar to the Tobin's q regressions I first examine the effect of Innovation Efficiency on monthly excess return using the whole sample data, and then split the data into three panels by different periods and different industrial technological level. The estimation results are shown and discussed in Section 3.4.4.

3.4.1 Tobin's q and Innovation Efficiency

3.4.1.1 Baseline Estimation

Table 3.7 presents the baseline estimation results based on Equation (3.15) using the whole sample data. Sample period is from 1950 to 2010. The response variable is Tobin's q, which is measured by the natural log of Tobin's q. Columns (1)-(3) present Tobin's q estimation results using $Ptechs/RD$ measuring Innovation Efficiency. Patent intensity and R&D intensity are gradually introduce into the estimations. Columns (4)-(6) present the estimation results using $Nselftechs/RD$ as the proxy of Innovation Efficiency. Columns (7)-(9) present the estimation results using $FCtechs/RD$ as Innovation Efficiency measure. All columns control for year, industry, and firms fixed effects. Advertising expense intensity, capital expense intensity, book-to-market ratio, and non-patent firms are controlled. The key measure is Innovation Efficiency, which is the explanatory variable in first row. All explanatory variables in the estimation use the lagged values. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

The estimation coefficients on the lagged Innovation Efficiency measures ($L.IE$) are positive and statistically significant at the 1% level for IE measures of $Ptechs/RD$ and $Nselftechs/RD$, and are also positive but not statistically significant even at the 10% level for IE measure of $FCtechs/RD$, except for the last estimation with insignificant negative coefficient. The coefficients suggest that an additional unit increase in firm's current Innovation Efficiency (measured by $Ptechs/RD$ and $Nselftechs/RD$) is associated with a at least 3.0 percent increase in future Tobin's q. Although the estimation coefficients on $FCtechs/RD$ sometime indicate Innovation Efficiency has negative effect on future Tobin's q (with coefficient of -0.005 in the last column), the coefficients are very small and are not statistically significant. In other words, using forward citations received in past five years maybe not a good measure of Innovation Efficiency because it contains a long time information (at least past two years) but investors may not care much about the long past information.

Table 3.7: Innovation Efficiency and Tobin's q, 1950-2010

IE Measures	Ptechs/RD			Nselftechs/RD			FCtechs/RD		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.IE	0.030***	0.029***	0.027***	0.032***	0.032***	0.032***	0.002	0.001	-0.005
	(0.008)	(0.008)	(0.009)	(0.007)	(0.008)	(0.009)	(0.005)	(0.005)	(0.005)
L.R&D/ME		-0.437***	-0.436***		-0.437***	-0.437***		-0.441***	-0.440***
		(0.028)	(0.028)		(0.028)	(0.028)		(0.028)	(0.028)
L.PAT/ME		-0.101***	-0.107***		-0.100***	-0.100***		-0.070**	-0.078**
		(0.033)	(0.036)		(0.033)	(0.035)		(0.031)	(0.031)
L.IE*(PAT/ME)			0.013			0.000			0.025***
			(0.023)			(0.022)			(0.009)
L.lnAD	0.013*	0.012*	0.012*	0.012	0.012	0.012	0.012	0.012	0.012
	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)
L.lnCapEx	0.045***	0.049***	0.049***	0.045***	0.049***	0.049***	0.044***	0.049***	0.049***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
L.lnBTM	-0.293***	-0.286***	-0.286***	-0.293***	-0.286***	-0.286***	-0.293***	-0.286***	-0.286***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
L.(G=0)	-0.017**	-0.024***	-0.024***	-0.018**	-0.024***	-0.024***	-0.019***	-0.026***	-0.026***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
R^2	0.369	0.374	0.374	0.369	0.374	0.374	0.369	0.373	0.373
N	177,355	177,355	177,355	177,355	177,355	177,355	177,355	177,355	177,355
# of Firms	16,769	16,769	16,769	16,769	16,769	16,769	16,769	16,769	16,769
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is 1950-2010, the response variable is Tobin's q, which is measured by the natural log of Tobin's q. "IE" stands for Innovation Efficiency, measured by $Ptechs/RD$, $Nselftechs/RD$, and $FCtechs/RD$. Variables are well defined in Table 3.2. "L." stands for the lagged value. "IE*(PAT/ME)" denotes the interaction of Innovation Efficiency and patent intensity. $G = 0$ is non-patent firm dummy. Columns (1)-(3) present the estimation results using $Ptechs/RD$ measuring Innovation Efficiency and using panel data with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using $Nselftechs/RD$ as the proxy of Innovation Efficiency. Columns (7)-(9) are the panel fixed effect estimation results using $FCtechs$ as the Innovation Efficiency measure. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

This result is consistent with the prediction in many theoretical models (Kogan and Papanikolaou, 2014; Kung and Schmid, 2015). In those models, high quality innovation is a key driver of stock appreciation since high quality innovation can provide firms with more market power and monopoly profits with the increased productivity. Innovation, as a profitable activity, can increase future market value and thus increase future Tobin's q. As one firm succeeds in its innovative activity and applies for new patents, investors can then forecast that other firms must cover a higher cost to obtain new knowledge, which makes innovation for other firms more difficult. Such a negative signal then increases the market value of firm that is successful in inventive activities and henceforth increases its Tobin's q.

In contrast, the estimation coefficients on the lagged patent intensity ($L.PAT/ME$) and R&D intensity ($L.R\&D/ME$) are all negative and statistically significant at the 1% level. On average, an additional unit increase in firm's current patent intensity is associated with a around 8 percent to 9 percent decrease in future Tobin's q. In addition, an additional unit increase in firm's current R&D intensity is associated with a around 44 percent decrease in future Tobin's q. The huge negative effects of patent intensity and R&D intensity on future market value cannot be explained by previous literature. Furthermore, the positive value of the estimation coefficient on the interaction term ($L.IE * (PAT/ME)$) indicates that patent intensity has a downside effect. The slope on the interaction term is around 0.02, which implies that a one-standard-deviation increase in PAT/RD slows down the mean reversion of Innovation Efficiency IE by 1.5 (0.03/0.02) relative to a firm with zero patents.

These results indicates that firms with high Innovation Efficiency can get higher market value and Tobin's q in the future, while higher innovation inputs or outputs does not necessary increases firm's market valuations. Dominated literature on innovation and market value reveal that R&D, patents, and citations (or innovation quantity), are positively associated with firm's market value (Hall et al., 2005b; Nicholas, 2008; Eberhart et al., 2004; Li, 2011). The estimation results I get in Table 3.7 contradict their findings. The main reason for this is because they only use innovation quantity, either input amount (R&D intensity) or output amount (patent or citation intensity), ignoring the effect of Innovation Efficiency. The positive effect of Innovation Efficiency on future Tobin's q is very solid because the value and robust standard errors of IE coefficients do not change much when other variables are controlled and additional variables are introduced into the regression. One more interesting thing is the estimation coefficients on non-patent firm dummy ($L.(G = 0)$). The coefficients in all regressions are negative and statistically significant at the 1% level with values vary around -0.02. This indicates that firms that do not have any granted patents have less future market value comparing to firms that succeed in inventive activities, which is consistent with the intuition that innovation success allows firms to maintain competitive advantage and sustainable higher market value.

3.4.1.2 Comparing Different Periods

As has been shown in Section 2, firms behaved differently in different sample periods. Although time fixed effect have been introduced into the estimations above, it cannot show directly how Innovation Efficiency affect firm's future market value and Tobin's q. To this end, I split the data into three panels–1950-1969, 1970-1989, and 1990-2010–and perform estimations for each period. All the regressions on these three panels are performed using the method in Equation (3.15). Table 3.8 reports the estimation results using natural log of Tobin's q as the response variable. Columns (1)-(3) present the estimation results using sample data in the period of 1950-1969 with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using sample data in the period of 1970-1989. Columns (7)-(9) are the panel fixed effect estimation results using sample data in the period of 1990-2010. For each period, three different regressions are performed using different innovation measures.

Beginning with the 1950-1969 panel, the coefficients on the first two Innovation Efficiency measures ($Ptechs/RD$ and $Nselftechs/RD$) are positive and statistically insignificant even at the 10% level. The results imply that an additional unit of the firm's number of technological fields per patent per million dollars of R&D leads to a 0.5 percent increase in market value. However, column (3) shows that the coefficient on the Innovation Efficiency reverses sign and significance when forward citation tech fields ($FCtechs$) is used to measure Innovation Efficiency. The contradiction here is because investors may care more about the financial status of a firm in this period, which requires analyzing of a long period financial statements. In contrast, the coefficients on patent intensity and R&D intensity are all negative, and the coefficients on R&D intensity are statistically significant. These facts confirm the results in the above part that higher innovation inputs or outputs does not necessary increases firm's market valuations, and sometimes slow down future

Table 3.8: Innovation Efficiency and Tobin's q in Different Periods

Periods	1950-1969			1970-1989			1990-2010		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IE Measure	Ptechs/RD	Nselftechs/RD	FCtechs/RD	Ptechs/RD	Nselftechs/RD	FCtechs/RD	Ptechs/RD	Nselftechs/RD	FCtechs/RD
L.IE	0.005	0.048	-0.037**	-0.007	0.008	-0.004	0.087***	0.098***	0.006
	(0.047)	(0.058)	(0.016)	(0.008)	(0.009)	(0.005)	(0.019)	(0.021)	(0.014)
L.R&D/ME	-0.636***	-0.681***	-0.575***	-0.291***	-0.289***	-0.290***	-0.444***	-0.448***	-0.452***
	(0.212)	(0.207)	(0.216)	(0.049)	(0.049)	(0.049)	(0.030)	(0.030)	(0.030)
L.PAT/ME	-0.104	-0.107	-0.088	0.021	0.015	0.023	-0.215**	-0.175**	-0.166**
	(0.157)	(0.157)	(0.156)	(0.031)	(0.030)	(0.027)	(0.085)	(0.081)	(0.074)
L.IQ*(PAT/ME)	-0.006	-0.038	0.073**	0.017	0.005	0.010	-0.014	-0.070	0.102**
	(0.137)	(0.113)	(0.031)	(0.019)	(0.018)	(0.007)	(0.072)	(0.071)	(0.045)
L.lnAD	-0.111*	-0.108*	-0.115*	-0.004	-0.003	-0.004	0.032***	0.031***	0.031***
	(0.062)	(0.062)	(0.063)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
L.lnCapEx	0.059***	0.059***	0.058***	0.083***	0.083***	0.083***	-0.007	-0.007	-0.007
	(0.017)	(0.017)	(0.017)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)
L.lnBTM	-0.403***	-0.402***	-0.403***	-0.300***	-0.300***	-0.300***	-0.253***	-0.253***	-0.254***
	(0.014)	(0.014)	(0.014)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
L.(G=0)	-0.000	0.000	-0.001	-0.006	-0.005	-0.006	-0.035***	-0.036***	-0.039***
	(0.022)	(0.022)	(0.022)	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)
R^2	0.583	0.583	0.583	0.432	0.433	0.432	0.318	0.318	0.318
N	5,804	5,804	5,804	66,800	66,800	66,800	104,751	104,751	104,751
# of Firms	1,894	1,894	1,894	8,077	8,077	8,077	12,873	12,873	12,873
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample is split into three panels 1950-1969, 1970-1989, and 1990-2010. The response variable is the natural log of Tobin's q. "IE" stands for Innovation Efficiency, measured by $Ptechs/RD$, $Nselftechs/RD$, and $FCtechs/RD$. Variables are well defined in Table 3.2. "L." stands for the lagged value. "IE*(PAT/ME)" denotes the interaction of Innovation Efficiency and patent intensity. $G = 0$ is non-patent firm dummy. Columns (1)-(3) present the estimation results using sample data in the period of 1950-1969 with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using sample data in the period of 1970-1989. Columns (7)-(9) are the panel fixed effect estimation results using sample data in the period of 1990-2010. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

Tobin's q. With respect to the period of 1970-1989, columns (4) and (6) reveal that the coefficients on the two Innovation Efficiency measures ($Ptechs/RD$ and $FCtechs/RD$) are negative but not significantly different from zero. Furthermore, the estimation coefficients on patent intensity in Table 3.8 reverse signs and statistical significance comparing to the estimation results in Table 3.7. In contrast, the coefficients on R&D intensity are still negative and statistically significant. These results contradict the results we get in the above part that Innovation Efficiency plays a key positive role in predicting future market value.

The evidence of a robust relationship between Innovation Efficiency and future Tobin's q is much stronger in certain specification for the period 1990-2010. Similar to the estimation results in Table 3.7, the estimation coefficients on the lagged Innovation Efficiency measures are positive and statistically significant at the 1% level except for the result in column (9). The coefficients suggest that increase in firm's current Innovation Efficiency increases firm's future market value or Tobin's q. In contrast, the estimation coefficients on the lagged patent intensity and R&D intensity are all negative and statistically significant at the 1% level. The magnitudes of patent intensity coefficients are even larger than the corresponding coefficients in Table 3.7. This confirms the fact that firms with high Innovation Efficiency can get higher market value and Tobin's q in the future, while higher innovation inputs or outputs does not necessary increases its market valuations.

Another interesting estimation result in Table 3.8 is the value of estimation coefficients on non-patent firm dummy ($G = 0$). In the first period of 1950-1969, the estimation coefficients are approximate to 0 and not statistical significantly different from zero. This result indicates that during 1950 and 1969, market value are almost the same for firms had granted patents and firms had zero granted patents. In other words, patents do not necessary affect firm's market value in this period. This is consistent with Figure 3.1-3.3 that average number of patents, citations, technological fields (no matter patents or citations), and Innovation Efficiency almost keep the same before 1970. The magnitudes of these coefficients increase slightly in the period 1970-1989, and are still not significantly different from zero. However, the coefficients become much large (more than

5 times) and statistically significant in the period 1990-2010. The importance of patents is much larger in recent periods.

Overall, the estimation results indicate that the role of Innovation Efficiency in predicting future market value changes over time. Innovation Efficiency becomes more and more important in recent decades. Similarly, the effect of patent intensity on market value also changes over time and it becomes significantly negative in recent decades. In contrast, the negative effect of R&D intensity is statistically significant and negative over the three periods.

3.4.1.3 Comparing Different Industrial Technologies

Table 3.4 has shown that Innovation Efficiency varies among industries. In all the regressions above, industry fixed effect have been introduced, however, it cannot show how the effect of Innovation Efficiency on firm's future market value and Tobin's q varies among industries. Following Hatzichronoglou (1997), I split the data into three panels–high-technology, medium-technology, and low-technology–based on the International Standard Industrial Classification (ISIC) code [5]. To simplify, I treat both medium-high-technology and medium-low-technology in his work as medium-technology[6]. After splitting the data, I perform the Tobin's q regressions on these three panels using the method in Equation (3.15). Table 3.9 reports the estimation results using natural log of Tobin's q as the response variable. Columns (1)-(3) present the estimation results using sample data for high-technology industries with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using firm-level data of medium-technology industries. Columns (7)-(9) are the panel fixed effect estimation results using firm-level data of low-technology industries. For each period, three different regressions are performed using different innovation measures.

For high-technology industries, the coefficients on the first two Innovation Efficiency measures ($Ptechs/RD$ and $Nselftechs/RD$) are positive and statistically significant at the 1% level. An additional unit of the firm's number of technological fields per patent per million dollars of R&D

[5] For more information please refer to the document via link https://www.oecd.org/sti/ind/48350231.pdf.

[6] Table A1 in the appendix shows how the three groups are classified in detail

Table 3.9: Innovation Efficiency and Tobin's q under Different Industrial Technologies, 1950-2010

Industries	High-Tech			Medium-Tech			Low-Tech		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IE Measure	Ptechs/RD	Nselftechs/RD	FCtechs/RD	Ptechs/RD	Nselftechs/RD	FCtechs/RD	Ptechs/RD	Nselftechs/RD	FCtechs/RD
L.IE	0.045**	0.041**	-0.008	0.031*	0.043**	-0.018*	0.069**	0.055*	0.008
	(0.019)	(0.020)	(0.013)	(0.019)	(0.021)	(0.009)	(0.031)	(0.032)	(0.024)
L.R&D/ME	-0.639***	-0.643***	-0.647***	-0.205***	-0.204***	-0.210***	-0.201	-0.203	-0.206
	(0.049)	(0.049)	(0.049)	(0.067)	(0.067)	(0.067)	(0.176)	(0.176)	(0.172)
L.PAT/ME	-0.265***	-0.323**	-0.231**	-0.070	-0.079	-0.021	0.100	0.102	0.119*
	(0.098)	(0.144)	(0.095)	(0.069)	(0.069)	(0.060)	(0.069)	(0.069)	(0.071)
L.IQ*(PAT/ME)	0.017	0.014	0.031	0.011	0.006	0.032***	-0.149	-0.115	-0.144
	(0.044)	(0.049)	(0.022)	(0.034)	(0.032)	(0.011)	(0.111)	(0.099)	(0.088)
L.lnAD	-0.000	-0.001	-0.001	0.000	0.000	-0.001	0.044*	0.044*	0.044*
	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)	(0.025)	(0.025)	(0.025)
L.lnCapEx	-0.034	-0.035	-0.035	0.085***	0.086***	0.084***	0.092**	0.091**	0.091**
	(0.031)	(0.031)	(0.031)	(0.022)	(0.022)	(0.022)	(0.037)	(0.037)	(0.037)
L.lnBTM	-0.309***	-0.309***	-0.310***	-0.317***	-0.317***	-0.317***	-0.292***	-0.292***	-0.292***
	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)	(0.015)	(0.015)	(0.015)
L.(G=0)	-0.061***	-0.062***	-0.064***	-0.024	-0.024	-0.027	0.005	0.004	0.001
	(0.016)	(0.016)	(0.016)	(0.018)	(0.018)	(0.018)	(0.023)	(0.023)	(0.023)
R^2	0.404	0.404	0.403	0.439	0.439	0.439	0.440	0.440	0.441
N	25,214	25,214	25,214	23,767	23,767	23,767	10,094	10,094	10,094
# of Firms	2,453	2,453	2,453	1,805	1,805	1,805	801	801	801
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample is split into three panels high-technology industries, medium-technology industries, and low-technology industries. Sample period is from 1950 to 2010. The response variable is the natural log of Tobin's q. "IE" stands for Innovation Efficiency, measured by $Ptechs/RD$, $Nselftechs/RD$, and $FCtechs/RD$. Variables are well defined in Table 3.2. "L." stands for the lagged value. "IE*(PAT/ME)" denotes the interaction of Innovation Efficiency and patent intensity. $G = 0$ is non-patent firm dummy. Columns (1)-(3) present the estimation results using sample data of high-technology industries with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using sample data of medium-technology industries. Columns (7)-(9) are the panel fixed effect estimation results using sample data of low-technology industries. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

leads to at least 4 percent increase in Tobin's q. Column (3) shows that the coefficient on the Innovation Efficiency reverses sign and significance when forward citation tech fields ($FCtechs$) is used to measure Innovation Efficiency. In contrast, the coefficients on patent intensity and R&D intensity are all negative, though the coefficients on R&D intensity are not statistically significant. These facts show that for high-technology industries higher Innovation Efficiency promotes market value increasing while higher innovation inputs or outputs does not necessary increases firm's market valuations.

For medium-technology and high-technology industries, the coefficients on the three Innovation Efficiency measures are almost all positive though they are not significantly different from zero. Furthermore, the estimation coefficients on patent intensity for medium-technology industries reverse signs and statistical significance comparing to the estimation results in Table 3.7. However, the coefficients on R&D intensity are still negative and mostly are statistically significant. These results are very similar to the estimation results for different periods shown in Table 3.8 and contradict the results in Table 3.7 that higher Innovation Efficiency predicts higher market value. Innovation Efficiency, inputs, and outputs play different roles in determine future market value among different technological industries. Innovation Efficiency is a key stimulus of future market value in high-technology industries, but its impact declines as industrial technology changes from high to low. Patent intensity, in contrast, has a great positive effect on the future Tobin's q of firms in low-technology industries.

There are also some other interesting estimation results in Table 3.9. The estimation coefficients on advertising expenses indicate that advertising expenses has no significant effect on future Tobin's q for high-tech and medium-tech firms, but it has great and significantly positive effect for low-tech firms. Similarly, capital expenses decreases future Tobin's q for firms in high-tech industries but increases market value of firms in medium-tech and low-tech industries. In addition, the estimation coefficients on non-patent firm dummy ($G = 0$) are approximate to 0 and not statistical significantly different from zero for firms in low-technology industries, which indicates that patents do not necessary affect the market value of firms in low-technology industries. However, the coefficients reverse signs and significance for firms in high-technology industries. The patents play an important role in determining future market value of firms in high-tech industries.

Overall, the estimation results indicate that the role of Innovation Efficiency in predicting future market value changes among industries. Innovation Efficiency plays an important role in high-technology industries. Similarly, the effect of patent intensity on market value also changes among industries and it is significantly negative in high-tech industries. In contrast, the negative effect of R&D intensity keeps statistically significant and negative in all industries.

3.4.2 Operating Performance and Innovation Efficiency

To examine more carefully the relation of Innovation Efficiency with subsequent operating performance, in this part I conduct several regression based on the Fama-MacBeth regressions (Fama and MacBeth, 1973; Fama and French, 2000) as denoted in Equation (3.16). I examine the effect of Innovation Efficiency on operating performance denoted by return on assets (ROA), return on equity (ROE), and cash flow (CF) using the whole sample data. Following Fama and French (2000) and Hirshleifer et al. (2018), I standardize all the three Innovation Efficiency measures to zero mean and one standard deviation to reduce the influence of outliers and facilitate the interpretation. I also introduce the interaction between Innovation Efficiency and patent intensity, interaction between Innovation Efficiency and change in operating performance, and other control variables (market size, advertising expense, capital expenditure, book-to-market assets, and non-patent firm dummy) into the regressions.

Table 3.10 presents the baseline estimation results based on Equation (3.15) using the whole sample data from 1950 to 2010. The response variable is the change in operating performance (ΔOP). Operating performance (OP) are measured by return on assets (ROA), return on equity (ROE), and cash flow (CF). Columns (1)-(3) present the estimation results using ROA with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using ROE. Columns (7)-(9) are the panel fixed effect estimation results using CF. All columns control for year, industry, and firms fixed effects. Advertising expense intensity, capital expense intensity, book-to-market ratio, and non-patent firms are controlled. The key measure of innovation is Innovation Efficiency, which is the explanatory variable in first row. All explanatory variables in the estimation use the lagged values. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

As the distributions of Innovation Efficiency measures are highly skewed and lot of values are zero, I use the natural log of one plus the measure ($ln(1 + IE)$) in the regression and denote it as $lnIE$. Because patent intensity and R&D intensity are sometimes zero as well, I also use the natural log of on plus patent (R&D) intensity in the regression. Innovation Efficiency IE are measured by $Ptechs/RD$, $Nselftechs/RD$, and $FCtechs/RD$. The estimation results indicate a significant positive relation between Innovation Efficiency measure and future ROA, ROE, and cash flows for all the specifications. The magnitude is substantial, regardless of which type of Innovation Efficiency measures I control for. Specially, a one percent increase in $lnIE$ raises subsequent change in ROA (ΔROA), ROE (ΔROE), and cash flow (ΔCF) by at least 0.4, 2.0, and 0.4 units, respectively. The slopes on the interaction terms between Innovation Efficiency, patent intensity, and the change in operating performance are all negative. All these effects are statistically significant at the 10% level, and most are significant at the 1% level. These effects are similar to Tobin's q regressions that higher Innovation Efficiency predicts higher operating performance no matter which measure of operating performance or Innovation Efficiency is used.

In contrast, the effect of patent intensity on the mean reversion of operating performance is insignificantly negative. The coefficients on patent intensity are all negative though they are not significantly different from zero for ROA and cash flow regressions. Since the slopes on the interaction terms between Innovation Efficiency and patent intensity ($lnIE * ln(PAT/ME)$) are all negative, this implies that patent intensity has a strong negative effect on future operating performance. For example, in column (1), the slope on $lnIE$ is 0.005, and the slope on $lnIE * ln(PAT/ME)$ is -0.008, this implies that a one percent increase in patent intensity slows down the mean reversion of ROA by 1.6 units (-0.008/0.005) relative to a firm with zero Innovation Efficiency. These effects contradict the current literature but confirm the finding in Section 3.4.1 that higher

Table 3.10: Innovation Efficiency and Operating Performance, 1950-2010

OP Measure	ROA			ROE			CF		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IE Measure	Ptechs/RD	Nselftechs/RD	FCtechs/RD	Ptechs/RD	Nselftechs/RD	FCtechs/RD	Ptechs/RD	Nselftechs/RD	FCtechs/RD
L.IE	0.005***	0.004***	0.003**	0.014**	0.019***	0.030***	0.005***	0.004***	0.003**
	(0.001)	(0.001)	(0.002)	(0.006)	(0.005)	(0.006)	(0.001)	(0.001)	(0.001)
L.ln(R&D/ME)	0.545***	0.546***	0.551***	2.952***	2.954***	2.958***	0.557***	0.558***	0.562***
	(0.053)	(0.053)	(0.054)	(0.162)	(0.162)	(0.162)	(0.039)	(0.039)	(0.039)
L.ln(PAT/ME)	-0.021	-0.025	-0.014	0.293	0.242	0.108	-0.038	-0.032	-0.029
	(0.033)	(0.031)	(0.027)	(0.180)	(0.160)	(0.153)	(0.028)	(0.025)	(0.023)
L.lnIE*(PAT/ME)	-0.008	-0.005	-0.007	-0.170***	-0.163***	-0.135***	-0.006	-0.007	-0.006
	(0.007)	(0.007)	(0.005)	(0.035)	(0.032)	(0.027)	(0.006)	(0.006)	(0.004)
L.lnIE*ΔOP	-0.075***	-0.069***	-0.052	-0.031	-0.031*	-0.015	-0.076***	-0.071***	-0.063**
	(0.025)	(0.026)	(0.032)	(0.019)	(0.017)	(0.024)	(0.021)	(0.022)	(0.031)
L.lnSIZE	-0.015***	-0.015***	-0.015***	-0.224***	-0.224***	-0.225***	-0.012***	-0.012***	-0.012***
	(0.003)	(0.003)	(0.003)	(0.008)	(0.008)	(0.008)	(0.002)	(0.002)	(0.002)
L.lnAD	-0.001	-0.001	-0.001	0.045**	0.045**	0.045**	0.006	0.006	0.006
	(0.007)	(0.006)	(0.007)	(0.021)	(0.022)	(0.022)	(0.005)	(0.005)	(0.005)
L.lnCapEx	-0.007	-0.007	-0.007	0.348***	0.349***	0.349***	0.010	0.010	0.009
	(0.015)	(0.015)	(0.015)	(0.049)	(0.049)	(0.049)	(0.011)	(0.011)	(0.011)
L.lnBTM	-0.060***	-0.060***	-0.060***	-0.695***	-0.695***	-0.695***	-0.058***	-0.058***	-0.058***
	(0.005)	(0.005)	(0.005)	(0.021)	(0.021)	(0.021)	(0.003)	(0.003)	(0.003)
L.(G=0)	-0.113***	-0.114***	-0.115***	-0.187***	-0.188***	-0.193***	-0.087***	-0.087***	-0.088***
	(0.009)	(0.009)	(0.009)	(0.025)	(0.025)	(0.025)	(0.006)	(0.006)	(0.006)
R^2	0.018	0.026	0.046	0.094	0.095	0.094	0.003	0.000	0.001
N	94,264	94,264	94,264	94,092	94,092	94,092	93,942	93,942	93,942
# of Firms	10,485	10,485	10,485	10,478	10,478	10,478	10,469	10,469	10,469
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is from 1950 to 2010. The response variable is the change in operating performance (ΔOP). Operating performance (OP) are measured by return on assets (ROA), return on equity (ROE), and cash flow (CF). "lnIE" stands for natural log of one plus Innovation Efficiency, measured by $Ptechs/RD$, $Nselftechs/RD$, and $FCtechs/RD$. "ln(PAT/ME)" and "ln(R&D/ME)" stands for natural log of one plus patent intensity and R&D intensity, respectively. All the variables are well defined in Table 3.2. "L." stands for the lagged value. "lnIE*ln(PAT/ME)" and "lnIE*Δ OP" denotes the interaction between log Innovation Efficiency and log patent intensity and log Innovation Efficiency and change in operating performance, respectively. $G = 0$ is non-patent firm dummy. Columns (1)-(3) present the estimation results using ROA with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using ROE. Columns (7)-(9) are the panel fixed effect estimation results using CF. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firms.

innovation output does not necessary raise future operating performance. Consistent with the literature, the slopes on the R&D intensity (innovation inputs) are all positive and statistically significant. In particular, higher R&D intensity predicts higher ROA, ROE, and cash flow.

3.4.3 Profitability and Innovation Efficiency

In this section, I examine whether Innovation Efficiency contains favorable information about a firm's future profitability. In particular, I conduct Fama-MacBeth regressions based on Equation (3.16) to study the relation between Innovation Efficiency and different aspects of future profitability: abnormal earnings (AE), gross margin (GM), and profit margin (PM). Similar to Section 3.4.2, I follow Fama and French (2000) and Hirshleifer et al. (2018) and standardize all the three Innovation Efficiency measures to zero mean and one standard deviation to reduce the influence of outliers and facilitate the interpretation. I also introduce the interaction between Innovation Efficiency and patent intensity and other control variables (market size, advertising expense, capital expenditure, book-to-market assets, and non-patent firm dummy) into the regressions.

Table 3.11 presents the baseline estimation results based on Equation (3.16) using all the sample data from 1950 to 2010. The response variable is profitability and is measured by abnormal earnings (AE), gross margin (GM), and profit margin (PM). Columns (1)-(3) present the estimation results using abnormal earnings with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using gross margin. Columns (7)-(9) are the panel fixed effect estimation results using profit margin. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firms. The estimation coefficients on Innovation Efficiency measures are almost all positive though they are not significantly different from zero. These results may provide some evidences on the positive effect of Innovation Efficiency on firm's future profitability. The effect of innovation quantity varies when using different measures of profitability and using innovation input or output. Specifically, for patent intensity, it has insignificantly negative effect on future abnormal earnings and gross margin, and the effect is very strong. For example, the coefficients on patent intensity using abnormal earnings measure is above

Table 3.11: Innovation Efficiency and Profitability, 1950-2010

Profitability	AE			GM			PM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IE Measure	Ptechs/RD	Nselftechs/RD	FCtechs/RD	Ptechs/RD	Nselftechs/RD	FCtechs/RD	Ptechs/RD	Nselftechs/RD	FCtechs/RD
L.IE	0.473	0.163	0.105	-0.027	0.067	-0.166	-0.264	0.071	0.041
	(0.580)	(0.417)	(0.145)	(0.118)	(0.150)	(0.145)	(0.255)	(0.058)	(0.044)
L.ln(R&D/ME)	3.181*	3.190*	3.201*	-0.888*	-0.879*	-0.891*	-0.360*	-0.330*	-0.330*
	(1.717)	(1.714)	(1.714)	(0.522)	(0.522)	(0.521)	(0.193)	(0.194)	(0.194)
L.ln(PAT/ME)	-0.258	-0.362	-0.546	0.376***	0.328**	0.368***	0.108	-0.005	-0.032
	(0.719)	(0.649)	(0.503)	(0.135)	(0.144)	(0.123)	(0.143)	(0.108)	(0.103)
L.lnIE*(PAT/ME)	-0.952	-0.473	-0.101	-0.049	-0.024	0.031	-0.052	-0.078	-0.013
	(1.429)	(0.948)	(0.248)	(0.181)	(0.149)	(0.045)	(0.084)	(0.061)	(0.027)
L.lnSIZE	-0.089*	-0.091*	-0.091*	0.147***	0.147***	0.147***	-0.028**	-0.027*	-0.028*
	(0.051)	(0.052)	(0.053)	(0.032)	(0.032)	(0.032)	(0.014)	(0.014)	(0.014)
L.lnAD	-0.326	-0.328	-0.328	-0.424***	-0.424***	-0.424***	0.116**	0.116**	0.116**
	(0.252)	(0.254)	(0.255)	(0.089)	(0.089)	(0.089)	(0.052)	(0.052)	(0.052)
L.lnCapEx	-0.102	-0.108	-0.109	-0.083	-0.082	-0.083	-0.022	-0.020	-0.020
	(0.462)	(0.463)	(0.464)	(0.155)	(0.155)	(0.155)	(0.052)	(0.052)	(0.052)
L.lnBTM	-0.146	-0.144	-0.144	0.178***	0.178***	0.178***	0.147***	0.147***	0.148***
	(0.139)	(0.139)	(0.139)	(0.056)	(0.056)	(0.056)	(0.027)	(0.027)	(0.027)
L.(G=0)	-0.653	-0.666	-0.670	-0.741***	-0.741***	-0.742***	0.139**	0.142**	0.141**
	(0.484)	(0.485)	(0.485)	(0.171)	(0.171)	(0.171)	(0.069)	(0.069)	(0.069)
R^2	0.000	0.000	0.000	0.044	0.044	0.044	0.057	0.057	0.057
N	95,696	95,696	95,696	95,777	95,777	95,777	95,692	95,692	95,692
# of Firms	10,547	10,547	10,547	10,551	10,551	10,551	10,546	10,546	10,546
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is from 1950 to 2010. The response variable is profitability and is measured by abnormal earnings (AE), gross margin (GM), and profit margin (PM). "lnIE" stands for natural log of one plus Innovation Efficiency, measured by $Ptechs/RD$, $Nselftechs/RD$, and $FCtechs/RD$. "ln(PAT/ME)" and "ln(R&D/ME)" stands for natural log of one plus patent intensity and R&D intensity, respectively. All the variables are well defined in Table 3.2. "L." stands for the lagged value. "lnIE*ln(PAT/ME)" denotes the interaction between log Innovation Efficiency and log patent intensity. $G = 0$ is non-patent firm dummy. Columns (1)-(3) present the estimation results using abnormal earnings with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using gross margin. Columns (7)-(9) are the panel fixed effect estimation results using profit margin. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firms.

-0.25. However, when using profit margin measure, the coefficients reverse signs and significance. It seems like patent intensity has great positive effect on firm's future profit margin.

Table 3.12: Innovation Efficiency, Profit Margin, and Productivity, 1950-2010

IE Measure	Ptechs/RD			Nselftechs/RD			Fctechs/RD		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.IE	0.398***	0.434**	1.254***	0.347*	0.203	0.596***	0.086	0.018	0.085
	(0.136)	(0.180)	(0.241)	(0.203)	(0.191)	(0.177)	(0.091)	(0.134)	(0.097)
L.ln(R&D/ME)		-0.790	-4.156***		-0.876*	-4.503***		-0.881*	-4.546***
		(0.513)	(0.969)		(0.521)	(0.986)		(0.521)	(0.990)
L.ln(PAT/ME)		0.380***	-0.051		0.342**	-0.110		0.390***	0.007
		(0.145)	(0.298)		(0.144)	(0.320)		(0.126)	(0.335)
L.lnIE*(PAT/ME)		-0.233	-0.683***		-0.069	-0.326*		-0.021	-0.152*
		(0.191)	(0.242)		(0.151)	(0.193)		(0.056)	(0.088)
L.lnTFP			14.536***			14.939***			14.808***
			(1.143)			(1.106)			(1.105)
L.lnIE*PM	1.624***	1.710***	0.892	0.542	0.694	-0.648*	1.292	1.582	0.262
	(0.490)	(0.517)	(0.659)	(0.528)	(0.594)	(0.391)	(1.009)	(1.113)	(0.871)
L.lnSIZE	0.181***	0.149***	-0.756***	0.182***	0.148***	-0.794***	0.182***	0.148***	-0.794***
	(0.023)	(0.032)	(0.083)	(0.023)	(0.032)	(0.081)	(0.023)	(0.032)	(0.081)
L.lnAD	-0.209***	-0.426***	-0.463***	-0.210***	-0.426***	-0.466***	-0.209***	-0.424***	-0.467***
	(0.063)	(0.089)	(0.085)	(0.063)	(0.089)	(0.084)	(0.063)	(0.089)	(0.084)
L.lnCapEx	-0.005	-0.086	1.925***	-0.004	-0.080	2.083***	-0.003	-0.081	2.039***
	(0.076)	(0.155)	(0.342)	(0.076)	(0.155)	(0.352)	(0.076)	(0.155)	(0.353)
L.lnBTM	0.163***	0.176***	-0.705***	0.163***	0.179***	-0.715***	0.163***	0.179***	-0.715***
	(0.039)	(0.055)	(0.092)	(0.039)	(0.055)	(0.092)	(0.039)	(0.055)	(0.092)
L.(G=0)	-0.376***	-0.750***	-0.678	-0.364***	-0.742***	-0.623	-0.367***	-0.745***	-0.620
	(0.126)	(0.171)	(0.474)	(0.127)	(0.171)	(0.472)	(0.127)	(0.171)	(0.473)
R^2	0.0396	0.0475	0.311	0.0387	0.0460	0.311	0.0378	0.0451	0.309
N	181,012	95,765	33,320	181,012	95,765	33,320	181,012	95,765	33,320
# of Firms	17,026	10,550	4,295	17,026	10,550	4,295	17,026	10,550	4,295
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is from 1950 to 2010. The response variable is profit margin (PM). "lnIE" stands for natural log of one plus Innovation Efficiency, measured by $Ptechs/RD$, $Nselftechs/RD$, and $FCtechs/RD$. "TFP" denotes firm's total factor productivity using the LP method. "lnTFP" stands for natural log of one plus TFP. "ln(PAT/ME)" and "ln(R&D/ME)" stand for natural log of one plus patent intensity and R&D intensity, respectively. All the variables are well defined in Table 3.2. "L." stands for the lagged value. "lnIE*ln(PAT/ME)" denotes the interaction between log Innovation Efficiency and log patent intensity. "lnIE*PM" stands for the interaction between log Innovation Efficiency and profit margin. $G = 0$ is non-patent firm dummy. Columns (1)-(3) present the estimation results using $Ptechs/RD$ measure Innovation Efficiency with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using $Nselftechs/RD$. Columns (7)-(9) are the panel fixed effect estimation results using $FCtechs/RD$. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firms.

In contrast, R&D intensity has great positive effect on firm's future abnormal earnings and significantly negative effect on firm's future gross margin and profit margin. These contradictions may be caused by the omitted variables. Some theoretical research suggests that innovation affects firm's profitability through productivity, while productivity is omitted in all the regressions above.

Innovation induces a positive shock to productivity; higher productivity reduces production costs and thus increases profits of the firm. There would be a future cash inflow because of the profitable activity and thus stock price would increase.

To this end, I introduce productivity (TFP) into the estimations based on Equation (3.16) and compare the estimation results in Table 3.11. Firm's productivity is measured by total factor productivity (TFP) using the LP method (Levinsohn and Petrin, 2003) [7]. Because the coefficients on patent intensity in Table 3.11 are positive and statistically significant when using profit margin and these results challenge the results in other parts mostly, I only focus on profit margin in this part and use profit margin as the only response variable. I also introduce the interaction between Innovation Efficiency and profit margin ($lnIE * PM$) into the regressions to further check the effect of Innovation Efficiency. Table 3.12 presents the estimation results based on Equation (3.16) using all the sample data from 1950 to 2010. Columns (1)-(3) present the estimation results using $Ptechs/RD$ and gradually introduce innovation quantity and TFP with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using $Nselftechs/RD$. Columns (7)-(9) are the panel fixed effect estimation results using $FCtechs/RD$.

Comparing the coefficients on Innovation Efficiency measures, patent intensity, and R&D intensity before and after introducing TFP intro the estimation, the coefficients on Innovation Efficiency increased a lot after introducing TFP, while the coefficients on patent intensity reverse signs and significance. The coefficients on TFP are all positive and statistically significant, with magnitudes are above 14.5 and are much larger than any other variables. These results indicate that productivity is a key driver of firm's future profitability, and is critical important in predicting firm's future market value. The negative coefficients on patent intensity and R&D intensity after controlling TFP are consistent with the estimation results in Section 3.4.1 and 3.4.2, which confirm the conclusion that higher inventive inputs or outputs does not necessarily indicate higher profitability or market valuations.

[7] The reason why I use LP method has been discussed in Section 3.2.5, I also use the OP method and do the robustness check in the appendix.

3.4.4 Productivity and Innovation Efficiency

As discussed above, higher Innovation Efficiency indicates higher probability to be succeed in inventive activities that may help create unique and superior products or new product lines, which may increase firm's productivity and allow firms to charge a price premium and maintain sustainable competitive productivity advantage. Therefor, in this section, I examine the relation between Innovation Efficiency and productivity, which is measured by total factor productivity using the LP method (Levinsohn and Petrin, 2003), based on Equation (3.16). Patent intensity as an innovation indicator is also included in the regressions though patents can only reflect the output side of a firm's innovative activities and thus may provide a negative signal to investors. Firm's R&D expenditure are also considered since R&D expenditure is the main component of a firm's innovation input. I also introduce the interaction between Innovation Efficiency and TFP ($lnIE * lnTFP$) into the regressions.

Table 3.13 presents the estimation results using all the sample data from 1950 to 2010. Columns (1)-(3) present the estimation results using $Ptechs/RD$ and gradually introduce innovation quantity and TFP with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using $Nselftechs/RD$. Columns (7)-(9) are the panel fixed effect estimation results using $FCtechs/RD$. Much similar to the estimation results in the earlier regressions, the coefficients on Innovation Efficiency are all positive and statistically significant from zero, and the magnitudes are around 0.01. Particularly, an one percent increase in Innovation Efficiency is associated with a one percent increase in subsequential productivity. Though this effect is not big enough, it is sustainable. Comparing to Innovation Efficiency, the coefficients on patent intensity are negative and not statistically different from zero. An one percent increase in patent intensity actually decrease future productivity by around 0.1 percent, which is so small that can be neglected.

In contrast, the estimation coefficients on R&D intensity are all positive and significant with values are around 0.17. In particular, an one percent increase in R&D intensity predicts a 17 percent of increase in future productivity. The positive and large effect of R&D intensity on productivity is consistent with empirical literature that productivity shocks are mainly caused by the change of innovation inputs, or R&D investment. This is also consistent with the prediction of many theoretical papers: R&D is highly correlated with firm's productivity, increasing R&D expenditures can increase probability of success in innovative activities and thus increase firm's productivity.

Table 3.13: Innovation Efficiency and Productivity, 1950-2010

IE Measure	Ptechs/RD			Nselftechs/RD			Fctechs/RD		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.IE	0.014***	0.013***	0.016***	0.008***	0.007**	0.007**	0.010***	0.011***	0.013***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
L.ln(PAT/ME)		-0.021	-0.050		-0.023	-0.048		-0.001	-0.017
		(0.025)	(0.040)		(0.025)	(0.038)		(0.029)	(0.044)
L.lnIE*(PAT/ME)		0.008	0.009		0.012	0.012		-0.008	-0.009
		(0.014)	(0.016)		(0.012)	(0.013)		(0.010)	(0.011)
L.ln(R&D/ME)			0.169**			0.176**			0.177**
			(0.075)			(0.076)			(0.075)
L.lnIE*lnTFP	-0.017	-0.017	-0.013	-0.020	-0.020	-0.013	-0.059***	-0.059***	-0.062***
	(0.024)	(0.024)	(0.026)	(0.019)	(0.019)	(0.020)	(0.017)	(0.017)	(0.017)
L.lnSIZE	-0.007***	-0.007***	-0.005**	-0.008***	-0.008***	-0.006***	-0.008***	-0.008***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
L.lnAD	-0.006	-0.006	-0.009	-0.006	-0.006	-0.009	-0.007	-0.007	-0.009
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
L.lnCapEx	0.491***	0.492***	0.451***	0.495***	0.496***	0.455***	0.493***	0.494***	0.450***
	(0.034)	(0.034)	(0.042)	(0.033)	(0.033)	(0.041)	(0.033)	(0.033)	(0.040)
L.lnBTM	-0.053***	-0.053***	-0.059***	-0.053***	-0.053***	-0.059***	-0.053***	-0.053***	-0.059***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
L.(G=0)	-0.016	-0.017	-0.016	-0.017	-0.019	-0.019	-0.018	-0.018	-0.018
	(0.031)	(0.031)	(0.039)	(0.031)	(0.031)	(0.039)	(0.032)	(0.032)	(0.039)
R^2	0.0273	0.0273	0.0292	0.0269	0.0269	0.0287	0.0291	0.0291	0.0317
N	28,125	28,125	23,490	28,125	28,125	23,490	28,125	28,125	23,490
# of Firms	3,078	3,078	2,723	3,078	3,078	2,723	3,078	3,078	2,723
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is from 1950 to 2010. The response variable is natural log of one plus total factor productivity (denoted as $lnTFP$). TFP is measured using the LP method. "lnIE" stands for natural log of one plus Innovation Efficiency, measured by $Ptechs/RD$, $Nselftechs/RD$, and $FCtechs/RD$. "ln(PAT/ME)" and "ln(R&D/ME)" stand for natural log of one plus patent intensity and R&D intensity, respectively. All the variables are well defined in Table 3.2. "L." stands for the lagged value. "lnIE*ln(PAT/ME)" denotes the interaction between log Innovation Efficiency and log patent intensity. "lnIE*lnTFP" stands for the interaction between log Innovation Efficiency and log TFP. $G = 0$ is non-patent firm dummy. Columns (1)-(3) present the estimation results using $Ptechs/RD$ measure Innovation Efficiency with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using $Nselftechs/RD$. Columns (7)-(9) are the panel fixed effect estimation results using $FCtechs/RD$. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firms.

Overall, if a firm is now increasing their R&D expenditures to invest more in innovative activities or has a lot of patents, it does not necessarily mean that the probability that the firm succeed in its innovative activities would increase. Only when its Innovation Efficiency is high enough, or the inventive outputs to inputs ratio is high enough, then it has a high probability to create new products or increase its product lines. The successful inventive activities would enhance its productivity, and then increase its future profitability, operating performance, and henceforth market value. In other words, high Innovation Efficiency firms are able to achieve higher and more persistent profitability and better operating performance through the effect of Innovation Efficiency on productivity.

Table 3.14: Innovation Efficiency and Excess Return, 1950-2010

IE Measure	Ptechs/RD			Nselftechs/RD			Fctechs/RD		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.IE	0.034	0.067	-0.123	0.039	0.081	-0.019	0.048	0.099*	0.035
	(0.028)	(0.045)	(0.146)	(0.034)	(0.054)	(0.130)	(0.037)	(0.059)	(0.150)
L.ln(R&D/ME)		-0.372***	-0.372***		-0.373***	-0.372***		-0.373***	-0.373***
		(0.090)	(0.090)		(0.090)	(0.090)		(0.090)	(0.090)
L.ln(PAT/ME)		-0.030***	-0.032***		-0.030***	-0.031***		-0.030***	-0.030***
		(0.009)	(0.009)		(0.009)	(0.009)		(0.009)	(0.009)
L.lnIE*(PAT/ME)			0.236			0.114			0.075
			(0.173)			(0.128)			(0.152)
L.lnSIZE	0.019***	0.011***	0.011***	0.019***	0.011***	0.011***	0.019***	0.011***	0.011***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
$Ret_{1,12}$	-1.010***	-0.827***	-0.827***	-1.009***	-0.826***	-0.827***	-1.009***	-0.826***	-0.826***
	(0.133)	(0.168)	(0.168)	(0.133)	(0.168)	(0.168)	(0.133)	(0.168)	(0.168)
L.lnAD	0.127***	0.237***	0.237***	0.127***	0.237***	0.237***	0.127***	0.237***	0.237***
	(0.047)	(0.052)	(0.052)	(0.047)	(0.052)	(0.052)	(0.047)	(0.052)	(0.052)
L.lnCapEx	-0.125***	-0.059	-0.059	-0.125***	-0.059	-0.058	-0.125***	-0.059	-0.059
	(0.033)	(0.039)	(0.039)	(0.033)	(0.039)	(0.039)	(0.033)	(0.039)	(0.039)
L.lnBTM	-0.242***	-0.248***	-0.248***	-0.242***	-0.248***	-0.248***	-0.242***	-0.248***	-0.248***
	(0.017)	(0.020)	(0.020)	(0.017)	(0.020)	(0.020)	(0.017)	(0.020)	(0.020)
L.(G=0)	0.088***	0.069***	0.069***	0.088***	0.069***	0.069***	0.088***	0.069***	0.069***
	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)
R^2	0.0265	0.0302	0.0303	0.0265	0.0302	0.0303	0.0265	0.0302	0.0303
N	779,422	505,430	505,430	779,422	505,430	505,430	779,422	505,430	505,430
# of Firms	9,055	6,356	6,356	9,055	6,356	6,356	9,055	6,356	6,356
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is from 1950 to 2010. The response variable is monthly excess return measured by monthly return subtract one-month Treasury bill rates. "lnIE" stands for natural log of one plus Innovation Efficiency, measured by $Ptechs/RD$, $Nselftechs/RD$, and $FCtechs/RD$. "ln(PAT/ME)" and "ln(R&D/ME)" stand for natural log of one plus patent intensity and R&D intensity, respectively. All the variables are well defined in Table 3.2. "L." stands for the lagged value. "lnIE*ln(PAT/ME)" denotes the interaction between log Innovation Efficiency and log patent intensity. "$Ret_{1,12}$" stands for the cumulative return over the prior 12 months. $G = 0$ is non-patent firm dummy. Columns (1)-(3) present the estimation results using $Ptechs/RD$ measure Innovation Efficiency with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using $Nselftechs/RD$. Columns (7)-(9) are the panel fixed effect estimation results using $FCtechs/RD$. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firms.

3.4.5 Excess Return and Innovation Efficiency

Turning to the excess return regressions, the main objective is to use monthly data to examine the effect of Innovation Efficiency on the market value. Following the approach of Equation (3.17), I first run baseline regressions using all sample data from 1950 to 2010 with time, industry, and firms fixed effect. In contrast to the Tobin's q regression, I assume serial correlation within time as opposed to firm units to adjust the standard errors for clustering. This is because equity returns are considerably less persistent than Tobin's q. In all the regressions I include monthly dummies to absorb time related effects.

Table 3.14 presents the baseline excess return estimation results based on Equation (3.17) using all sample data from 1950-2010. The response variable is monthly excess returns, which is measure by the monthly returns subtract one-month Treasury bill rates. Columns (1)-(3) present the estimation results using $Ptechs/RD$ measure Innovation Efficiency with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using $Nselftechs/RD$. Columns (7)-(9) are the panel fixed effect estimation results using $FCtechs/RD$. In all the regressions I also introduce a new variable $Ret_{1,12}$ which is the cumulative return over the prior 12 months. I also use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units. In all the regressions I include monthly dummies to absorb time related effects.

Similar to the the q regressions, the estimation coefficients on the lagged Innovation Efficiency measures ($L.IE$) are positive but not statistically significant. The coefficients become much bigger after controlling the interaction term between Innovation Efficiency and patent intensity. Because none of the coefficients on Innovation Efficiency measures is distinguishable from zero at the customary levels of significance, there is no obvious evidence that knowledge capital of firms was earning excess returns during this period. In contrast, the estimated coefficients on patent intensity and R&D intensity are all negative and statistically significant at the 1% level. Though Innovation Efficiency has no significant effect on future excess returns, patent intensity and R&D intensity have strong and negative effects on future excess returns. A further insight into the economic magnitude of the estimates can be gained by the coefficients on $G = 0$. Across the

Table 3.15: Innovation Efficiency and Excess Returns in Different Periods

Periods	1950-1985			1986-2000			2001-2010		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IE Measure	Ptechs/RD	Nselftechs/RD	FCtechs/RD	Ptechs/RD	Nselftechs/RD	FCtechs/RD	Ptechs/RD	Nselftechs/RD	FCtechs/RD
L.IE	0.113**	0.146**	0.145**	-0.147*	-0.248**	-0.241*	0.135	0.029	0.029
	(0.057)	(0.067)	(0.071)	(0.077)	(0.101)	(0.131)	(0.179)	(0.249)	(0.335)
L.ln(R&D/ME)	0.098	0.099	0.098	-0.249*	-0.250*	-0.249*	-1.180***	-1.181***	-1.181***
	(0.098)	(0.098)	(0.098)	(0.129)	(0.129)	(0.129)	(0.164)	(0.164)	(0.164)
L.ln(PAT/ME)	-0.013	-0.015	-0.013	-0.026**	-0.026**	-0.026**	-0.026	-0.023	-0.023
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.027)	(0.027)	(0.027)
L.lnSIZE	-0.011**	-0.011**	-0.011**	0.018***	0.018***	0.018***	0.034***	0.033***	0.033***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.010)	(0.010)	(0.010)
$Ret_{1,12}$	-2.193***	-2.194***	-2.193***	-0.146	-0.146	-0.146	-2.405***	-2.405***	-2.405***
	(0.134)	(0.134)	(0.134)	(0.281)	(0.281)	(0.281)	(0.276)	(0.276)	(0.276)
L.lnAD	0.169***	0.169***	0.169***	0.107*	0.107*	0.107*	0.602***	0.602***	0.602***
	(0.057)	(0.057)	(0.057)	(0.056)	(0.056)	(0.056)	(0.197)	(0.197)	(0.197)
L.lnCapEx	-0.110***	-0.110***	-0.110***	0.047	0.047	0.047	-0.431***	-0.431***	-0.431***
	(0.039)	(0.039)	(0.039)	(0.066)	(0.066)	(0.066)	(0.158)	(0.158)	(0.158)
L.lnBTM	-0.273***	-0.273***	-0.273***	-0.288***	-0.288***	-0.288***	-0.298***	-0.298***	-0.298***
	(0.023)	(0.023)	(0.023)	(0.042)	(0.042)	(0.042)	(0.043)	(0.043)	(0.043)
L.(G=0)	0.057***	0.057***	0.056***	0.059***	0.059***	0.060***	0.088***	0.087***	0.087***
	(0.013)	(0.013)	(0.013)	(0.015)	(0.015)	(0.015)	(0.022)	(0.022)	(0.022)
R^2	0.0179	0.0179	0.0179	0.0147	0.0147	0.0147	0.0443	0.0443	0.0443
N	157,787	157,787	157,787	175,301	175,301	175,301	172,342	172,342	172,342
# of Firms	2,634	2,634	2,634	3,617	3,617	3,617	2,768	2,768	2,768
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample is split into three panels 1950-1985, 1986-2000, and 2001-2010. The response variable is monthly excess returns measured by the monthly returns subtract one-month Treasury bill rates. "IE" stands for Innovation Efficiency, measured by $Ptechs/RD$, $Nselftechs/RD$, and $FCtechs/RD$. Variables are well defined in Table 3.2. "L." stands for the lagged value. $G = 0$ is non-patent firm dummy. Columns (1)-(3) present the estimation results using sample data in the period of 1950-1985 with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using sample data in the period of 1985-2000. Columns (7)-(9) are the panel fixed effect estimation results using sample data in the period of 2001-2010. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

specifications, the estimates in Table 3.14 imply that zero patenting firms performed better than otherwise similar stocks. Interestingly, the estimated coefficients on the interaction term between Innovation Efficiency and patent intensity ($lnIE * ln(PAT/ME)$) are all positive and statistically significant at the 10% level. Particularly, for example, keep patent intensity ($ln(PAT/ME)$) at the value of 0.1, an one percent increase in Innovation Efficiency actually increases excess return around 30 percent of excess return.

As discussed above, the role of Innovation Efficiency in predicting future market value changes over time. Though there is no significant evidence that Innovation Efficiency affects future excess returns over the period 1950-2010, the effect of Innovation Efficiency may vary in different periods. To further examine this, I split the data into three panels–1950-1985, 1986-2000, and 2001-2010– and perform estimations for each period. Different from Section 4, the time periods in this part are not evenly split. The three time periods here are based on Figure 3.3 and 3.5 that excess returns did not change much before 1986 and then surged in the 1990s. All the regressions on these three panels are performed using the method in Equation (3.17). Table 3.15 examines the effect of Innovation Efficiency in the three different periods. Columns (1)-(3) present the estimation results using sample data in the period of 1950-1985 with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using sample data in the period of 1986-2000. Columns (7)-(9) are the panel fixed effect estimation results using sample data in the period of 2001-2010.

Interestingly, although the coefficients on Innovation Efficiency measures are positive during the first period from January 1950 to December 1985, none is distinguishable from zero even at the 10% significant level. The results are consistent with the estimation results I get in Table 3.14 that there is no significant evidence during this particular time window that Innovation Efficiency of firms was earning excess returns. In contrast, an important result to emerge from the panel from January 2001 to December 2010 is the coefficients on Innovation Efficiency measures are all positive and statistically significant.

Innovation Efficiency were a key driver of equity returns during the late 2001-2010. Particularly, an one percent increase in Innovation Efficiency is associated with around 12 percent subsequential monthly excess returns increase. But the results in column (4)-(6) suggest that they had significantly negative effect on excess returns. These results suggest that the effect of Innovation Efficiency is not persistent, it change in different period but it became much stronger in the most recent decades. A further insight into the economic magnitude of the estimates can be gained by the coefficients on patent intensity and R&D intensity. Across the specifications, the estimated coefficients on patent intensity ($ln(PAT/ME)$) are all negative. The estimates imply that one percent increase in patent intensity actually decreases future excess return by 2.3-3 percent. The estimates on R&D intensity in column (1)-(6) imply that R&D intensity had a strong negative effect on excess returns in the early period between 1950 and 1985, and a smaller but still strong negative effect during 1986-2000. However, there is no evidence of a significant effect in the late period 2001-2010. Interestingly, the estimated coefficients on $G = 0$ in Table 3.15 imply that zero patenting firms performed better than otherwise similar stocks. Across the specifications, the estimates imply that zero patenting firms better performed otherwise similar stocks by 6-8 percent during the whole sample period.

These results indicate that Innovation Efficiency provides incremental value-related information. In contrast, patent intensity and R&D intensity have significant negative effect on future excess return. These results also indicate that the explanatory power of Innovation Efficiency is distinct from other commonly known return predictors and innovation-related variables such as patent intensity and R&D intensity.

3.5 Conclusion

Does innovation induce the U.S. stock market to appreciate? The results presented in this paper suggest that the answer is yes at some points. Different from previous literature on innovation and stock returns that only focus on the innovation inputs (R&D or R&D intensity) or outputs (patents or citations), this paper proposes a new innovation-related variable, Innovation Efficiency, that combines the breadth of knowledge used to innovate and R&D investments. The paper introduces three measures of Innovation Efficiency: technology fields of granted patents per patents scaled by R&D expenditures, technology fields of non-self citations per patent scaled by R&D expenditures, and technology fields of citations received in previous five years per patent scaled by R&D expenditures. A central finding is that the Innovation Efficiency conveys important information about changes in stock market value, operating performance, and excess returns, no matter which measure is used to identify the Innovation Efficiency. The results suggest that investors were sophisticated in their market pricing decisions. The positive effect of Innovation Efficiency becomes larger as time change from 1950 to 2010 and as firms move from low-technology industries to high-technology industries.

In contrast, the changing market value of innovation quantity measured by patent intensity or R&D intensity was not a key explanatory factor. Particularly, patent has significantly negative effect on market value, operating performance, and excess returns. R&D intensity has strong and significantly negative effect on market value and excess returns, but has significantly positive effect on operating performance. These findings are not aligned with the literature that patent intensity (or citation intensity) and R&D intensity are the key driven of market value increases. The negative relation between innovation quantity and future market valuation is also robust to a variety of controls, for different time periods, and for different technology level industries.

This paper further find that high Innovation Efficiency firms, on average, experience higher subsequent market value, operating performance, profitability, and excess returns through the effect of productivity. These findings are consistent with the intuition that higher Innovation Efficiency indicates higher probability of success in creating unique and superior products or new product lines, which increase firm's productivity competitive advantage and allow firms to charge a price premium and maintain sustainable higher market value. Innovation Efficiency reflects the capability of a firm's managers and scientists in effectively combining technologies from various knowledge domains to create new products or product lines that are difficult for competitors to match.

There are several directions this work could be taken. First, it is necessary to investigate more deeply the impact of innovation on stock returns, especially the portfolio approaches. Second, it would be valuable to complement the U.S. stock markets analysis with a similar exercise for other countries. In particular, China has experienced a much more dramatic increase in innovation in recent years; countries which are technologically closer to the US may also be worthy of study. Third, the endogenous production-based asset pricing model should be improved and modified.

CHAPTER 4. POLICY UNCERTAINTY, INNOVATION, AND FIRM ENTRY AND EXIT UNDER OPEN ECONOMY – THEORY AND EVIDENCE FROM CHINESE FIRMS

This study is divided into theoretical and empirical components, each of which examines the impact of policy uncertainty on firm level innovation, and entry and exit decisions. In the theoretical portion of the paper, I introduce a dynamic general equilibrium growth model with policy uncertainty where policy uncertainty endogenously affects the dynamics of technical change, market leadership, firm entry and exit selection, and trade flows, in a world with two large open economies at different stages of development. The theoretical investigation illustrates that increase in policy uncertainty has significant negative effect on exports and imports, but has ambiguous effects on innovation and welfare, while dynamically, trade liberalization boosts domestic innovation through induced international competition. In the empirical portion, the paper studies how policy uncertainty affect innovation and firm decisions to enter into and exit from export markets by estimating the impact of trade policy uncertainty on patents applied by Chines manufacturing firms, as well as firm's entry and exit. Using Chinese patent applications and Chinese customs transactions between 2000-2006, this paper exploit time-variation in product-level trade policy and the empirical results show that: (i) Chinese firms have less incentive in innovation activities when facing increased trade policy uncertainty; (ii) Chinese firms are less likely to enter new foreign markets when their products are subject to increased trade policy uncertainty; (iii) Chinese firms are more likely to exit from established foreign markets when policy uncertainty increases.

4.1 Introduction

When reading newspaper or watching TV news in recent days, you may find it is interesting that lots of reports contain discussion of trade policy, trade war, and future uncertainty of international markets. After a long time of free trade liberalization, it has been a time that free trade is not as secure as previously thought. Over the last few years since President Trump won the election,the trade dispute escalated between the US and the rest of the world, especially with China. The United States has pulled out of the Trans-Pacific Partnership (TPP), resigned the North American Free Trade Agreement, imposed tariffs on variety of goods from China, Japan and Europe that value billions of dollars, and triggered a trade war with China. The United States imposed 25% tariff on $34 billion of U.S. imports from China in July 2018 and then extend to another $16 billion imports in August 2018 and $200 billion imports in May 2019 in response to Chinese retaliatory tariffs. Table 4.1 below summarized the main trade affairs related to the US since 2017.

Table 4.1: Main Trade Affairs Since 2017

Date	Trade Policy-related Action	Related Countries
23-Jan-17	Withdrew from the TPP	Japan, Canada, etc
27-Apr-17	Tax reduction act	United States
2-Jun-17	Withdrew from the Paris Agreement	All countries
19-Aug-17	Announced start of Section 301 investigation of China	China
1-Jun-18	Increased Steel tariff to 25%	All countries
1-Jun-18	Increased Aluminum tariff to 10%	All countries
6-Jul-18	Totaling $34 billion of products with a tariff of 25%	China
23-Aug-18	Totaling $16 billion of products with a tariff of 25%	China
27-Aug-18	New NAFTA agreements with Mexico	Mexico
24-Sep-18	Imposed 10% tariffs on $200 billion of U.S imports from China	China
1-Dec-18	Announced new negotiations with China to resolve U.S. concerns	China
17-Jan-19	India Retaliatory Tariffs on nuts and 27 goods of US origin	India
10-May-19	Increased 20% tariffs on $200 billion of U.S imports from China	China
13-May-19	China announced increase tariffs on $60 billion imports from U.S.	China
22-Jun-19	EU imposed %25 tariff on $2.8 billion imports from U.S.	European Union
1-Sep-19	Imposed 15% tariffs on $300 billion of U.S. imports from China	China
6-Dec-19	Proposed 100% tariffs on French digital service products.	France
15-Jan-20	United States and China sign Phase One deal	China
27-Jan-20	Addition of 232 tariffs to Derivative Articles of Steel and Aluminum	All countries

Increasing trade negotiations and proposals result in an increase in uncertainty about the future and the outlook for international trade. In the past decades, there was limited uncertainty in trade policy and uncertainty has been trending upwards since President Trump's campaign was announced in 2015. Compared to history, trade policy uncertainty has reached a particularly high levels since 2015 (Caldara et al., 2020; Baker et al., 2016). Figure 4.1 presents the historical trend of trade policy uncertainty based on a news-based index. As is shown in the figure, we are experiencing a dramatic rise in overall trade policy uncertainty since 2017. These and related developments drove a tremendous upsurge in anxiety and uncertainty about trade policy and its economic fallout. Since 2017, the trade policy uncertainty index increased above 200, reached an initial high in the first half of 2018 (first wave), and, after subsiding, reached a new peak in the first half of 2019. There was widespread fear of protectionism following the election in 2016.

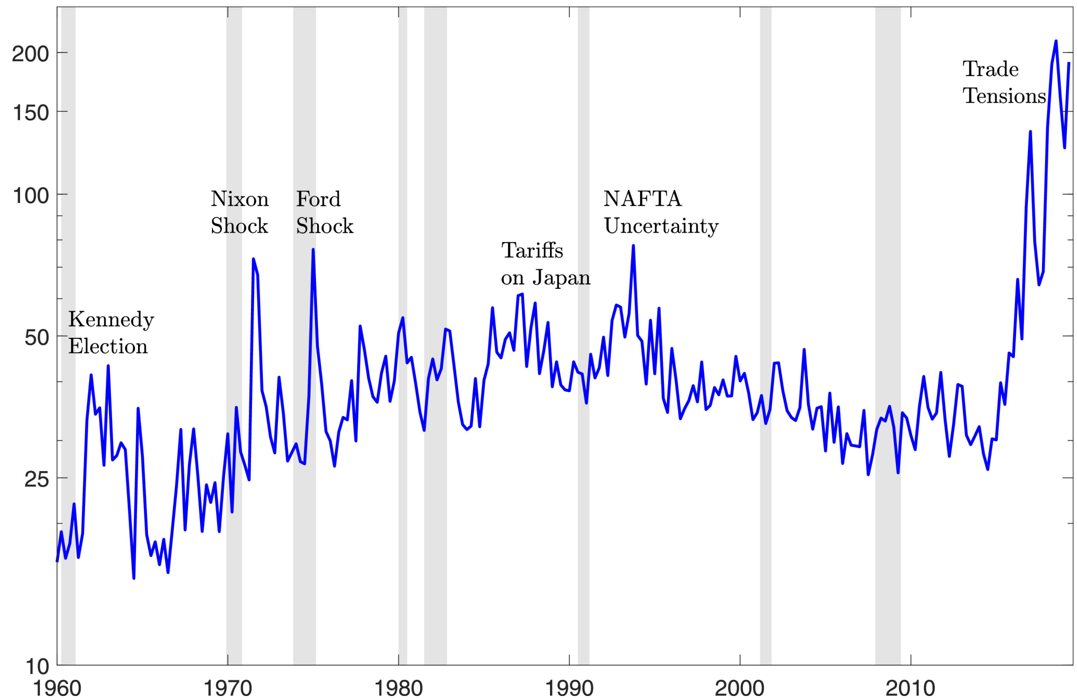


Figure 4.1: News-Based Index of Aggregate Trade Policy Uncertainty [1]

Note: The data is from Caldara et al. (2020), trade policy uncertainty is news-based and extending through 2019Q2. A value of 100 indicates that 1% of all newspaper articles discuss trade policy uncertainty. The vertical gray areas represent NBER recession dates. The y-axis represent the value of trade policy uncertainty.

In classic trade models, trade policy is assumed to be exogenous and in static. Most theoretical and empirical trade research focuses on trade policy inviolable. However, growing evidence suggests that trade policy is not in static and that policy-related economic uncertainty matters for firms' investment (Handley and Limo, 2015; Gulen and Ion, 2016; Kost, 2019), R&D (Luke and Stone,

[1]The measure of trade policy uncertainty is based on searches of newspaper articles that discuss trade policy uncertaintyin seven newspapers: Boston Globe, Chicago Tribune, Guardian, Los Angeles Times, New York Times, Wall Street Journal, and Washington Post. The aggregate measure represents the monthly share of articles discussing trade policy uncertainty which was indexed to equal 100 for an article share of 1%. Please refer to Caldara et al. (2020) for details.

2010), and labor dynamic (Baker et al., 2016; Handley and Limo, 2017; Caliendo et al., 2019). Emerging evidence suggests that policy uncertainty plays a key role in firm's decision to invest and export to new markets because firms must incur sunk costs to start exporting and when uncertainty increases firms do not invest and wait until uncertainty is resolved (Handley, 2014; Handley and Limo, 2017; Caliendo et al., 2019). Although a growing literature has examined various empirical links between policy uncertainty and firms' investment, R&D, and employment, few studies explore how policy uncertainty affects firms' investment in innovation, exporting decision, and social welfare.

Innovation plays an important role in promoting long-term economic growth (Acemoglu et al., 2018). In a open economy, innovation improves firm's productivity and goods quality and as such promoting competitive advantage and exports (Akcigit et al., 2018). However, firms' innovation decisions are partially depended on policies because politicians make policy and regulatory decisions that affect the economic environment in which innovative firms operate (Bhattacharya et al., 2017). Innovation demands large amount of irreversible investment in advance and it takes relative long time to commercialize. Changing policies and regulations causes future economic environment uncertain and reduce innovation investment. Trade liberalization largely removes policy uncertainty and make future market conditions more transparent and predictable, and therefore encourages firms to invest in innovation. Existing studies show that policy uncertainty adversely affects investment (Gulen and Ion, 2016) and technological innovation (Bhattacharya et al., 2017). As is shown in Figure 4.2, the aggregate trade policy uncertainty index and average number of applied patents move consistently but with a obvious negative relationship.

Starting from Bernanke (1983), various research show that firms become cautious and hold back on investment in face of uncertainty when investment projects are not fully reversible (Bloom et al., 2007; Gilchrist et al., 2014). Firms choose to wait because the value of the option to wait increase with policy uncertainty. Given that innovation requires considerable irreversible investment, the value of the option to wait is important for innovation in an uncertain political environment.

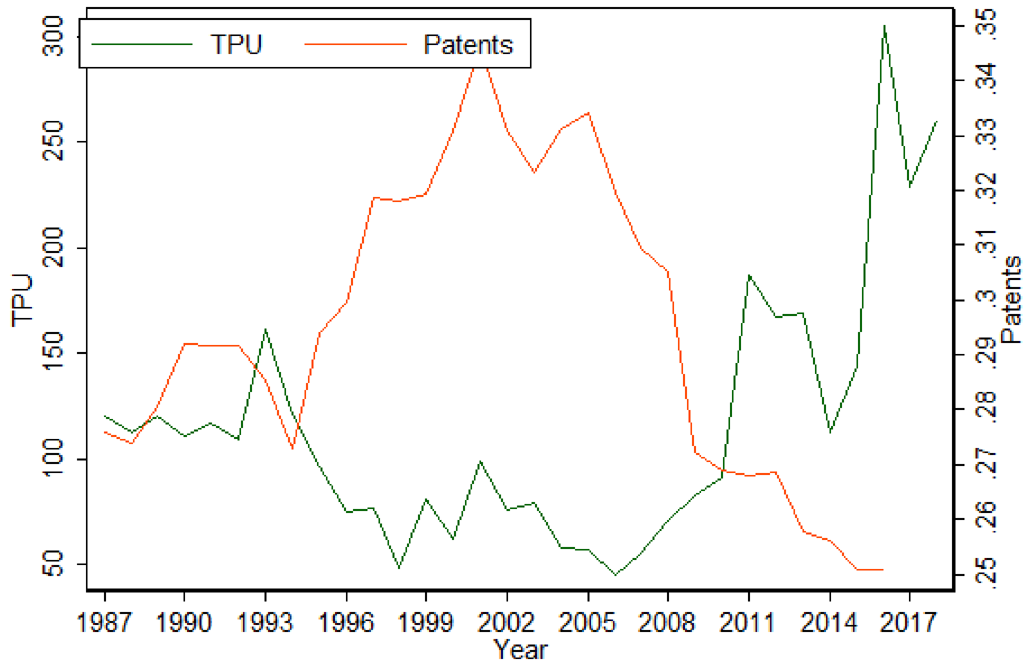


Figure 4.2: News-Based Index of Aggregate TPU and Average Patent Counts

Note: Trade policy uncertainty (TPU) data is from Caldara et al. (2020). The generating process of TPU is discussed in details above. Patent data is from Kogan et al. (2017). Patents is measured by number of patents applied in the US each year divided by number of firms observed in Compustat. Because lots of firms do not have any patents in some years, the average number of applied patents is relatively small.

Reducing policy uncertainty may encourage incumbents to undertake grater investments under certain economy, increase productivity, and protect employment (Acemoglu et al., 2018).

In this paper, I develop a model of international trade economy with policy uncertainty and innovation. The basic idea of the model is that policy uncertainty causes risks and loss in intermediate goods production and hence affects firms' profit. Firms reduce investment in innovation due to production profit deduction. Less R&D investment prohibits productivity progress and goods' quality improvements, and induces a larger decrease in innovation profit and production profit. Further more, entrants observe policy uncertainty and suspend their entry decision till policy is finally announced or withdraw. To compensate this risk spillover, firms increase prices and hire less skilled and unskilled labor. Welfare drops as wage decrease and price increases.

The two-country dynamic endogenous growth model suggests that firms from the two countries compete in intermediate-good production and have same production technology in final-good production. Final goods are used for consumption, inputs of intermediate goods production, and inputs of innovative activities. Final goods are freely traded between the two countries. While intermediate good is only used in final good production and can be import from or export to the other country. Import and export are depend on the relative quality of intermediate good in home and foreign country. Each intermediate good has two active firms, one from each country, and several potential entrants. The two incumbents compete in price and the winner will earn the whole market. Export firms pay iceberg costs and tariffs in order to trade intermediate goods. There is no trade in assets, or there is no international borrowing and lending and no financial constraints.

Firm that produces higher quality intermediate goods has relative price advantage after adjusting trade cost. To acquire price advantage, incumbents in both countries invest in innovation and hence improve product quality or get new product lines. Once the quality difference of two firms is large enough, then the firm with better quality can cover the trade cost and export to the foreign country and the foreign firm is supplanted by the exporter. Intermediate firms differ in terms of their innovative capacities which are exogenously determined. In addition to trade in intermediate goods, technology can diffusion through international knowledge spillovers, which is called trade in ideas. Besides incumbent firms, there is a pool of several entrant firms that also invest in innovation based on current and future policies. Once entrant deciding investing in R&D, it has a chance to replace the domestic incumbent in a particular product line or own a new product line. Policy uncertainty affects entrant's decision and also incumbent's exporting decision.

Innovation is achieved step-by-step following Acemoglu et al. (2018). Innovation determines the dynamics of technology and global market leadership. Leader firm has an incentive to move away from the follower in domestic and foreign market in order to escape competition. Incumbents and entrants hire skilled labor to perform innovation. Successful innovation enables a firm to take over a leading-edge technology from existing firm. Firms have heterogeneous high and low types, which determine their innovative capacity. High-type firms may change to low-type hitting by an exogenous shock. This kind of selection effect allows firm dynamic and promote firms to innovation to keep their product lines.

For import and export in country c, there are two cutoffs, import cutoff and export cutoff. The import cutoff and export cutoff are depended on the relative quality of domestic intermediate goods to foreign counterpart. Specifically, when the quality of domestic intermediate goods in country c is relatively inferior comparing to foreign, final-good producers in country c decide to import intermediate goods, which determines country $c's$ import cutoff. Likewise, foreign final-good producers import intermediate goods from country c if the relative quality of domestic intermediate goods in country c is above a certain threshold, which determines country $c's$ export cutoff.

Comparing to deterministic economy, policy uncertainty increases firm's option value of waiting. Only firms with high quality goods will choose to enter the foreign market because their option value of waiting is relatively lower than their entry value. Policy uncertainty also decrease foreign market competition and increasing markups. Increasing markups in turn allow less productive firms enter the domestic market,reallocating resources from exporter towards domestic surviving firms, increasing domestic firms' average size and aggregate productivity. Although exporting firms exit foreign market as policy uncertainty increases casing reduction in those firm's innovation, the increase number of surviving firms in domestic market stimulates cost-reducing innovation thereby leading to faster productivity growth. Finally, firm selection of exporting involves potential welfare losses since exit reduces the number of varieties available to consumers and more low productivity firms enter domestic market actually decreases the average productivity.

Specifically, when foreign country decides to increase its import tariff on intermediate goods from country c, final-good producers in country c must pay a higher cost in order to get intermediate goods aboard. Policy uncertainty adds additional trade cost and only when goods quality in foreign country is high enough and above a certain threshold that can trigger imports. Import quality cutoff under policy uncertainty is higher than deterministic economy. Likewise, under policy uncertainty foreign final-good producers import intermediate goods from country c only if the relative quality of domestic intermediate goods in country c is high enough. Below the import cutoff, domestic firms exert additional effort to gain leadership in the home market. Lower import cutoff promotes more entries and innovation by entrants. When a domestic firm is just below the export cutoff, it exerts additional effort to improve its lead and conquer the foreign market. As such, higher export cutoff encourage domestic firms invest more innovation.

To empirically investigate the impact of policy uncertainty on innovation and firm decisions to enter into and exit from export markets, I embody five major data sources: patent data from the State Intellectual Property Office (SIPO) of China, firm-level production and financial information from the Annual Survey of Industrial Production (ASIP), firm-level export data from the Chinese Customs Database, trade policy data from the Global Antidumping Database (GAD), and macroeconomic data on real GDP and real exchange rates from the World Bank's World Development Indicators and the USDA Economic Research Service, respectively. The sample period is set to be 2000-2006 around innovative firms that are in operation. The combination of these data sources permits us to study the impact of policy uncertainty on innovation and firms' entry and exit selection.

Trade policy uncertainty in this research is premised on an important feature of antidumping duties. Antidumping duties in one country can be used to identify an increase in trade policy uncertainty for the same product in other countries because the application of antidumping duties is correlated over time across foreign markets. Antidumping policy occur rarely, but if one importing country changes its policy, there is increased probability of a future tariff hike on the same product in other markets around the world. Uncertainty about the tariff rate of a product increases when an antidumping duty is imposed on that product somewhere in the world.

For firms' innovation activities, the empirical results show that increased policy uncertainty significantly decreases patent applications: one percent increase in policy uncertainty is associated with roughly an average of 1.5 percent decrease in the number of patent applications by Chinese firms. The overall effect of increasing market uncertainty is sizeable even when we introduce heterogenous effects with exporters to the U.S and time-varying specifics. The results imply that increases in policy uncertainty induces less domestic innovation. The negative impact of policy uncertainty on innovation is stable and significant.

Turning to firms' decisions on entry and exit, I define Entry as when a firm is observed exporting to: (1) a new country with existing product, (2) a new country with a new product, or (3) an existing country with a new product. Similarly, exit is defined when a firm is observed stop export to: an existing country, or an existing country with one or more products. For entry, the empirical results show that increased uncertainty about the future tariff rate in destination h reduces participation in exporting activity. Entry into foreign markets declines as policy uncertainty increases. There is a average of 3.3 percentage point decline in the entry for manufacturing firms and a average of 3.4 percentage point decline in entry for trading firms. The threat of a tariff hike reduces the probability of entry by 20 percent (3.3/16.5) for manufacturing firms and 58.7 percent (3.4/5.79) for trading firms.

For firms' exit decisions, estimation results show that increased uncertainty about the future tariff rate in destination h increases exits from existing exporting market. Exit from existing foreign markets increases as policy uncertainty increases. We see that there is a average of 2.3 percentage point increase in the exit for manufacturing firms and a average of 4.3 percentage point increase in exit for trading firms. The threat of a tariff hike increases the probability of exit by 11.4 percent (2.3/20.1) for manufacturing firms and 15.6 percent (4.3/27.6) for trading firms. The impact of a tariff threat on market exit is substantial. As such, policy uncertainty shows a larger effect on trading firms. These estimates also show that Chinese firms use information about policy changes in market h and historical use of antidumping policy in other markets to update their beliefs about future trade policy changes in other markets. Firms then act on this updated information through their entry decisions.

The rest of the paper is as follows. Section 4.2 summarize the related literature. Section 4.3 presents the model. Section 4.4 describes the data and quantitative framework. Section 4.5 provides quantitative results. The last section concludes the paper.

4.2 Literature Review

This research is related to several strands of literature related to innovation, policy uncertainty and trade. The endogenous growth model with step-by-step innovation under open economy that used as the framework is originally steamed from Aghion et al. (2001, 2005, 2009). Acemoglu et al. (2018) extend the firm innovation and dynamic model to feature endogenous exit and innovation capacity heterogeneity. These closed-economy models are solved in steady state. Akcigit et al. (2018) extend the endogenous innovation model to open economy and introduce free entry to study the role of innovation in open economies and the gains from globalization. I extend their model to introduce policy uncertainty and firm selection, solve for its transition path, and provide a quantitative exploration of the role of policy uncertainty in innovation and the gains from trade.

Following Melitz (2003), the trade model in this research the trade analyzes the impact of trade exposure on aggregate productivity with heterogeneous firm productivities. The structural general equilibrium framework in this research incorporates several forces, such as competition and market size. The impact of those forces on firm innovation is highlighted by lots of empirical work that focuses on the relationship between innovation and trade by (Bustos, 2011; Iacovone, 2012; Autor et al., 2016; Chen and Steinwender, 2019). Bloom et al. (2016) use the Chinese import data from 12 European countries and show that increase of Chinese import has a positive effect on the technical change in those European countries. Aghion et al. (2018) examine the differential impact of market size and competition effects on innovation using French exporting firms data based on a heterogeneous productivity open economy model. Their results indicate that the market size effect is the major force of innovation from firms that have hiher productivity at times of increased demand. Cameron et al. (2005) provide empirical evidence that technical change or firm innovation is the sources of productivity growth. Aghion et al. (2005) show that competition promotes innovation but the effect changes as competition intensifies and resulting in an "inverted U shape" relationship between competition and innovation. This research contributes to this literature by formalizing and quantifying a new theory of endogenous firm decisions under policy uncertainty and open economy.

This research also makes a novel contribution to the understanding of the impact of trade on firms' innovation. Pioneering research by Grossman and Helpman (1991); Grossman and Lai (2004) emphasizes technology transfers embodied in products imported by developing countries. A growing research show that international trade can promote innovation by either intensifying competition or extensive access to foreign markets based on firm level data. Bloom et al. (2016) use China's exporting and European importing data and find that import competition from China largely induced the technical changes of firms in European countries, in terms of number of patents, information technology and total factor productivity. Boler et al. (2015) use the firm level data and show that imported intermediates may complement investment in R&D, so improved access to imported inputs promotes innovation and technical change. Bustos (2011) use the Argentina exporting firm level data and point out that increased export sales due to trade integration can promote exporting firms investment in R&D and upgrade technology. However, Liu and Qiu (2016) find decrease import tariff may discourage indigenous innovation by Chinese exporters. Similarly, Coelli et al. (2016) provide evidence that trade liberalization encourages firms' investment in R&D in terms of patent filings using an ex ante variations in firms' exposure to different markets. However, this work differs because we focus on trade policy uncertainty and its impact on firm innovation.

This research is also related to a line of research that tackle the hard task of quantifying the role of firm's innovation decisions in shaping policy-induced aggregate dynamics and these dynamic gains (Rivera-Batiz and Romer, 1991; Grossman and Helpman, 1991). For example, Perla et al. (2015) show that opening to trade increases the profit spread through increased export opportunities and foreign competition, induces more rapid technology adoption and generates faster growth. In a recent research by Buera and Oberfield (2020), they provide evidence that both gains from trade and the fraction of variation of total factor productivity (TFP) growth accounted for by changes in trade more than double relative to a situation without diffusion. Similarly, Sampson (2016) develop an idea flows theory of trade and growth with heterogeneous firms and show that dynamic selection is a new source of gains from trade that selection causes technology diffusion, and this dynamic selection process leads to endogenous growth without scale effects. Impullitti and Licandro (2018) study gains from trade in a model of heterogeneous productivity firms and find that accounting for firm's innovation responses doubles the gains from trade obtained from the static competition and selection channels. Burstein and Melitz (2011) discuss the effects of trade liberalization on firms dynamics and analyzes various extensions of the Melitz (2003) framework. They show that firms' innovation responses determine transitional dynamics induced by trade liberalization. This work contributes to this strand of literature by emphasizing the role of policy uncertainty in shaping innovation responses and the dynamic gains from trade.

This work also contributes to the increasing attention on the impact of policy uncertainty. The pioneering work by Baldwin and Gu (2004) adopts a real options approach to explain the impact of policy change on trade during large swings in the exchange rate. In a series of studies, Handley (2014); Handley and Limo (2015, 2017) emphasize the uncertainty induced by trade policies and examine its impact on trade, investment, and welfare. They find that in a dynamic model with sunk export cost, trade policy uncertainty decreases firms' export investment while trade agreements increase trade and investment even if current tariffs are low. Reduction of trade policy uncertainty increases export, lowers prices and increases consumers' income. Similarly, Gulen and Ion (2016) use a news-based index of policy uncertainty and find that firm-level capital investment and the aggregate level of uncertainty are strongly negative related.

Feng et al. (2016) use a firm-product level dataset on Chinese exports to the US and the European Union to examine the effect of trade policy uncertainty on firm export decisions. They provide strong evidence that reduction in trade policy uncertainty induced firm entries and exit dynamics. A recent research by Liu and Qiu (2016) show that trade liberalization may encourage firm innovation in terms of patent applications by largely removing policy uncertainties in the destination market. Following the same approach, Pierce and Schott (2016) link the sharp drop in U.S. manufacturing employment to changes in U.S. trade policy that removed the tariff uncertainty on Chinese imports. Their results indicate that industries with more exposure to the policy change experienced a greater loss in employment. Recent research by Chen and Steinwender (2019) show that Chinese cities experiencing a larger increase in their exports to the US due to trade policy reduction, and therefore promoting growth in population, output, and employment.

4.3 Model

This section introduces the theoretical framework under international trade economy with policy uncertainty and innovation. The basic idea of the model is that policy uncertainty causes risks and loss in intermediate goods production, and hence affects firms' profit. Firms reduce investment in innovation due to production profit reduction. Less R&D investment inhibits productivity progress and goods' quality improvements, and induces a larger decrease in innovation profit and production profit. Furthermore, entrants observe policy uncertainty and suspend their entry decision until policy is finally announced or withdraw. To compensate this risk spillover, firms increase prices and hire less skilled and unskilled labor. Welfare drops as wage decrease and price increases.

The model is mainly based on Acemoglu et al. (2018), which investigates how innovation affects labor reallocation and economic growth in a closed economy. This model extend their research to an open economy with policy uncertainty. Akcigit et al. (2018) also develop a model which embodies innovation in Acemoglu et al. (2018) under multiple countries open economy without policy uncertainties. Handley and Limo (2017) introduce a simple policy uncertainty model in a open economy. In their model, the only uncertainty is caused by trade policy, in other words tariffs, and there is no innovation and goods quality improvement. It shows how policy uncertainty affects firms entry decision into the foreign market. My model follows their assumption of policy uncertainty, but extends to a wider dimension with innovation uncertainty.

To simplify, I only consider two countries, indexed by $c \in \{A, B\}$. Firms from the two countries compete in intermediate-good production and have the same technology in final-good production. Final goods are used for consumption, inputs of intermediate goods production, and inputs of innovative activities. Final goods are freely traded between the two countries, whereas the intermediate good is only used in final good production and can be imported from or exported to the other country. Imports and exports depend on the relative quality of the intermediate good in the home and foreign countries. Each intermediate good has two active firms, one from each country, and several potential entrants. The two incumbents compete in price, and the winner earns the whole market. Export firms pay iceberg costs and tariffs in order to trade intermediate goods. There is no trade in assets, there is no international borrowing and lending, and no financial constraints.

The firm that produces higher quality intermediate goods has a relative price advantage after adjusting for trade costs. To acquire a price advantage, incumbents in both countries invest in innovation and hence improve product quality or get new product lines. Once the quality difference of two firms is large enough, the firm with better quality can cover the trade cost and export to the foreign country and the foreign firm is supplanted by the exporter. Intermediate firms differ in terms of their innovative capacities which are exogenously determined. In addition to trade in intermediate goods, technology can diffuse through international knowledge spillovers, which is called trade in ideas.

Besides incumbent firms, there is a pool of several entrant firms that also invest in innovation based on current and future policies. Once an entrant decides to investing in R&D, it has a chance to replace the domestic incumbent in a particular product line or own a new product line. Policy uncertainty affects entrant's decision and also incumbent's exporting decision.

4.3.1 Preferences

Assume the economy is in continuous time. In each country, utility of a representative household follows the CRRA form which is defined as

$$U_{ct} = \int_t^{\infty} e^{-\rho(s-t)} \frac{C_{cs}^{1-\sigma} - 1}{1-\sigma} ds \tag{4.1}$$

where C_{cs} is household's consumption at time t in country $c \in \{A, B\}$, $\sigma > 0,\ \ \sigma \neq 1$ is the degree of relative risk aversion that is implicit in the utility function, and $\rho > 0$ is the discount rate. Aggregate consumption is given by

$$C_{ct} = \left(\int_{\Omega_{ct}} c_{cjt}^{\frac{\nu-1}{\nu}} dj \right)^{\frac{\nu}{\nu-1}} \tag{4.2}$$

where c_{cjt} is the consumption of product j at time t in country c, $\nu > 1$ is the elasticity of substitution between products, and $\Omega_{ct} \subset [0,1]$ is the set of active product lines at time t in country c. The aggregate consumption is set to be the numeraire.

The representative household in country c at time t maximizes her utility (4.1) subject to the flow budget constraint

$$\dot{A}_{ct} + P_{ct}C_{ct} + G_{ct} \leq r_{ct}A_{ct} + L^S_{ct}w^S_{ct} + L^U_{ct}w^U_{ct} \tag{4.3}$$

where P_{ct} is the aggregate price index of the consumption good in country c at time t, G_{ct} is the lump-sum taxes/transfers in country c, and r_{ct} is the return to asset holdings of the household.

There are two types of labor in each country, skilled (total labor supply denoted as L^S_{ct}) and unskilled (total labor supply denoted as L^U_{ct}). Unskilled workers are used in the production of the intermediate products. Assume the representative household has 1 unit of unskilled labor supply and both types of labor are supplied inelastically. Skilled workers are used in performing innovation (total labor demand is L^I_{ct}). w^U_{ct} and w^L_{ct} denote unskilled and skilled wages in country c at time t, respectively. The labor market-clearing condition for each type of labor in country c at time t is

$$L^U_{ct} = 1 \;\text{ and }\; L^I_{ct} = L^S_{ct}$$

Households in each country own all the firms in the country, therefore, the asset position of the representative household is equal to the sum of firm values

$$A_{ct} = \int_{\Omega_{ct}} (\tilde{V}_{cjt} + V_{cjt})dj$$

where $\tilde{V}_{cjt}$ denotes values of entrant firms (in the following parts, tilde "$\sim$" denotes entrant firms) and the usual non-Ponzi condition is satisfied

$$\int_0^\infty e^{-r_{ct}t}A_{ct}dt \geq 0$$

4.3.2 Final Good Production

Final goods are used for consumption, inputs of intermediate goods production, and inputs of innovative activities. Final goods production is perfectly competitive in both countries. Both countries have the same technology in final good production. For country c, the final goods production function is denoted as:

$$Y_{ct} = L_{ct}^{U\,\beta} \int_{\Omega_{ct}} \left(\varphi_{cjt} q_{cjt}^{1-\beta} + \varphi_{c'jt} q_{c'jt}^{1-\beta} \right) dj \tag{4.4}$$

where $c,\ c' \in \{A, B\}$, q_{cjt} refers to the inputs of intermediate good from country j at time t, φ_{cjt} is the quality (productivity) of intermediate good j, $\beta \in (0,1)$ is the share of unskilled labor in final good production. Intermediate goods can be obtained from any country, while labor is assumed to be immobile across countries but mobile within country. As discussed above, the supply of unskilled labor is normalized to be $L_{ct}^U = 1$ in both countries.

Each intermediate good j may be produced in both countries. In a closed economy, final goods producers in country c can only use their own domestic intermediate good cj, whereas in an open economy with no trade cost intermediate firms in the two countries are perfectly competitive and a final good producer can choose to use intermediate inputs from any country. In an open economy with frictions, final-good producers will choose to buy their inputs from the firm that offers a higher quality with lower prices after being adjusted by the trade costs. Both countries have the same technology in final good production, which implies that the price of final good in both countries must be identical. Without loss of generality, I normalize the price of the final good to be the numerative. Similarity, the price index of consumption is also normalized to be the numerative ($P_{ct} = 1$).

4.3.3 Intermediate Good Production

Intermediate good j is potentially produced by two incumbent firms, one from each country. The two incumbent firms compete via Bertrand model and have the same marginal cost of η. However, in each country, intermediate good j is produced by a monopolist who has the best technology in that product line, whereas one firm can own multiple product lines and can produce multiple intermediate goods simultaneously.

In addition, there are two different sets of firms in each country at any given point at time t: (i) a set of active firms $\mathcal{F}$ that own at least one product line and investment in R&D to get access to a new product line or improve the quality of a particular variety; and (ii) a set of potential entrants of measure 1 that do not currently own any product line but invest in R&D to enter the market.

Firms differ in terms of their innovative capacities and their output quality, φ_{cj}. Home country A has higher quality in product line j at time t if $\varphi_{Ajt} > \varphi_{Bjt}$ and has lower quality in product line j if $\varphi_{Ajt} < \varphi_{Bjt}$. Firms are in a neck-and-neck position in two countries if $\varphi_{Ajt} = \varphi_{Bjt}$

Once a firm successfully enters into the economy, it draws its type $\mu \in \{\mu^H, \mu^L\}$ from two possible types of high (H) and low (L), where $\mu^H > \mu^L$ indicates high type firms have higher productivity in innovation. Assume the probability of the high type is:

$$Pr(\mu = \mu^H) = \theta$$

where $\theta \in (0, 1)$. Respectively, the probability of low type is $Pr(\mu = \mu^L) = 1 - \theta$. While firms' types are exogenously determined and low-type firms cannot transfer to high type, high-type firms may be affected by exogenous shocks and transition to low-type. Assume the probability of such exogenous shocks happening is ϵ. In addition to the exogenous shock that transform high-type firms to low type, each firm is also subject to an exogenous destructive shock: once a firm hit by the shock, it exits the market and its value falls to zero. Assume the flow rate of the exogenous destructive shock is ξ.

4.3.4 Innovation

Incumbents and entrants can invest in innovation. For incumbents, firm j in country c with innovative capacity type $\mu_{cjt} \in \{\mu^H, \mu^L\}$ hires h_{cjt} skilled workers to improve the quality of product line j at time t based on the current quality level φ_{cjt} for keeping its leadership in that product line. The arrival rate is a function of the current quality level, innovation capacity, and skilled workers:

$$X_{cjt} = \varphi_{cjt}^{\alpha}(\mu_{cjt}^{1-\beta} h_{cjt}^{\beta})^{1-\alpha} \tag{4.5}$$

where $\alpha \in (0, 1)$ is the share of knowledge stock (or current quality) in innovation production, φ_{cjt} is the current quality of product line j at time t, $\mu_{cjt} \in \{\mu^H, \mu^L\}$ is the firm's innovation capacity, and h_{cjt} is the skilled labor input in innovation production. Innovation requires the input of skill labor, which is the only resource of cost. As such, innovation cost is the total wage paid to the skilled labor, i.e $w_{ct}^{S} h_{cjt}$ for a specific product line j. The corresponding cost function for R&D is denoted as

$$C(X_{cjt}, \varphi_{cjt}, \mu_{cjt}) = w_{ct}^{S} h_{cjt} = w_{ct}^{S} X_{cjt}^{\frac{1}{(1-\alpha)\beta}} \varphi_{cjt}^{-\frac{\alpha}{(1-\alpha)\beta}} \mu_{cjt}^{-\frac{1-\beta}{\beta}} \tag{4.6}$$

Define $x_{cjt} = \frac{X_{cjt}}{\varphi_{cjt}}$ as the "innovation intensity" or innovation effort per product. The total innovation cost (4.6) can be computed as

$$C(x_{cjt}, n_{cjt}, \mu_{cjt}) = w_{ct}^{S} \varphi_{cjt}^{\frac{1}{\beta}} x_{cjt}^{\frac{1}{(1-\alpha)\beta}} \mu_{cjt}^{-\frac{1-\beta}{\beta}} = w_{ct}^{S} \varphi_{cjt}^{\frac{1}{\beta}} S(x_{cjt}, \mu_{cjt}) \tag{4.7}$$

where $S(x_{cjt}, \mu_{cjt}) = x_{cjt}^{\frac{1}{(1-\alpha)\beta}} \mu_{cjt}^{-\frac{1-\beta}{\beta}}$ is the skilled workers required by a firm with innovative capacity μ_{cjt} to achieve an innovation arrival rate of x_{cjt} per product.

Assume firms do not know which product line they can success in innovation, meaning that firms do not know in which particular product they should invest. Firms invest in innovation across all product lines and the expected return to innovation is the expected value across all product lines $j \in [0, 1]$

When a firm in country c innovates over a product line j, it may improve the quality of this product line j by $\lambda^{m_{cjt}} \bar{\varphi}_c$ during an interval of time Δt, that is,

$$\frac{\varphi_{cj(t+\Delta t)}}{\varphi_{cjt}} = \lambda^{m_{cjt}} \bar{\varphi}_c \tag{4.8}$$

where $\lambda > 0$, $m_{cjt} \in \mathcal{N}$ is potential number of quality jumps during time period Δt on product line j, and

$$\bar{\varphi}_c = \int_0^1 \varphi_{cj} dj$$

is the average quality over all product lines in country c. Assume that initially $\varphi_{cj0} = 1, \forall j \in [0, 1]$ for any product line j in country c. Without loss of generality, assume $\bar{\varphi}_c = 1$ for country $c \in \{A, B\}$. Hence, the quality of a firm at time t in country c is

$$\varphi_{cjt} = \lambda^{\int_0^t m_{cjs} ds} \bar{\varphi}_c^{t} = \lambda^{M_{cjt}} \tag{4.9}$$

where $M_{cjt} = \int_0^t m_{cjs} ds$ is the total number of quality jumps up to time t on product line j. Total number of quality jumps determines the quality level of a product line j in country c at time t.

To compare the quality level in home and foreign country, further I assume that in both countries, firm's quality jumps m_{jt} during a time period Δt on a particular product line j is determined randomly by the same Poisson distribution defined as

$$P(m_{jt} = m) = \frac{(\gamma \Delta t)^m e^{-\gamma \Delta t}}{m!} \quad \forall m \in \{0, 1, \ldots, \bar{m}\} \tag{4.10}$$

where $\bar{m}$ is the largest quality jumps firms can make in a given period t and γ is the average jumps happened in the past.

The relative quality of particular product j with respect to its foreign competitor is called the quality gap between country $c \in \{A, B\}$ and its counterpart $c' \in \{A, B\}$can be denoted as

$$\frac{\varphi_{cjt}}{\varphi_{c'jt}} = \frac{\lambda^{M_{cjt}} \bar{\varphi}_c^t}{\lambda^{M_{c'jt}} \bar{\varphi}_{c'}^t} = \lambda^{M_{cjt} - M_{c'jt}} \left(\frac{\bar{\varphi}_c}{\bar{\varphi}_{c'}} \right)^t.$$

Similarly, assume both countries have the same average quality over all products, $\varphi_c = \varphi_{c'} = 1$. The quality gap then can be summarized by a single integer $G_{cjt} \in \mathcal{N}$ such that

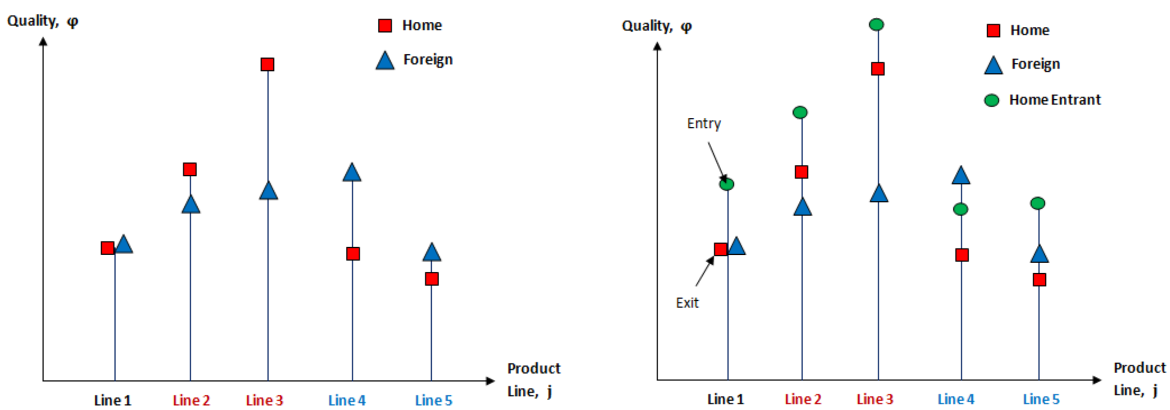
$$\frac{\varphi_{cjt}}{\varphi_{c'jt}} = \lambda^{M_{cjt} - M_{c'jt}} = \lambda^{G_{cjt}}$$

where $G_{cjt} = M_{cjt} - M_{c'jt}$. Assume there is a relatively large but exogenously given limit in the quality gap, $\bar{G}$, such that the gap between two firms is $G_{cjt} \in \{-\bar{G}, \ldots, 0, \ldots, \bar{G}\}$

For entrants, a new firm in each product line from each country invests in innovation to enter the market in every period t. If the entrant succeeds, the entrant firm replaces the domestic incumbent and the incumbent is forced to quit the market; otherwise, the entrant firm disappears. Similar to the cost function (4.7) of incumbent firms, the cost function for an entrant firm is defined as

$$C(\tilde{x}_{cjt}, \varphi_{cjt}, \tilde{\mu}_{cjt}) = w_{ct}^S \varphi_{cjt}^{\frac{1}{\beta}} \tilde{x}_{cjt}^{\frac{1}{(1-\alpha)\beta}} \tilde{\mu}_{cjt}^{-\frac{1-\beta}{\beta}} = w_{ct}^S \varphi_{cjt}^{\frac{1}{\beta}} S(\tilde{x}_{cjt}, \tilde{\mu}_{cjt}). \tag{4.11}$$

Figure 4.3 demonstrates the changes of product lines, entry and exit caused by entrant innovation. Figure 4.3a illustrates the relative quality positions of incumbent firms in Home and Foreign countries with heterogeneous quality gaps in a set of product lines. For product line 1, firms from the two countries are in a neck-and-neck position. For product lines 2 and 3, Home firms are quality leaders. Conversely, firms from Foreign country are technological leaders in product lines 4 and 5. Panel 4.3b exhibits the effects of innovation by Home entrants on entry and exit dynamics. In product line 1, an entrant from Home country succeeds in innovation and moves ahead of the previous leader in both Home and Foreign countries and drives the previous incumbent in Home country out of business. Similarly, in lines 2, 3 and 5, an entrant in Home country gains a large enough quality improvement and moves ahead of the previous leader in country H and F. Entrant enters the market and forces the previous incumbent in Home country to exit. In line 4, Home entrant exceeds previous Home leader but fails to move ahead of Foreign leader. The entrant drives the previous incumbent in Home country out of business.



(a) Product Lines

(b) Entry and Exit

Figure 4.3: Innovation and Changes of Product Lines

Notes: Panel 4.3a shows the relative quality positions of incumbent firms in Home and Foreign countries with heterogeneous quality gaps in a set of product lines. For line 1, firms from the two countries are in a neck-and-neck position. For lines 2 and 3, Home firms are quality leaders. On the contrary, firms from Foreign country are technological leaders in product line 5. Panel 4.3b exhibits the effects of innovation by Home entrants on entry and exit dynamics. For line 1, Home entrant succeeds in innovation and moves ahead of the previous leader in both Home and Foreign countries. In lines 2, 3 and 5, Home entrant moves ahead of the previous leader in country H and F. In line 4, Home entrant exceeds previous Home leader but fails to move ahead of Foreign leader.

In each country c, exit of products and firms has four causes:

1. There is an *exogenous destructive* shock at the rate of $\xi > 0$, which causes the incumbent firms to exit the market and shut down all product lines.

2. There is a *creative destruction* with incumbent firms replaced by entrants because of innovation by entrants

3. There is *import/export effect*, so that domestic incumbent firms are replaced by foreign firms because of the higher quality of foreign products.

4. There is *endogenous obsolescence*, by which firms will voluntarily shut down some product lines because they are no longer sufficiently profitable relative to the fixed cost.

Notice that firms' quality improvements are potentially caused by the innovative activities of domestic incumbents or entrants, and knowledge spillovers from the foreign country. The law of motion for the quality level of a particular product line j from country c during a small time interval $\Delta t \to 0$ can be summarized as

$$\varphi_{cj(t+\Delta t)} = \begin{cases} \bar{\varphi}_c \lambda^{m_{cjt}} \varphi_{cjt} & \text{with } Pr = (x_{cjt} + \tilde{x}_{cjt}) \frac{(\gamma\Delta t)^{m_{cjt}} e^{-\gamma\Delta t}}{m_{cjt}!} \\ \bar{\varphi}_c \lambda^{m_{c'jt}} \varphi_{cjt} & \text{with } Pr = (x_{c'jt} + \tilde{x}_{c'jt}) \frac{(\gamma\Delta t)^{m_{c'jt}} e^{-\gamma\Delta t}}{m_{c'jt}!} \\ \varphi_{cjt} & \text{with } Pr = 1 - (x_{cjt} + \tilde{x}_{cjt}) \frac{(\gamma\Delta t)^{m_{cjt}} e^{-\gamma\Delta t}}{m_{cjt}!} \\ & \qquad -(x_{c'jt} + \tilde{x}_{c'jt}) \frac{(\gamma\Delta t)^{m_{c'jt}} e^{-\gamma\Delta t}}{m_{c'jt}!} \end{cases} \tag{4.12}$$

where $m_{cjt} \in \{0, 1, \ldots, \bar{m}\}$.

Consider the quality levels associated with the incumbent firms from country c. In the first case, the quality improves when either the domestic or entrant innovates in product line j. The second case reflects knowledge spillovers from foreign country c' that the quality in a product line where firm from country c improves with innovations by the foreign incumbent or entrant. Knowledge spillover implies technology can flow across countries and countries converge in technology and long term growth. In the last case, both home and foreign countries fail to improve the quality of product line j.

4.3.5 Trade and Trade Policy

In line with the trade literature, assume that an exporting firm needs to pay a transportation cost κ for every unit of intermediate good it exports. Besides the transportation cost, the exporting firm needs to pay tariffs. Assume that a firm in country c exporting to country c' ($c, c' \in \{A, B\}$) pays $\tau_c' \geq 1$ units of ad valorem import tariff. This means that when the firm decides to export, it will charge a tariff-augmented price. Producers of any product j in country c that export to foreign country receive $p_{cjt}/(\kappa + \tau_{c'jt})$, or have higher marginal cost of $(\kappa + \tau)\eta$.

Following Handley and Limo (2017), assume trade policy is an exogenous stochastic process. Each period there is some probability of $\phi \in [0, 1]$ policy shock. Once the shock occurs, the current tariff changes from τ_c to τ_c'. Otherwise, the tariff is unchanged. Firms observe the policy shock but do not know what the tariff will be before policymaker announces the new tariff. However, firms form their expectations over future policies based on their belief of ε and possible tariff outcomes with $\tau_c' \in [\tau_c^L, \tau_c^H]$ with a probability of $F(\tau_c')$, where $\tau_c^H > \tau_c^L$. Assume that both ε and probability distribution $F(\tau)$ are similar across firms within country.

4.3.6 Equilibrium

In this section, I solve for the equilibrium of the model where the strategies are functions of the product quality φ and technology improvements λ^m. The static equilibrium for households, final and intermediate good production are solved first. The value functions for the intermediate producers and entrants are based on the static equilibrium and the closed-form solutions are determined by the R&D decisions. The value functions help characterize the evolution of technology and labor reallocation over time. As a result, the time index t will be dropped unless it causes confusion.

4.3.6.1 Households

Start with households' utility maximization problem, the representative household maximizes its utility (4.1) subject to the flow budget constraint given by (4.3) and the usual no-Ponzi condition. The representative household utility maximization problem delivers the standard Euler equation,

$$g_{ct} = \frac{\dot{C}_t}{C_t} = \frac{r_{ct} - \rho}{\sigma} \tag{4.13}$$

4.3.6.2 Final Good Production

The profit maximization problem of the final good producer in country $c \in \{A, B\}$ is to maximize the final good production profit

$$\Pi_{ct} = P_{ct}Y_{ct} - w_{ct}^{U}L_{ct}^{U} - \int_{\Omega_t} \left(p_{cjt}q_{cjt} + p_{c'jt}q_{c'jt}\right) dj$$

subject to the final good production function (4.4). The final-good producers generate the following demand for the unskilled labor L_{ct}^{U} and intermediate good $j \in \Omega_t$:

$$w_{ct}^{U} = \beta \int_{\Omega_t} \left(p_{cjt}q_{cjt}^{1-\beta} + p_{c'jt}q_{c'jt}^{1-\beta}\right) dj \tag{4.14}$$

$$p_{cjt} = (1-\beta)\varphi_{cjt}q_{cjt}^{-\beta} \tag{4.15}$$

where $P_{ct} = 1$ and $L_{ct}^{U} = 1$ as discussed above.

4.3.6.3 Intermediate Good Production

Now consider the profit maximization problem of intermediate-good producers. Under open-economy, intermediate-good producers can potentially sell their goods both in home country and foreign country. Producers face different marginal cost and demand selling in domestic and foreign market because of iceberg trade costs. Profits from selling in domestic and foreign market are different. Considering an intermediate-good producer that only sells in the home country with constant marginal cost of η, the profit maximization problem of the monopolist in product line j is

$$\begin{aligned}\pi(\varphi_{cjt}) &= \max_{q_{cjt}} \left\{(p_{cjt} - \eta)q_{cjt}\right\} \\ &= \max_{q_{cjt}} \left\{((1-\beta)\varphi_{cjt}q_{cjt}^{-\beta} - \eta)q_{cjt}\right\}\end{aligned}$$

The optimal quantity and price for intermediate product j selling in home country are solved from the above problem:

$$\begin{aligned}p_{cj} &= \frac{\eta}{1-\beta} \\ q_{cjt} &= \left[\frac{(1-\beta)^2}{\eta}\right]^{\frac{1}{\beta}} \varphi_{cjt}^{\frac{1}{\beta}}.\end{aligned} \tag{4.16}$$

The optimal domestic price is a constant markup ($p_{cj} > \eta$) over the marginal cost and is independent of the individual product quality and remains unchanged over time. The optimal quantity of a particular product j is increasing in its quality. The high quality product is more demanded and produced, which is consistent with common sense. The profit earned by selling intermediate good j in home country is given by

$$\pi(\varphi_{cjt}) = \pi\varphi_{cjt}^{\frac{1}{\beta}} = \frac{\eta\beta}{1-\beta}\left[\frac{(1-\beta)^2}{\eta}\right]^{\frac{1}{\beta}}\varphi_{cjt}^{\frac{1}{\beta}}, \tag{4.17}$$

where $\pi = \frac{\eta\beta}{1-\beta}\left[\frac{(1-\beta)^2}{\eta}\right]^{\frac{1}{\beta}}$. Notice that the maximum profit is a constant markup of product quality. Firms offering high-quality products gain more market share and earn higher profits.

4.3.6.4 Trade of Intermediate Good

For intermediate producers that sell their goods in foreign country, the profit maximization problem is different due to trade cost. Producers exporting to foreign country receive $p_{cjt}/\tau_{c't}$, where $\tau_{c'}$ is the tariff factor set by foreign country. Free trade is represented by $\tau_c = 1$. The profit maximization problem for exporters is

$$\begin{aligned}\pi^*(\varphi_{cjt}) &= \max_{q^*_{cjt}}\left\{(p^*_{cjt} - (\kappa + \tau_{c't})\eta)q^*_{cjt}\right\}\\ &= \max_{q^*_{cjt}}\left\{((1-\beta)\varphi_{cjt}{q^*_{cjt}}^{-\beta} - (\kappa + \tau_{c't})\eta)q^*_{cjt}\right\}.\end{aligned}$$

The optimal quantity, price, and profit for exporter are solved from the above problem:

$$\begin{aligned}p^*_{cj} &= \frac{(\kappa + \tau_{c't})\eta}{1-\beta}\\ q^*_{cjt} &= \left[\frac{(1-\beta)^2}{(\kappa + \tau_{c't})\eta}\right]^{\frac{1}{\beta}}\varphi_{cjt}^{\frac{1}{\beta}}\\ \pi^*(\varphi_{cjt}) &= (\kappa + \tau_{c't})^{\frac{\beta-1}{\beta}}\frac{\eta\beta}{1-\beta}\left[\frac{(1-\beta)^2}{\eta}\right]^{\frac{1}{\beta}}\varphi_{cjt}^{\frac{1}{\beta}}.\end{aligned} \tag{4.18}$$

Notice that the optimal price is increasing in tariff factor and the optimal quantity and profit are decreasing in tariff. Given the trade costs, the quality condition that a firm is indifferent between exporting and non-exporting satisfies $\pi^*(\varphi_{cjt}) = \pi(\varphi_{c'jt})$. Therefore, the firm from country c

exports intermediate good j to foreign country c' if and only if the profit from exporting to country c' for an intermediate producer in country c is greater or equal to the profit gained from domestic selling by an intermediate producer in country c', which is

$$(\kappa+\tau_{c't})^{\frac{\beta-1}{\beta}}\frac{\eta\beta}{1-\beta}\left[\frac{(1-\beta)^2}{\eta}\right]^{\frac{1}{\beta}}\varphi_{cjt}^{\frac{1}{\beta}} \geq \frac{\eta\beta}{1-\beta}\left[\frac{(1-\beta)^2}{\eta}\right]^{\frac{1}{\beta}}\varphi_{c'jt}^{\frac{1}{\beta}}$$

or

$$\frac{\varphi_{cjt}}{\varphi_{c'jt}} \geq (\kappa+\tau_{c't})^{1-\beta} \geq 1. \tag{4.19}$$

In other words, only the firm with the higher cost-adjusted quality will gain additional profit from exporting. Under the Bertrand competition, the quality leader (exporter) has the motivation to limit the price and push the competitor out of the market. To ensure that only the incumbent with the highest cost-adjusted quality is able to set the monopoly price in 4.18, the following assumption should be satisfied:

Assumption 4. *In each product line, exporter and domestic incumbent play a two-stage game if the exporter decides to enter foreign market. In the first stage, firms pay a small fee $o>0$ to enter the market. In the second stage, incumbents offer their prices based on a Bertrand competition.*

Assumption (4) ensures the optimal exporting price and profit in equation (4.18) is achievable. As discussed above, there is a quality condition on domestic intermediate firms that want to export. Denote G_{ct}^E as the smallest quality gap which a leader from country $c \in \{A, B\}$ needs to exceed its follower in order to be able to export its good to foreign. Notice that an intermediate good producer in country c may be not able to export to country c' even though it has higher quality compared to its foreign competitor ($\varphi_{ct} > \varphi_{c't}$) because of the trade cost. A firm's exporting decision is based on its cost-adjusted quality compared to foreign counterpart. The cutoff quality gap for domestic intermediate producer to export is defined as

$$\lambda^{G_{ct}^E} = arg\min_{m\in\mathcal{N}}\left\{\frac{\varphi_{cjt}}{\varphi_{c'jt}} \geq (\kappa+\tau_{c't})^{1-\beta}\right\}, \tag{4.20}$$

or

$$G_{ct}^E = \left\lceil\frac{(1-\beta)ln(\kappa+\tau_{c't})}{ln\lambda}\right\rceil,$$

where ceiling function $\lceil x \rceil$ maps x to the smallest integer greater than or equal to x. The domestic cutoff exporting quality gap is the same for all product lines $j \in \Omega_t$ and is increasing in import tariff factor in foreign country $\tau_{c't}$. When foreign country decides to increase its import tariff, only firms in the home country with higher enough cost-adjusted quality can cover the high trade cost and export. In order to export, intermediate producers in the home country face a higher exporting quality threshold that their quality gap relative to foreign counterparts must be greater or equal to the cutoff export quality gap G^E_{ct}.

Similarly, the cutoff quality that country c imports intermediate goods from foreign country given its own import tariff factor τ_{ct} is

$$G^I_{ct} = \left\lfloor \frac{(\beta - 1)ln(\kappa + \tau_{ct})}{ln\lambda} \right\rfloor,$$

where floor function $\lfloor x \rfloor$ maps x to the greatest integer smaller than or equal to x. Home country will import intermediate goods from the foreign country if home intermediate goods producers have low-quality gap which is smaller or equal to the cutoff import quality gap G^I_{ct}.

Lemma 5. *Home country's import/export decision is depended on its quality gap relative to foreign country $G_{ct} \in \{-\bar{G}, \dots, 0, \dots, \bar{G}\}$. For country $c \in \{A, B\}$, it will import intermediate good from country $c' \in \{A, B\}$ if $G_{ct} \leq \left\lfloor \frac{(\beta-1)ln(\kappa+\tau_{ct})}{ln\lambda} \right\rfloor$, will export intermediate good to foreign country c' if $G_{ct} \geq \left\lceil \frac{(1-\beta)ln(\kappa+\tau_{c't})}{ln\lambda} \right\rceil$, and will choose no trade if $G_{ct} \in (\left\lfloor \frac{(\beta-1)ln(\kappa+\tau_{ct})}{ln\lambda} \right\rfloor, \left\lceil \frac{(1-\beta)ln(\kappa+\tau_{c't})}{ln\lambda} \right\rceil)$.*

Lemma (5) summarizes home country's import and export decisions based on its relative quality gaps. Moreover, Figure 4.4 illustrates the possible quality frontiers (PQF) in countries A and B and the import and export decisions for country A. The PQF is defined as the possible product qualities of incumbent firms over all product lines, where products are sorted by their quality from low to high. Without loss of generality, Figure 4.4 describes a special case where the possible quality frontiers of the two economies cross. The solid green line shows the PQF of country A when there is no trade. The solid red line represents the PQF of country B when selling at home. Dashed lines are PQFs of A and B when selling abroad. The PQFs when selling abroad are lower than the actual PQFs because of the trade costs.

For firms from the home country A, if the cost-adjusted quality is higher than the domestic quality in the foreign country, they can export their products to foreign country. As illustrated in Figure 4.4, the home country A will export their intermediate goods to foreign B if the quality gap is greater or equal to G^E_{At}. When the reverse occurs, the home country A imports the higher-quality products from foreign country (home quality gap is smaller or equal to G^I_{At}). Otherwise, firms from each country serve only their domestic markets.

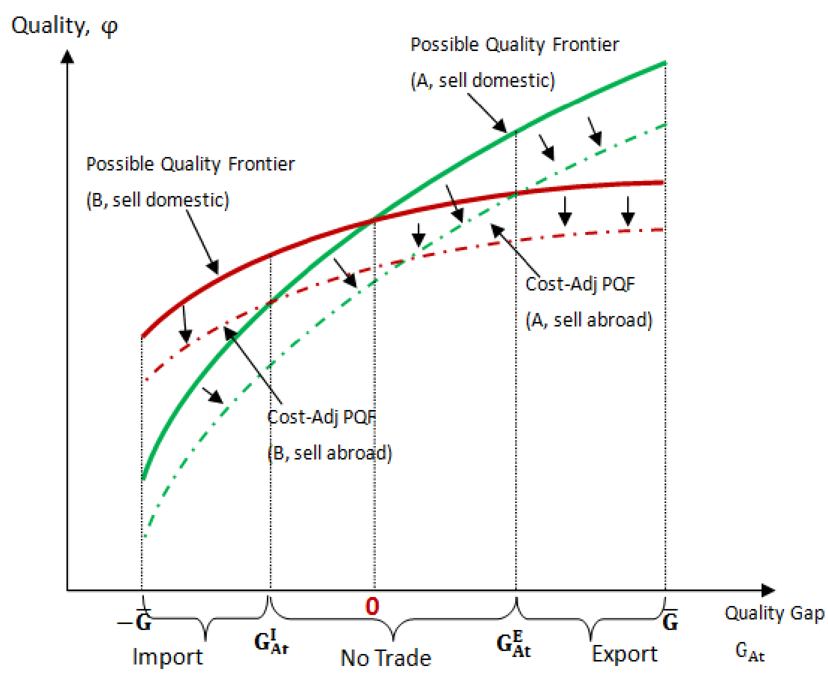


Figure 4.4: Possible Quality Frontier, Trade Cost, and Trade Flows

Notes: The figure exhibits the Possible Quality Frontiers (PQF) in both countries and the effect of trade cost on quality and trade flows. PQF is defined as the possible product qualities of incumbent firms over all product lines, where products are sorted by their quality from low to high. The solid green line shows the PQF of country A when there is no trade. The solid red line represents the PQF of country B when selling at home. Dashed lines are PQFs of A and B when selling abroad. The PQFs when selling abroad are lower than the actual PQFs because of the trade costs.

For the aggregate quality, it is defined as an aggregate of all product lines but indexed by $\frac{1}{\beta}$. Specifically, define the aggregate quality index of country c at time t as

$$\Psi_{G,ct} = \int_{\Omega_{ct}} \varphi_{cjt}^{\frac{1}{\beta}} dj. \tag{4.21}$$

where quality gap is equal to G_{ct}. Therefore, total output of intermediate goods in country c at time t given the aggregate quality index $\Psi_{G,ct}$ is given as

$$\mathcal{Q}_{ct} = \underbrace{\sum_{G=G^I_{ct}}^{G^E_{ct}} \left[\frac{(1-\beta)^2}{\eta}\right]^{\frac{1}{\beta}} \Psi_{G,ct}}_{\text{Total Domestic Demand}} + \underbrace{\sum_{G=G^E_{ct}}^{\bar{G}} \left[\frac{(1-\beta)^2}{(\kappa+\tau_{c't})\eta}\right]^{\frac{1}{\beta}} \Psi_{G,ct}}_{\text{Total Foreign Imports}}. \tag{4.22}$$

The first term on the left-hand side is the total domestic demand or the total intermediate goods that are produced and sold in home country. The second term is the total home intermediate goods imported by foreign country.

4.3.6.5 Valuation Functions and Innovation

Consider incumbent firms in country c. The stationary equilibrium value function for a low-type firm can be written as

$$\begin{aligned} r_{ct}V^L_{G,ct}(\varphi_{ct}) - \dot{V}^L_{G,ct}(\varphi_{ct}) = \max_{x^L_{G,ct}} \Bigg\{ & \underbrace{\Pi(G;\tau_{c't},\varphi_{ct})}_{\text{Production Profit}} - \underbrace{(1-s_{ct})w^S_{ct}\varphi_{ct}^{\frac{1}{\beta}}S(x^L_{G,ct},\mu^L)}_{\text{Innovation Cost}} \\ & + \underbrace{x^L_{G,ct}\sum_{g_{ct}=G+1}^{\bar{G}} f(g_{ct},G)[V^L_{g,ct}(\lambda^{g_{ct}-G}\varphi_{ct}) - V^L_{G,ct}(\varphi_{ct})]}_{\text{Value Change by Incumbent Innovation}} \\ & + \underbrace{\tilde{x}_{G,ct}[0 - V^L_{G,ct}(\varphi_{ct})]}_{\text{Creative Destruction by Domestic Entrants}} + \underbrace{\xi[0 - V^L_{G,ct}(\varphi_{ct})]}_{\text{Exogenous Destructive Shock}} \\ & + \underbrace{(x_{-G,c't} + \tilde{x}_{-G,c't})\sum_{g_{ct}=-G+1}^{\bar{G}} f(g_{ct},-G)[V^L_{-g,ct}(\lambda\varphi_{ct}) - V^L_{G,ct}(\varphi_{ct})]}_{\text{Knowledge Spillovers from Foreign}} \Bigg\}, \end{aligned} \tag{4.23}$$

where probability function $f(g_{ct}, G)$ is defined as

$$f(g_{ct}, G) = \frac{\gamma^{(g_{ct}-G)}e^{-\gamma}}{(g_{ct}-G)!}.$$

The first term on the right-hand side of value function (4.24) denotes the expected profits from production of intermediate goods, $\Pi(G;\tau_{c't},\varphi_{ct})$, which is

$$\Pi(G;\tau_{c't},\varphi_{ct}) = \begin{cases} \pi\varphi_{ct}^{\frac{1}{\beta}} + \Pi^*(\tau_{c't},\varphi_{ct}) & \text{if } G \geq G_{ct}^E \\ \pi\varphi_{ct}^{\frac{1}{\beta}} & \text{if } G \in (G_{ct}^I, G_{ct}^E) \\ 0 & \text{if } G \leq G_{ct}^I \end{cases},$$

$\pi = \frac{\eta\beta}{1-\beta}\left[\frac{(1-\beta)^2}{\eta}\right]^{\frac{1}{\beta}}$, and $\Pi^*(\tau_{c't},\varphi_{ct})$ is the expected value of a firm that exports at time t conditional on it observing tariff $\tau_{c't}$, which is given by

$$\Pi^*(\tau_{c't},\varphi_{ct}) = \pi^*(\tau_{c't},\varphi_{ct}) + \delta[\underbrace{(1-\phi)\Pi^*(\tau_{c't},\varphi_{ct})}_{\text{No Policy Shock}} + \underbrace{\phi E\Pi^*(\tau'_{c't},\varphi_{ct})}_{\text{Policy Shock}}]. \tag{4.24}$$

Expected value of exporting includes current operating profits in the export market, $\pi^*(\tau_{c't}) = (\kappa+\tau_{c't})^{\frac{\beta-1}{\beta}}\frac{\eta\beta}{1-\beta}\left[\frac{(1-\beta)^2}{\eta}\right]^{\frac{1}{\beta}}\varphi_{cjt}^{\frac{1}{\beta}}$, and discounted future value (discount rate δ). The second term on the right-hand side of (4.24) is the expected exporting profits when there is no policy shock with probability $1-\phi$, the third term is the ex ante expected value of exporting following a shock with probability of ϕ, and E denotes the expectation over the tariff distribution $F(\tau'_{c't})$.

By transferring of equation 4.24, the expected value of a firm that exports is given by

$$\Pi^*(\tau_{c't},\varphi_{ct}) = \frac{\pi^*(\tau_{c't},\varphi_{ct})}{1-\delta(1-\phi)} + \frac{\delta\phi}{1-\delta}\frac{E\pi^*(\tau'_{c't},\varphi_{ct})}{1-\delta(1-\phi)}. \tag{4.25}$$

Proof see Appendix D.1.

The interpretation of (4.25) is straightforward: after investment, the firm value from exporting conditional on $\tau_{c't}$ equals the discounted value of expected profits. If $\phi = 0$, there is no policy shock and firm exporting value would be the deterministic value. But the policy changes with probability ϕ and the per period expected profits are $E\pi^*(\tau'_{c't},\varphi_{ct})$. If the current tariff is above a given trigger, $\tau_{c't} > \bar{\tau}$, then it does not export today and its exporting value would be zero if the tariff remained above that trigger.

From (4.25) we see that reductions in the current tariff, $\tau_{c't}$, increase the firm value, $\Pi^*(\tau_{c't},\varphi_{ct})$, and innovation at any ϕ. Moreover, that impact is higher under a credible policy regime ($\phi = 0$)

than when the policy is expected to change ($\phi > 0$). This complementarity between reductions in current tariffs and uncertainty is one possible reason why countries that obtain temporary preferential tariffs spend considerable resources trying to eliminate any uncertainty about their future reversal.

The second term on the right hand side of equation (4.23) denotes the innovation cost where s_{ct} is the R&D subsidy in country c and $S(x^L_{G,ct}, \mu^L) = x_{cjt}^{\frac{1}{(1-\alpha)\beta}} \mu_{cjt}^{-\frac{1-\beta}{\beta}}$. The third-term denotes the expected gains from low-type incumbent innovation. This expected value is determined by the step size of innovation and its probability. Incumbent firms' innovation investment decisions are based on two different cases. Firstly, domestic incumbent's quality is lower than foreign exporter and the incumbent invests in R&D to gain access to domestic production. The second case is domestic incumbent's quality is not higher enough to export and it invests in R&D to improve its quality and gain access to export markets.

The two terms in the third line on the right hand side of equation (4.23) capture the creative destruction by domestic and exogenous destructive shock. The first term reveals that entry by domestic firms forces the incumbent to exit with probability one, as by construction every product line is forced to have one firm from each country. The domestic creative destruction effect reduces the value of an incumbent firm and therefore decreases investment innovation. The second term indicates that the incumbent is forced to exit the market with probability ξ if the incumbent is hit by exogenous destructive shock. This exogenous destructive shock reduces incumbent's value and incentive to innovate.

The last line on the right hand side of equation (4.23) represents the knowledge spillovers from foreign competitors. Any innovation in the foreign country, regardless of the source being an entrant or an incumbent, flows into the home country and is mimicked by domestic incumbents. Similarly, we can write the value function of a high-type incumbent as

$$
\begin{aligned}
r_{ct}V^S_{G,ct}(\varphi_{ct}) - \dot{V}^H_{G,ct}(\varphi_{ct}) = \max_{x^L_{G,ct}} \Bigg\{ & \underbrace{\Pi(G;\tau_{c't},\varphi_{ct})}_{\text{Production Profit}} - \underbrace{(1-s_{ct})w^S_{ct}\varphi_{ct}^{\frac{1}{\beta}}H(x^H_{G,ct},\mu^H)}_{\text{Innovation Cost}} \\
& \underbrace{+ x^H_{G,ct}\sum_{g_{ct}=G+1}^{\bar{G}} f(g_{ct},G)[V^H_{g,ct}(\lambda^{g_{ct}-G}\varphi_{ct}) - V^H_{G,ct}(\varphi_{ct})]}_{\text{Value Change by Incumbent Innovation}} \\
& + \underbrace{\tilde{x}_{G,ct}[0 - V^H_{G,ct}(\varphi_{ct})]}_{\text{Creative Destruction by Domestic Entrants}} + \underbrace{\xi[0 - V^H_{G,ct}(\varphi_{ct})]}_{\text{Exogenous Destructive Shock}} \\
& \underbrace{+ (x_{-G,c't} + \tilde{x}_{-G,c't})\sum_{g_{ct}=-G+1}^{\bar{G}} f(g_{ct},-G)[V^H_{-g,ct}(\lambda\varphi_{ct}) - V^H_{G,ct}(\varphi_{ct})]}_{\text{Knowledge Spillovers from Foreign}} \Bigg\} \\
& \underbrace{+ \epsilon[V^L_{G,ct}(\varphi_{ct}) - V^H_{G,ct}(\varphi_{ct})]}_{\text{Exogenous Transition Shock}}.
\end{aligned}
\tag{4.26}
$$

The major difference from (4.23) is in the last line, where we incorporate the possibility of a transition to a low-type status at the rate ϵ. The remaining terms have the same interpretation as in (4.23).

The firms' problems are characterized by an infinite-dimensional space of intermediate-good qualities. The next lemma shows that the value of each firm can be expressed by reducing the state space to finite dimensions.

Lemma 6. *The value functions are a function of $\varphi_{G,ct}$ such that $V_{G,ct}(\varphi_{ct}) = \varphi_{ct}^{\frac{1}{\beta}} v_{G,ct}$ for $G \in \{G^I_{ct}, \bar{G}\}$. Value function for a low-type firm is therefore given by*

$$
\begin{aligned}
r_{ct}v^L_{G,ct} - \dot{v}^L_{G,ct} = \max_{x^L_{G,ct}} \Bigg\{ & \pi(G;\tau_{c't}) - (1-s_{ct})w^S_{ct}S(x^L_{G,ct},\mu^L) \\
& + x^L_{G,ct}\sum_{g_{ct}=G+1}^{\bar{G}} f(g_{ct},G)[\lambda^{g_{ct}-G}v^L_{g,ct} - v^L_{G,ct}] \\
& + \tilde{x}_{G,ct}[0 - v^L_{G,ct}] + \xi[0 - v^L_{G,ct}] \\
& + (x_{-G,c't} + \tilde{x}_{-G,c't})\sum_{g_{ct}=-G+1}^{\bar{G}} f(g_{ct},-G)[\lambda v^L_{-g,ct} - v^L_{G,ct}] \Bigg\}.
\end{aligned}
$$

Similarly, the value function for a high-type firm follows the same term but have an additional term regarding the transition of high type firm to low type. Specifically, the value function for a high-type firm is given by

$$
\begin{aligned}
r_{ct} v^H_{G,ct} - \dot{v}^H_{G,ct} = \max_{x^H_{G,ct}} \Big\{ & \pi(G;\tau_{c't}) - (1-s_{ct}) w^S_{ct} S(x^H_{G,ct}, \mu^H) \\
& + x^H_{G,ct} \sum_{g_{ct}=G+1}^{\bar{G}} f(g_{ct}, G)[\lambda^{g_{ct}-G} v^H_{g,ct} - v^H_{G,ct}] \\
& + \tilde{x}_{G,ct}[0 - v^H_{G,ct}] + \xi[0 - v^H_{G,ct}] \\
& + (x_{-G,c't} + \tilde{x}_{-G,c't}) \sum_{g_{ct}=-G+1}^{\bar{G}} f(g_{ct}, -G)[\lambda v^H_{-g,ct} - v^H_{G,ct}] \\
& + \epsilon[v^L_{G,ct} - v^H_{G,ct}] \Big\}.
\end{aligned}
$$

Proof. See Appendix D.2.

The first order conditions of the value functions defined above yield the following equilibrium R&D decisions for an incumbents of type $T \in \{H, L\}$ in state G:

$$
x^T_{G,ct} = \begin{cases} \left[\frac{(1-\alpha)\beta}{(1-s_{ct})w^S_{ct}} \mu^{\frac{1-\beta}{\beta}} \sum_{g_{ct}=G+1}^{\bar{G}} f(g_{ct}, G)(\lambda^{g_{ct}-G} v^T_{g,ct} - v^T_{G,ct}) \right]^{\frac{(1-\alpha)\beta}{1-(1-\alpha)\beta}} & \text{if } G < \bar{G} \\ \left[\frac{(1-\alpha)\beta}{(1-s_{ct})w^S_{ct}} \mu^{\frac{1-\beta}{\beta}} (\lambda - 1) v^T_{g,ct} \right]^{\frac{(1-\alpha)\beta}{1-(1-\alpha)\beta}} & \text{if } G = \bar{G} \end{cases}. \tag{4.27}
$$

As discussed above, reductions in the current tariff, $\tau_{c't}$, increase firms' profits and market value, v_{ct}. Firms expend their investment in innovation, as measured by R&D expenditure, x_{ct}. From (4.27) we see that reductions in the current tariff increase firm market value and further increase R&D investment.

Now consider the value function for entrants. Recall that entry is directed at individual lines and a successful entrant improves quality. The problem of an entrant of type $T \in \{H, L\}$ that aims at a product line where the current domestic incumbent is at state G is as follows:

$$
\tilde{V}^T_{G,ct}(\varphi_{ct}) = \max_{\tilde{x}^T_{G,ct}} \left\{ -w^S_{ct} \varphi_{ct}^{\frac{1}{\beta}} H(\tilde{x}^T_{G,ct}, \tilde{\mu}^T) + \tilde{x}^T_{G,ct} \sum_{g_{ct}=G+1}^{\bar{G}} f(g_{ct}, G) \tilde{V}^H_{g,ct}(\lambda^{g_{ct}-G} \varphi_{ct}) \right\} \tag{4.28}
$$

Solving the problem leads to the following equilibrium value of the entrant firm with type T:

$$
\tilde{V}^T_{G,ct}(\varphi_{ct}) = [\frac{1}{(1-\alpha)\beta} - 1] w^S_{ct} \varphi_{ct}^{\frac{1}{\beta}} H(\tilde{x}^T_{G,ct}, \tilde{\mu}^T).
$$

The equilibrium value is independent of the product line and is determined by quality level, φ_{ct}, and the current innovation capacity, μ. As such, the equilibrium R&D decisions for an entrant in state G become

$$\tilde{x}^T_{G,ct} = \begin{cases} \left[\frac{(1-\alpha)\beta}{w^S_{ct}}\tilde{\mu}^{\frac{1-\beta}{\beta}} \sum_{g_{ct}=G+1}^{\bar{G}} f(g_{ct},G)\lambda^{g_{ct}-G}\tilde{v}^T_{g,ct}\right]^{\frac{(1-\alpha)\beta}{1-(1-\alpha)\beta}} & \text{if } G < \bar{G} \\ \left[\frac{(1-\alpha)\beta}{w^S_{ct}}\tilde{\mu}^{\frac{1-\beta}{\beta}} \lambda\tilde{v}^T_{g,ct}\right]^{\frac{(1-\alpha)\beta}{1-(1-\alpha)\beta}} & \text{if } G = \bar{G} \end{cases}. \tag{4.29}$$

From (4.29), equilibrium innovation rates for entrants are similar to incumbents. Reductions in the current tariff increase firm value and investment in R&D investment.

4.3.6.6 Impact of Policy Uncertainty

Now consider the impact of policy changes on entry and investment in innovation. First consider the benchmark case where the policy is deterministic. A firm in country $c \in \{A, B\}$ with quality in a state $G \geq G^E_{ct}$ decides to export if the present discounted value of its profit exceeds the sunk investment cost of entry, i.e., $\pi^*(\tau_{c't}\varphi_{cjt}) \geq (1-\delta)K_e$, given the fixed entry cost of K_e. In a deterministic economy with no policy uncertainty, the zero-profit cutoff quality condition of exporting given by

$$\varphi^D_{cjt} = (\kappa + \tau_{c't})^{1-\beta}\left[\frac{(1-\delta)K_e}{\pi}\right]^{\beta}, \tag{4.30}$$

where $\pi = \frac{\eta\beta}{1-\beta}\left[\frac{(1-\beta)^2}{\eta}\right]^{\frac{1}{\beta}}$, and D denotes deterministic. The zero-profit cutoff condition is common to all firms that face a same tariff and trade entry sunk cost. For all firms with $\varphi_{cjt} \geq \varphi^D_{cjt}$ enter the export market. Reductions in tariffs increase demand and decrease entry cutoff condition and thus induce more entry.

Now consider policy uncertainty where potential exporters can choose when to enter the export market so policy uncertainty generates an option value of waiting. The expected value of a firm in country c waiting to export under policy uncertainty is given by

$$\begin{aligned}\Pi_w(\tau'_{c't},\varphi_{ct}) =& 0 + \delta\Big\{\underbrace{(1-\phi)\Pi_w(\tau'_{c't},\varphi_{ct})}_{\text{No Policy Shock}} + \underbrace{\phi(1-F(\bar{\tau}))\Pi_w(\tau'_{c't},\varphi_{ct})}_{\text{Policy Shock above Trigger}} \\ &+ \underbrace{\phi F(\bar{\tau})\left[E(\Pi^*(\tau'_{c't},\varphi_{ct})|\tau'_{c't} \leq \bar{\tau}) - K_e\right]}_{\text{Policy Shock below Trigger}}\Big\},\end{aligned} \tag{4.31}$$

where $\bar{\tau}$ is a threshold tariff that makes a firm indifferent between exporting today or waiting (trigger tariff). The expected profit from exporting is given by $\Pi^*(\tau_{c't}, \varphi_{ct})$ and the expected value of waiting is given by $\Pi_w(\tau_{c't}, \varphi_{ct})$, as such, the trigger tariff $\bar{\tau}$ is given by:

$$\Pi^*(\bar{\tau}, \varphi_{ct}) - K_e = \Pi_w(\bar{\tau}, \varphi_{ct}) \tag{4.32}$$

where $\Pi^*(\tau, \varphi_{ct})$ is given by (4.25). Any tariff below $\bar{\tau}$ triggers entry by firms with quality of φ_{ct} or higher.

Notice that the first term on the right-hand side of (4.31) indicates that a nonexporter receives zero profits from exporting today. Firm receives the continuation value of Π_w if there is no shock or the shock entails a tariff above the trigger. If a policy shock arrives, it will be below $\bar{\tau}$ with probability $F(\bar{\tau})$ and the firm will choose to pay the entry cost K_e and start exporting. Combining (4.24), (4.25), and (4.31), the equilibrium expected waiting value is

$$\Pi_w(\tau'_{c't}, \varphi_{ct}) = \frac{\delta\phi F(\bar{\tau})}{1-\delta(1-\phi F(\bar{\tau}))}\left[\frac{E[\pi^*(\tau'_{c't}, \varphi_{ct})|\tau'_{c't} \leq \bar{\tau}]}{1-\delta(1-\phi)} + \frac{\delta\phi}{1-\delta}\frac{E[\pi^*(\tau'_{c't}, \varphi_{ct})]}{1-\delta(1-\phi)} - K_e\right]. \tag{4.33}$$

Proof. See Appendix D.3.

The interpretation of (4.33) is straightforward: the firm value from waiting to export conditional on $\tau'_{c't}$ equals the discounted value of expected profit when tariff is below trigger tariff plus the discounted value of expected profit when tariff does not change.

Using (4.25), (4.32), and (4.33), the cutoff condition for waiting and exporting for any given current tariff is given by

$$\varphi^U_{ct} = \varphi^D_{ct} \times R_{c't} \tag{4.34}$$

$$R_{c't} = \left[\frac{1-\delta(1-\phi)}{1-\delta(1-\phi\Gamma(\tau'_{c't}))}\right]^{\beta} \geq 1 \tag{4.35}$$

$$\Gamma(\tau'_{c't}) = E\left(\frac{\kappa+\tau'_{c't}}{\kappa+\tau_{c't}}\right)^{-\frac{1-\beta}{\beta}} + F(\bar{\tau})\left(1 - E[(\frac{\kappa+\tau'_{c't}}{\kappa+\tau_{c't}})^{-\frac{1-\beta}{\beta}}|\tau'_{c't} \leq \bar{\tau}]\right) \leq 1 \tag{4.36}$$

Proof. See Appendix D.4 and D.5.

$R_{c't}$ is the uncertainty factor that captures the frequency of policy shock arrivals arrivals and expectations about future tariffs. Notice that, when there is no policy uncertainty, $\phi = 0$, then

$R_{c't} = 1$, $\varphi_{ct}^{U} = \varphi_{ct}^{D}$, and $\Pi_w(\tau'_{c't}, \varphi_{ct}) = 0$. The economy is the same as deterministic and expected waiting value is zero. If $\phi > 0$, there is policy shock making the uncertainty factor $R_{c't} > 1$ and the cutoff condition is higher than the deterministic condition $\varphi_{ct}^{U} > \varphi_{ct}^{D}$. Entry to exporting market requires higher product quality and lower entry.

$\Gamma(\tau'_{c't})$ measures the expected profit loss, that is, the expected growth in operating profits when a shock occurs and increases tariffs. $\Gamma(\tau'_{c't})$ is a function of export iceberg cost, κ, current tariff, $\tau_{c't}$, and future tariff $\tau'_{c't}$. The expected profit loss is independent of firm's product quality, φ_{ct}. Notice that even though policy shock can trigger a lower or higher tariff, only higher tariffs affect the expected profit loss and entry.

Now consider the impact of policy uncertainty on import/export. Based on (4.20) and (4.34), the cutoff quality gap for domestic exporting under policy uncertainty is given by

$$G_{ct}^{U,E} = \left\lceil \frac{(1-\beta)ln(\kappa+\tau_{c't}) + lnU_{c't}}{ln\lambda} \right\rceil \geq G_{ct}^{E},$$

and the cutoff quality gap for domestic importing is

$$G_{ct}^{U,I} = \left\lfloor \frac{(\beta-1)ln(\kappa+\tau_{ct}) - lnU_{ct}}{ln\lambda} \right\rfloor \leq G_{ct}^{I}.$$

Lemma 7. *Under policy uncertainty, country $c \in \{A, B\}$ will import intermediate good from country $c' \in \{A, B\}$ if $G_{ct} \leq \left\lfloor \frac{(\beta-1)ln(\kappa+\tau_{ct})-lnU_{ct}}{ln\lambda} \right\rfloor$, will export intermediate good to foreign country c' if $G_{ct} \geq \left\lceil \frac{(1-\beta)ln(\kappa+\tau_{c't})+lnU_{c't}}{ln\lambda} \right\rceil$, and will choose no trade if $G_{ct} \in (G_{ct}^{U,I}, G_{ct}^{U,E})$.*

Lemma (7) summarizes home country's import and export decisions under policy uncertainty based on its relative quality gaps. Notice that the cutoff quality gap condition for exporting under policy uncertainty is higher than in the deterministic case, while the cutoff quality gap condition for importing under policy uncertainty is lower than in the deterministic scenario. Both exports and imports decrease as a result of policy uncertainty.

Figure 4.5 illustrates the possible quality frontiers (PQF) in country A and B and the import and export decisions for country A under policy uncertainty. Without loss of generality, Figure 4.5 describes a special case where the possible quality frontiers of two economies cross. The solid green line shows the PQF of country A when there is no trade. The solid red line represents the PQF of country B when selling at home. Dashed lines are PQFs of A and B when selling abroad. The PQFs when selling abroad are lower than the actual PQFs because of the trade costs.

Policy uncertainty makes future profits more volatile and is treated as a part of trade cost. Firms face higher risk investing in the exporting market, and the possible profit loss due to future uncertainty inhibit exports. As illustrated in Figure 4.5, PQF moves down to a lower level because of higher trade cost. Comparing to the deterministic case, the import cutoff quality gap for home country A is lower, $G^{U,I}_{At} \leq G^{I}_{At}$, while the export cutoff quality gap is higher, $G^{U,E}_{At} \geq G^{E}_{At}$. As a result, both imports and exports decrease in home country. Firms are forced to exit the trade market because of higher trade costs and concentrate more on domestic market.

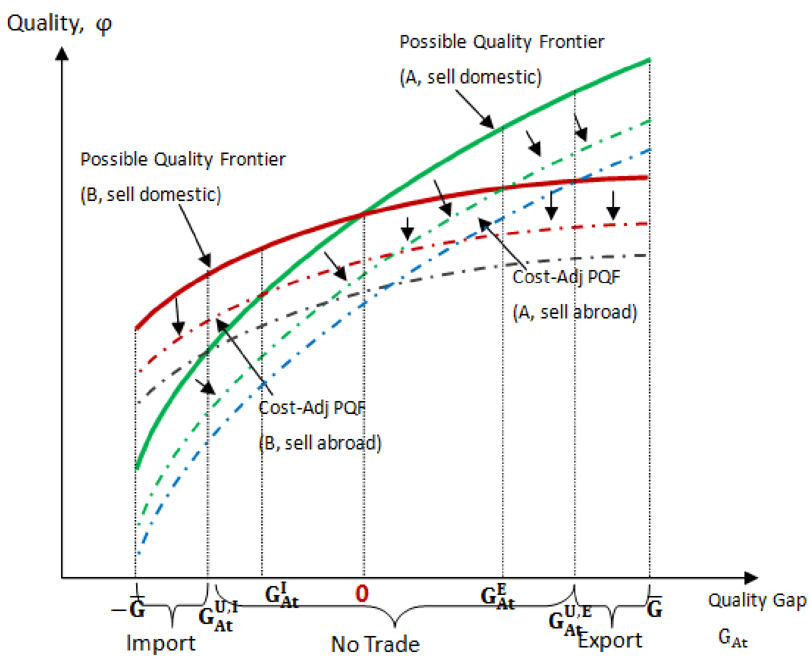


Figure 4.5: Impact of Policy Uncertainty on Home Imports and Exports

Notes: The figure exhibits the effect of policy uncertainty on quality and trade flows. PQF is defined as the possible product qualities of incumbent firms over all product lines, where products are sorted by their quality from low to high. The solid green line shows the PQF of country A when there is no trade. The solid red line represents the PQF of country B when selling at home. Dashed lines are PQFs of A and B when selling abroad and facing tariffs. The PQFs when selling abroad are lower than the actual PQFs because of the trade costs.

Consider the impact of policy uncertainty on innovation investment. At the firm level, as is shown in (4.27) and (4.29), so long as the product line remains active, firm's expected value decreases as flow of profits declines due to policy uncertainty. The R&D investment for either incumbent or entrant firm decreases in reaction to higher trade cost and profit loss.

At the aggregate level, the impact of policy uncertainty is unpredictable because firm-level innovation investment decreases whereas the number of innovation firms increases. In a deterministic economy, the aggregate R&D spending R_{ct} in country $c \in \{A, B\}$ is derived from (4.7), (4.11), (4.27), and (4.29):

$$RD_{ct}^{D} = w_{ct}^{S} \sum_{T=H,L} \sum_{G=G_{ct}^{I}}^{\bar{G}} \left(x_{G,ct}^{T \frac{1}{(1-\alpha)\beta}} \mu_{G,ct}^{T - \frac{1-\beta}{\beta}} + \tilde{x}_{G,ct}^{T \frac{1}{(1-\alpha)\beta}} \tilde{\mu}_{G,ct}^{T - \frac{1-\beta}{\beta}} \right) \Psi_{G,ct}. \tag{4.37}$$

Under policy uncertainty, the aggregate R&D spending R_{ct} becomes

$$RD_{ct}^{U} = w_{ct}^{S} \sum_{T=H,L} \sum_{G=G_{ct}^{U,I}}^{\bar{G}} \left(x_{G,ct}^{U,T \frac{1}{(1-\alpha)\beta}} \mu_{G,ct}^{T - \frac{1-\beta}{\beta}} + \tilde{x}_{G,ct}^{U,T \frac{1}{(1-\alpha)\beta}} \tilde{\mu}_{G,ct}^{T - \frac{1-\beta}{\beta}} \right) \Psi_{G,ct}^{U}. \tag{4.38}$$

Policy uncertainty has three effects on aggregate R&D spending. First, each firm's R&D spending decreases due to profit loss caused by uncertainty and higher trade cost. Second, it changes the aggregate quality index, $\Psi_{G,ct}^{U}$. As more firms focus only on domestic market and include more product lines, both high and low quality firms exit in domestic market. Third, policy uncertainty lower import cutoff quality gap and push foreign firms to exit. Lower quality firms have incentive to invest in R&D to enter the market.

4.3.6.7 Aggregates and Welfare

Aggregate consumption and aggregate final output are derived from (4.4), (4.16), and (4.18), and can be expressed as

$$C_{ct} = Y_{ct} = \underbrace{\sum_{G=G_{ct}^{I}}^{G_{ct}^{E}} \left[\frac{(1-\beta)^2}{\eta} \right]^{\frac{1-\beta}{\beta}} \Psi_{G,ct}}_{\text{Total Consumption of Domestic Final Goods}} + \underbrace{\sum_{G=-\bar{G}}^{G_{ct}^{I}} (\kappa + \tau_{ct})^{\frac{\beta-1}{\beta}} \left[\frac{(1-\beta)^2}{\eta} \right]^{\frac{1-\beta}{\beta}} \Psi_{G,c't}}_{\text{Total Consumption of Foreign Final Goods}}. \tag{4.39}$$

From (4.39), policy uncertainty decreases the consumption of total final goods import from foreign home country and increases the consumption of domestic final goods. The effect on total consumption is ambiguous and depends on how large the policy uncertainty is believed to be.

Total intermediate-production output is given by (4.22). Based on (4.14), (4.16), and (4.18), wage of unskilled labor in country c is given by

$$w_{ct}^U = \beta \underbrace{\sum_{G=G_{ct}^I}^{G_{ct}^E} \frac{\eta}{1-\beta}\left[\frac{(1-\beta)^2}{\eta}\right]^{\frac{1-\beta}{\beta}} \hat{\Psi}_{G,ct}}_{\text{Total Demand from Domestic Market}} + \underbrace{\sum_{G=G_{ct}^E}^{\bar{G}} \frac{\eta(\kappa+\tau_{c't})}{1-\beta}\left[\frac{(1-\beta)^2}{\eta(\kappa+\tau_{c't})}\right]^{\frac{1-\beta}{\beta}} \hat{\Psi}_{G,ct}}_{\text{Total Demand from Foreign Market}}, \tag{4.40}$$

where $\hat{\Psi}_{G,ct} = \int_{\Omega_{ct}} \varphi_{cjt}^{\frac{1-\beta}{\beta}} dj$

Aggregate government spending S_{ct} in country $c \in \{A, B\}$ is given by

$$S_{ct} = s_{ct} w_{ct}^S \sum_{T=H,L} \sum_{G=G_{ct}^I}^{\bar{G}} x_{G,ct}^{T\frac{1}{(1-\alpha)\beta}} \mu_{G,ct}^{T-\frac{1-\beta}{\beta}} \Psi_{G,ct}. \tag{4.41}$$

Aggregate welfare in economy c over horizon T calculated at time t_0 is given by

$$\mathcal{W}_{ct_0} = \int_{t_0}^{t_0+T} e^{-\rho(s-t)} \frac{C_{cs}^{1-\sigma}-1}{1-\sigma} ds, \tag{4.42}$$

where C_{ct} is given by (4.39).

Now we define the equilibrium.

Definition 8. *Consider an economy consist of two countries $c \in \{A, B\}$. An equilibrium of this economy is an allocation*

$$\left\{r_{ct}, w_{ct}^U, w_{ct}^S, p_{cjt}, p_{c'jt}, q_{cjt}, q_{c'jt}, x_{cjt}^T, \tilde{x}_{cjt}^T, Y_{ct}, C_{ct}, \mathcal{Q}_{ct}, RD_{ct}, S_{ct}, L_{ct}^S, \{\Psi_{G,ct}, \hat{\Psi}_{G,ct}\}_{G\in\{-\bar{G},\cdots,\bar{G}\}}\right\}$$

where $j \in [0,1], T \in \{H, L\}, t \in [0,\infty), c, c' in\{A, B\}$ such that (i) capital price r_{ct} solves representative household's utility maximizing problem given by (4.1) and satisfies the Euler's equation; (ii) sequences of prices $w_c t^U$, p_{cjt}, $p_{c'jt}$ and quantities q_{cjt}, $q_{c'jt}$ solve the profit maximizing problem of final goods and intermediate goods production given by (4.4); (iii) the R&D decisions $\{x_{cjt}^T, \tilde{x}_{cjt}^T\}$ of incumbent and entrant are defined in equations (4.27) and (4.29) and R&D expenditure RD_{ct} is given in equation (4.37); (iv) supply of skilled labor L_{ct}^S is equal to the profit-maximizing demand by *innovation defined by equation (4.5) and skilled wage w^S_{ct} clear the labor markets at every time t; (v) Y_{ct} and C_{ct} are as given in equation (4.39); (vi) $\mathcal{Q}_{ct}$ is given in equation (4.22); (vii) government has a balanced budget at all times in line with equation (4.41); (viii) and $\{\Psi_{G,ct}, \hat{\Psi}_{G,ct}\}_{G\in\{-\bar{G},\cdots,\bar{G}\}}$ are consistent with optimal R&D decisions.*

4.4 Estimation Analysis

In this section, I present the empirical model and identification strategy that is used to estimate firms' innovation decisions, and firm entry and exit to foreign markets in response to increases in trade policy uncertainty. I first introduce model specifications for innovation and firm entry respectively. Then, the data and main variables used in the estimation are described. The estimation results are presented in the last part of this section.

4.4.1 Empirical Specification

4.4.1.1 Innovation and Policy Uncertainty

I examine the link between increases in policy uncertainty and Chinese manufacturing firms' innovation behaviour, measured by R&D and number of patents. Policy uncertainty is in terms of expected future tariff and are identified from time $t-1$ increases in the tariff against Chinese exporters in some market. Specifically, first assume that firms update their beliefs about the likelihood of a policy shock for a specific product in all foreign markets after directly observing a policy (or tariff) change for the product in a market to which the firm exported at time $t-1$. Firms which did not observe the policy change do not update their beliefs about the tariff for other markets. Industry and firm fixed effects are included in the linear model. The estimation equation is as follows:

$$ln(PATENT_{ijt}) = \alpha_i + \beta TPU_{ijt-1} + X'_{ijt}\gamma + \delta_{jt} + \lambda_t + \varepsilon_{ijt}, \tag{4.43}$$

where the dependent variable $ln(PATENT_{ijt})$ is the innovation activity of firm i in industry j at time t, which is measured by number of patents or R&D. TPU_{ijt-1} measures the trade policy uncertainty faced by firm i in industry j at time t. α_i is the firm fixed effect, controlling for all time-invariant firm characteristics. It also controls for industrial and regional differences that does not vary over time but may affect industrial propensity to innovate. For example, certain industrial institutional features may make firms in one industry more likely to innovate than other industries (IT v.s. Mining). The year fixed effect, λ_t is involved in the estimation because if both innovation and policy uncertainty are related to the business cycles or other common shocks such as worldwide pandemic,the relationship between innovation and uncertainty may be overestimated. A set of time-varying firm-level variables (X_{ijt}), and a time-varying industry trend fixed effect (δ_{jt}) that may affect innovation are included in the estimation. ε_{ijt} is the error term. Standard errors are clustered at the firm level to deal with the potential heteroskedasticity and serial autocorrelation.

Following Bhattacharya et al. (2017), Aghion et al. (2005), Klette and Kortum (2004), and Liu and Qiu (2016), I use the number of patent applications as a direct measure for innovation. Lots of firms do not have any patents in some years, to deal with the zeros in patents I use the transformation $1 + PATENT$ where PATENT is the number of patent applications.

The key explanatory variable is the industry-level policy uncertainty. A change in beliefs about trade policy uncertainty for firm i in industry j at time t is captured by a dummy variable, TPU_{ijt-1}, which equals 1 if foreign market j imposed a tariff increase at time $t-1$. Policy uncertainty measurement in this research is different from most empirical research (Liu and Qiu, 2016; Liu and Ma, 2017; Handley, 2014; Handley and Limo, 2017), which is based on the difference between the column 2 tariff and the MFN tariff in 2001, manified by the substitutability coefficient. Their measurements are industry-specified, while the measurement in this research is firm-specified. Because the U.S. is the most important export destination market for Chinese manufacturers, therefore any uncertainty regarding the U.S. market may be transmitted to firms that export to the U.S. and firms that do not. To investigate this case, this research further include an indicator for exporters to the U.S. and interact it with the TPU measures in the following estimation specification:

$$ln(PATENT_{ijt}) = \alpha_i + \beta_1 TPU_{ijt-1} + \beta_2 TPU_{ijt-1} \cdot US_{ijt-1} + X'_{ijt}\gamma + \delta_{jt} + \lambda_t + \varepsilon_{ijt}, \quad (4.44)$$

where US_{ijt} is a dummy variable that equals one for firms that export to the U.S. in year $t-1$, and zero otherwise. β_1 measures the spillovers to other firms.

Because the measure of trade policy uncertainty might be picking up time-varying firm-specific demand or supply, I introduce a further refinement to address this concern. The sample is split into a activist users of contingent tariffs and those that rarely or never use anti-dumping policy over 1995-2013. Following Liu and Ma (2017), I define activist users as those countries whose cumulative import coverage by antidumping over 1995-2013 was 2% or higher. The expanded estimating equation is given by:

$$ln(PATENT_{ijt}) = \alpha_i + \beta_1 TPU_{ijt-1} + \beta_2 TPU_{ijt-1} \cdot NonACT_{ijt-1} + X'_{ijt}\gamma + \delta_{jt} + \lambda_t + \varepsilon_{ijt}, \quad (4.45)$$

where $NonACT_{ijt}$ is a dummy variable that equals one for firms that export to countries that defined as not active in year $t-1$, and zero otherwise. We expect $\beta_2 = 0$ as firms update their beliefs about trade policy that there is no reason to expect changes in non-activist countries.

From the discussion in Section 3.6.6, the coefficient on measure of increased trade policy uncertainty, β (and β_1), is not determinate because an increase in policy uncertainty reduces the value of being an exporter relative to waiting, reduce the innovation incentive for high quality producer but increases the innovation of entrants.

4.4.1.2 Entry and Exit under Policy Uncertainty

The empirical strategy of this section is to estimate a linear probability model of firm entry into foreign markets under policy uncertainty. For this part, the increases in uncertainty are product-specific. Industry, destination country, and firm fixed effects are controlled in this linear probability model. Standard errors are clustered on HS02 industry dummies and destination countries. Industry fixed effects are included because some of the entries come from comparing entry into new markets within the same industry. Destination country fixed effects are included to capture propensities to enter different foreign markets that vary with features like market size, and unobservable barriers to entry. The basic estimating equation for entry is given by:

$$y_{ijht} = \alpha_i + \beta TPU_{ijht-1} + X'_{it}\gamma + Z'_{ht}\theta + \lambda_t + \delta_h + \eta_{HS02} + \varepsilon_{ijht}, \quad (4.46)$$

where h indexes the foreign market, y_{ijht} is a dummy variable equal to one if firm i enters/exits foreign market h with HS06 product j in year t and zero otherwise, α_i are fixed effects for firms, X_{it} are firm specific controls such as total output, Z_{ht} are country level controls such as GDP and exchange rates, λ_t is year fixed effect, δ_h are fixed effects for foreign markets, η_{HS02} are industry fixed effects at the HS02 level. Two country level controls are included in the estimation: the growth rate of GDP in country h in year $t-1$ noted by $\Delta ln(GDP_{ht})$, and the real exchange rate between China and country h in year $t-1$ expressed as foreign currency/RMB and noted by $ln(ex_{ht})$.

From the discussion in Section 3.6.6, the coefficient on measure of increased trade policy uncertainty, β, will be less than zero because an increase in policy uncertainty reduces the value of being an exporter relative to waiting.

As mentioned above, the measure of trade policy uncertainty might be picking up time-varying firm-specific demand or supply. Following the same logic, the sample is split into a activist users of contingent tariffs and those that rarely or never use anti-dumping policy over 1995-2013. The expanded estimating equation is given by:

$$y_{ijht} = \alpha_i + \beta_1 TPU_{ijht-1} + \beta_2 TPU_{ijht-1} \cdot NonACT_{iht-1} + X_{it}'\gamma + Z_{ht}'\theta + \lambda_t + \delta_h + \eta_{HS02} + \varepsilon_{ijht}, \quad (4.47)$$

where $NonACT_{iht}$ is a dummy variable that equals one for firm i that export to country h that defined as not active in year $t-1$, and zero otherwise. For the same reason above, we expect $\beta_1 < 0$ and $\beta_2 = 0$.

Now consider firms' exit decision under policy uncertainty. For exit, define y_{ijht} as a dummy variable which equals 1 if firm i exit foreign market h with product j in year t and 0 otherwise. Same as entry specification, I use Equation (4.46) and (4.47)to estimate firm exit from established markets. From the discussion in Section 3.6.6, the coefficient on measure of increased trade policy uncertainty, β, will be greater than zero because an increase in policy uncertainty reduces the value of being an exporter relative to waiting and push firms exit the foreign market.

Because firms with larger market shares are more productive and, thus, are expected to be less likely to exit the foreign market when policy uncertainty increases (Melitz, 2003). Thus, I introduce firm's export market share (EXP_{ijht-1}) for product j in country h at time $t-1$ into the basic estimation equation (4.46). Besides, I also introduce a interaction term between policy uncertainty and export share into the estimation. Specifically, the expanded estimating equation is given by:

$$y_{ijht} = \alpha_i + \beta_1 TPU_{ijht-1} + \beta_2 EXP_{ijht-1} + \beta_3 TPU_{ijht-1} \cdot EXP_{ijht-1} + X'_{it}\gamma + Z'_{ht}\theta + \lambda_t + \delta_h + \eta_{HS02} + \varepsilon_{ijht}, \tag{4.48}$$

where $EXP_{ijht} = \frac{value\ \ of\ \ exports_{ijht}}{\sum_{i=1}^{N} value\ \ of\ \ exports_{ijht}}$ and N is the total number of Chinese firms exporting j to country h in year t. We expect $\beta_1 > 0$ and $\beta_3 < 0$.

4.4.2 Data

The empirical analysis in this research relies on data that include firm-level information on production, trade, and innovation, as well as macroeconomic data and industry-level characteristics. To this end, I construct a unique dataset by merging five major data sources: (1) patent data from the State Intellectual Property Office (SIPO) of China, (2) firm-level production and financial information from the Annual Survey of Industrial Production (ASIP), provided by the National Bureau of Statistics of China, (3) firm-level export data from the Chinese Customs Database (CCD) maintained by China's General Administration of Customs, (4) trade policy (antidumping policy) data from the Global Antidumping Database (GAD) maintained by the World Bank, and (5) macroeconomic data on real GDP and real exchange rates from the World Bank's World Development Indicators and the USDA Economic Research Service, respectively.

Firstly, I use firm patent applications as a direct measure of innovation activities because patents reflect the actual output of the innovation process, while R&D expenditure measures the input that goes into the innovation process and the R&D expenditure information is only available for a very limited number of firms for a few years for Chinese firms.

Patent data used in this research comes from the State Intellectual Property Office (SIPO) of China. The SIPO takes records on all patent applications in China. This dataset contains detailed information of all patent filings since 1985, including assignee, address of assignee, name and type of the patent, and patent application and assigned date. Patents are classified into three categories based on China's Patent Law: utility, design, and invention. Patents are dated by application year.

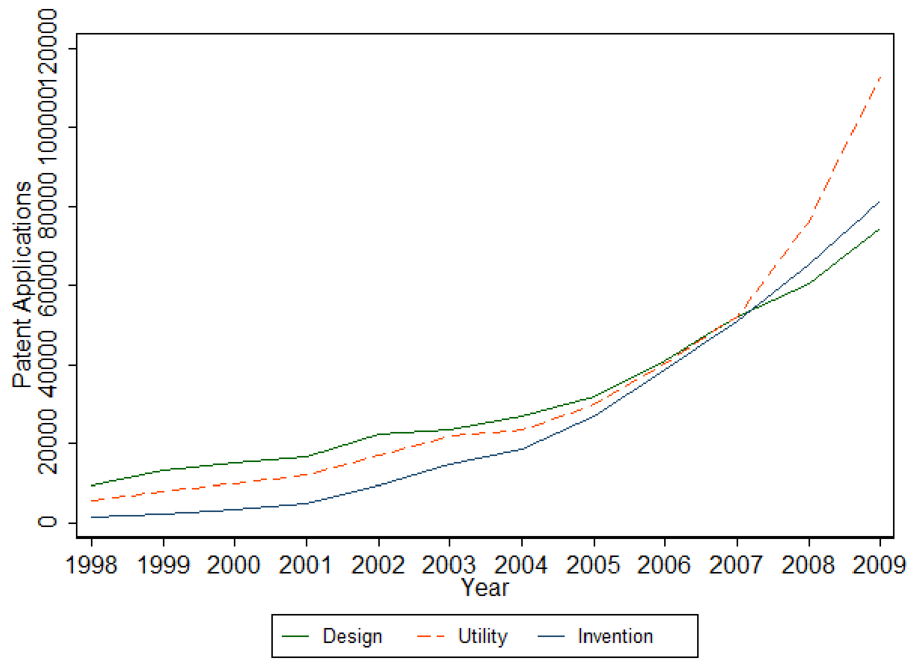


Figure 4.6: Patent Applications by Type in China

However, SIPO does not provide citation data of the assigned patents, thus we are unable generate innovation variables that related to citations, such as originality. Figure 4.6 shows the growth of patent applications by the three types in China during 1998-2009. It's easy to observe that patent applications in China increases drastically for all the three types and the growth is even higher after China joined the WTO in 2001.

Secondly, firm-level production and financial information data comes from the Annual Survey of Industrial Production (ASIP). The ASIP data is the most comprehensive firm-level dataset in China, including all non-state-owned enterprises with annual sales above 0.6 million US dollars (in 2002 exchange rate) and all state-owned enterprise. It covers all 31 mainland provinces and 425 manufacturing industries in 4-digit Chinese industry classification (CIC) system between the years 1998-2007. The ASIP data provides detailed information at the firm level, including location, ownership, and accounting information such as employment, capital stock, material inputs, wage bills, total revenue, and export revenue.

Thirdly, firm-level export data are from the Chinese Customs Database (CCD). The CCD contains the universe of trade transactions for 2000-2006 with detailed information on the firm, product, origin, and destination of each transaction. From this dataset we are able to identify export firms and export products. We also know the value and quantity exported by a firm at 6-digit HS product level.

The key variable in this empirical research is policy uncertainty. Following Crowley et al. (2018) this research uses antidumping policy data to calculate product and firm-level policy uncertainty. The antidumping policy data comes from Global Antidumping Database (GAD). The GAD includes information on increases in tariffs at the 6-digit HS product level by 17 importing countries/regions against China under the WTO's Agreement on Antidumping. Table 4.2 provide the list of the 17 importing countries and their cummulative coverage of imports by antidumping duties over 1995-2013. The data have 514 antidumping investigations against China involving 813 6-digit HS products during 2000-2009. This represents approximately 15% of all 6-digit HS products.

Table 4.2: Countries in Antidumping Database

Country	Coverage	Activist User	Country	Coverage	Activist User
Argentina	4.6	Yes	Mexico	22.8	Yes
Australia	2.5	Yes	Pakistan	0.4	No
Brazil	2.4	Yes	Philippines	0.3	No
Canada	3.4	Yes	South Africa	2.1	Yes
Colombia	1.2	No	South Korea	1.4	No
European Union	6.6	Yes	Thailand	0.6	No
India	7.6	Yes	Turkey	2.5	Yes
Indonesia	1.1	No	United States	9	Yes
Japan	0.1	No			

Notes: The cumulative coverage of a country's imports by antidumping duties over 1995-2013 comes from Crowley et al. (2018), Table1. A country is an "activist user" of antidumping policy if the cumulative share of imports under an antidumping duty over 1995-2013 is greater than or equal to 2 percent.

To construct the estimation dataset, data sample is restricted to only multi-product exporters. Only firms that export at least 2 products at the 6-digit level in at least one year over 2000-2006. The sample used in this research is restricted to 33 countries that include China's top 20 destination markets by value in each year during 2000-2006 and 17 destinations that have applied antidumping duties against China (list in Table 4.2). Firms in this search are restricted to "manufacturers" or "trading" firms using the Chinese characters in the firm's name and use this classification to split the sample into two groups.

The merge of the five datasets is a big challenge. Following Feng et al. (2016) and Liu and Qiu (2016), I merge the SIPO patents data with ASIP firm-level production data and CCD firm-level export data by carefully matching firms' name and location. The matched sample accounts for above 34% of total patent fillings by all firms (including both manufacturing and non-manufacturing firms) in the SIPO data for the period 2000-2006. The matching approach is based on the names and location of firms, applies to all firms across industries and in the whole sample period. The degree of mismatch across industries does not seem to be correlated with the degree of market uncertainty reduction across industries. After all the matches and data cleaning, we have an unbalanced panel of 367,466 firms and a total of around 938,209 observations, spanning 425 four-digit industries by the China Industrial Classification (CIC) between the years 2000-2006. Table 4.3 presents the summary statistics and definitions of the main variables used in the patent spcification. The key variables are patents (or lnPATENT) and TPU. On average, each firm filed 0.01 patents each year during 2000-2006. The mean of firm-level TPU is 0.0156.

Table 4.3: Descriptive Statistics of Patent Specification

variable	Variable Definition	N	Mean	Std.Dev	Min	Max
Patents	Number of totoal patent applications	983,209	0.285	10.96	0	6122
Design	Number of design patent applications	983,209	0.111	3.435	0	1101
Utility	Number of Utility patent applications	983,209	0.0936	2.327	0	518
Invention	Number of Invention patent applications	983,209	0.0799	8.759	0	5757
lnPATENT	Logarithm of 1 puls Patents	983,209	0.0513	0.312	0	8.720
TPU	Trade Policy Uncertainty	983,209	0.0156	0.106	0	1
TFP	TFP using Olley and Pakes (1996)	973,902	6.809	1.040	-2.404	13.44
CapitalIntensity	Capital-labor ratio	973,902	238.2	487.6	0.154	132352
lnLabor	Logarithm of labor size	973,902	4.779	1.099	2.079	11.99
Export	Exporting dummy	983,209	0.302	0.459	0	1
lnage	Logarithm of firm age	983,209	1.923	0.820	0	6.695
lnage2	Square logarithm of firm age	983,209	4.370	3.339	0	44.82

Notes: There are 367,466 Chinese firms and a total of around 938,209 observations in the sample. Firm age is calculated use fiscal year minus the first filling year. TPU is generated based on Antidumping policy which is 6-digit HS product specificated. Firm-level TPU is calculated using average of all firm product-level TPU.

The next step is to merge trade policy data. Following Crowley et al. (2018), I merge the CCD data with the Globa Antidumping Database and identify the firm-product-destination-year observations in which an antidumping duty was imposed. Specifically, if a firm-product faced an antidumping duty in country h at time t, I flag the exports of that product to all other countries in the following year as having faced an increase in trade policy uncertainty. After all the matches and data cleaning, we have an unbalanced panel of 44,106 firms with a total of 1,787,615 product based observations of manufacturing firms, and an unbalanced panel of 683 firms with a total of 98,0404 product based observations of trading firms between the years 2000-2006.

Table 4.4 reports summary statistics on firm entry and exit to foreign market for both manufacturers and trading firms. The key variable for entry is *Entry* which is a dummy variable equal to 1 if a firm enters destination country and 0 otherwise. Similarly, the variable *Exit* is a 0-1 indicator equal to 1 if a firm exits destination country. Entry is defined when a firm is observed exporting to: (1) a new country with existing product, (2) a new country with a new product, or (3) an existing country with a new product. Similarly, exit is defined when a firm is observed stop export to: an existing country, or an existing country with one or more products.

Table 4.4 shows that on average manufacturing firms have much higher probability of entry and lower probability of exit than trading firms. The average probability of entry by manufacturing firms is around three times as high as that for trading firms. On average, trading firms have more export destinations than manufacturers. The average number of product-destination pairs is around 40 for manufacturing firms, while it is more than 143 for trading firms. Trading firms have larger market shares than manufacturing firms or trading firms are more intensive than manufacturers. The policy uncertainty variable TPU is a dummy variable that captures whether a firm-product-destination observation was exposed to trade policy uncertainty arising from the imposition of a tariff hike in one of China's export markets.

Table 4.4: Descriptive Statistics of Firm Entry and Exit Specification

variable	Variable Definition	N	Mean	Std.Dev	Min	Max
	Manufacturing Firms Entry					
Entry	Foreign market entry dummy	1,788,000	0.165	0.371	0	1
TPU	Trade Policy Uncertainty	1,788,000	0.00663	0.0811	0	1
TPU*ACT	TPU and Activist interaction	1,788,000	0.00284	0.0532	0	1
TPU*NonACT	TPU and Non Activist interaction	1,788,000	0.00379	0.0614	0	1
GDP	GDP	1,715,000	3.599	2.321	-10.89	14.43
Realexrate	Real Exchange rate	1,788,000	33.29	153.0	0.0633	1328
	Trading Firms Entry					
Entry	Foreign market entry dummy	98,040	0.0579	0.234	0	1
TPU	Trade Policy Uncertainty	98,040	0.00623	0.0787	0	1
TPU*ACT	TPU and Activist interaction	98,040	0.00559	0.0746	0	1
TPU*NonACT	TPU and Non Activist interaction	98,040	0.000643	0.0253	0	1
GDP	GDP	96,294	3.474	2.269	-10.89	14.43
Realexrate	Real Exchange rate	98,040	41.75	185.6	0.0633	1328
	Manufacturing Firms Exit					
Exit	Foreign market exit dummy	1,788,000	0.201	0.401	0	1
TPU	Trade Policy Uncertainty	1,788,000	0.00663	0.0811	0	1
EXP	Export Share	1,788,000	0.120	0.253	0	1
TPU*EXP	TPU and Export Share interaction	1,788,000	0.000328	0.0135	0	1
GDP	GDP	1,715,000	3.599	2.321	-10.89	14.43
Realexrate	Real Exchange rate	1,788,000	33.29	153.0	0.0633	1328
	Trading Firms Exit					
Exit	Foreign market exit dummy	98,040	0.276	0.447	0	1
TPU	Trade Policy Uncertainty	98,040	0.00623	0.0787	0	1
EXP	Export Share	98,040	0.580	0.422	0	1
TPU*EXP	TPU and Export Share interaction	98,040	0.00193	0.0393	0	1
GDP	GDP	96,294	3.474	2.269	-10.89	14.43
Realexrate	Real Exchange rate	98,040	41.75	185.6	0.0633	1328

Notes: There are 44,106 Chinese manufacturing firms and a total of around 1,787,615 6-digit HS product level observations and 683 Chinese trading firms with a total of 98,0404 product level observations in the sample. Firm age is calculated use fiscal year minus the first filling year. *ACT* is equal to 1 if cumulative import coverage by antidumping policy over 1995-2013 was 2% or higher and 0 otherwise. *NonACT* equals 1 if cumulative import coverage by antidumping policy over 1995-2013 was less than 2% and 0 otherwise. TPU is generated based on Antidumping policy which is 6-digit HS product specificated.

4.4.3 Estimation Results

As indicated by the theoretic model in Section 4.3, policy uncertainty increases are associated with a reduction in foreign market entry, a increase in foreign market exit, and also have an unclear effect on on innovation. This section focuses on investigating how policy uncertainty affects innovation, firms entry and exit. To this end, I perform innovation regression, firm entry regression, and firm exit regression based on the estimation models discussed in Section 4.4.1. For innovation regression, I examine the effect of policy uncertainty on innovation by regressing Chinese firms' innovation activities denoted by number of patent applications on a policy uncertainty index based on antidumping policies. Section 4.4.3.1 below provides the main estimation results for this part. To further investigate how policy uncertainty affects firms entry and exit, I estimate entry and exit on policy uncertainty index. Section 4.4.3.2 below provides the main estimation results for firms entry and exit. The empirical results in this section show that Chinese firms innovate less and are deterred from entering foreign market as a result of increases in the expectation of the future tariff rate. Exporters are more likely to exit established foreign market in a climate of greater policy uncertainty.

4.4.3.1 Innovation and Policy Uncertainty

A. Baseline Results.

The baseline estimation examines the impact of policy uncertainty on innovation activities of Chinese manufacturing firms based on Equation (4.43). Sample period is from 2000 to 2006. The baseline results are reported in Table 4.5.

The response variable is $lnPATENT$, which is measured by the natural log of 1 plus number of patent applications. Columns (1), (3), and (5) present the estimation results using policy uncertainty (TPU) only. Columns (2), (4), and (6) present the estimation results using all controls. All columns control for year fixed effect. Columns (1)-(2) control industry fixed effect additionally. Columns (3)-(4) control firm fixed effect while columns (5)-(6) control both firm and industry-year-trend fixed effect. The key explanatory variable is policy uncertainty, which is measured based on antidumping policies. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

Table 4.5: Policy Uncertainty and Innovation, 2000-2006

Innovation Measures	lnPATENT					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TPU_{it-1}	-0.113***	-0.020***	-0.013***	-0.012***	-0.015***	-0.014***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
TFP_{it-1}		0.018***		0.005***		0.005***
		(0.001)		(0.001)		(0.001)
$lnkl_{it-1}$		0.034***		0.014***		0.013***
		(0.001)		(0.001)		(0.001)
$lnLabor_{it-1}$		0.048***		0.027***		0.025***
		(0.001)		(0.001)		(0.001)
$lnage_{it-1}$		-0.018***		-0.014***		-0.010***
		(0.002)		(0.002)		(0.002)
$lnage2_{it-1}$		0.005***		0.002***		0.001**
		(0.001)		(0.001)		(0.001)
$Export_{it-1}$		0.019***		0.008***		0.007***
		(0.001)		(0.002)		(0.002)
Adj R^2	0.252	0.283	0.341	0.367	0.359	0.401
N	983,209	973,902	983,209	973,902	983,209	973,902
# of Firms	367,466	365,682	367,466	365,682	367,466	365,682
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y				
Firm FE			Y	Y	Y	Y
Industry Year Trend					Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. i stands for firm, t stands for year. Sample period is 2000-2006, the response variable is innovation, which is measured by the natural log of 1 plus number of patent applications. Variables are well defined in Table 4.3. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

My regressor of interest is the policy uncertainty term (TPU). Its coefficient is statistically significant at the 1% level and negative, suggesting that domestic firms in high uncertainty climate experienced larger decrease in patent applications than firms in higher uncertainty climate. The results imply that increases in policy uncertainty induces less domestic innovation. Specifically, one percent increase in policy uncertainty is associated with roughly an average of 1.3 percent decrease in the number of patent applications by Chinese firms. These results are consistent with previous research by Liu and Ma (2017), Feng et al. (2016), and Coelli et al. (2016). In their research, they use the log difference between the column 2 tariff and the Most Favourable Nation (MFN) tariff in 2001 to measure the policy uncertainty in the destination market and found that reduction in policy uncertainty in destination market induces innovation. Comparing to their measure of policy uncertainty which is nation-based, my measure of policy uncertainty is product based and more focus on antidumpting policies that affects special exports directly.

The negative coefficient can be partially explained by the theoretical model prediction in Section 3.6.6. Policy uncertainty forces more firms focus on domestic market and increase competition in domestic as more firms will choose to stay only in domestic. Because of the uncertainty of future economic climate, firms have incentive to wait to invest in new product or to increase the quality of existing products. As such, innovation decreases. Besides, policy uncertainty also push importers exit domestic market, as such, competition in domestic market become lower and firms have less incentive to invest in innovation in domestic market. This is also consistent with theoretical research by Akcigit et al. (2018), which shows that policy uncertainty has negative effects on innovation and ambiguous effect on welfare as increased trade policy uncertainty reduces domestic competition.

The estimation coefficients on the lagged TFP are all positive and statistically significant at the 1% level. The positive coefficients are in line with lots of research in productivity and innovation. Higher productivity (TFP) firms actively participate in innovation in terms of having more patent applications. Productive firms tend to be more actively engaged in innovation. One percent increase in productivity is associated with roughly 5 percent increase in the number of patent applications by Chinese firms. Firm's characteristics that related to innovation also plays an important role in innovative activities. The effect of firm size measured by labor on innovation is positive and statistically significant at the 1% level. Firms with bigger size in terms of larger employers are more likely to bear sunk costs of investment and costs caused by policy uncertainty increases.

In addition, there is a positive and statistically significant estimate of capital intensity. Firms with intensive capital relative to labor appear to have more patent applications. The negative estimates of firm age suggesting that firm age has an negative effect on innovation. When it comes to exporter dummy, the estimated coefficient is positive and statistically significant at 1% level.

The positive sign of the coefficient on exporter dummy indicates that Chinese exporters have more patent application comparing to firms which do not export. This is consistent with the model prediction that exporters usually have higher productivity and can cover high sunk cost to do innovation.

Table 4.6: Policy Uncertainty and Innovation with US Exporter, 2000-2006

Innovation Measures	lnPATENT					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TPU_{it-1}	-0.116***	-0.023***	-0.013***	-0.011**	-0.015***	-0.013***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
$TPU_{it-1} * US_{it-1}$	-0.015	-0.014	0.003	0.004	0.001	0.001
	(0.017)	(0.016)	(0.014)	(0.014)	(0.014)	(0.014)
TFP_{it-1}		0.018***		0.005***		0.005***
		(0.001)		(0.001)		(0.001)
$lnkl_{it-1}$		0.034***		0.014***		0.013***
		(0.001)		(0.001)		(0.001)
$lnLabor_{it-1}$		0.048***		0.027***		0.025***
		(0.001)		(0.001)		(0.001)
$lnAge_{it-1}$		-0.018***		-0.014***		-0.010***
		(0.002)		(0.002)		(0.002)
$lnAge2_{it-1}$		0.005***		0.002***		0.001**
		(0.001)		(0.001)		(0.001)
$Exporter_{it-1}$		0.019***		0.008***		0.007***
		(0.001)		(0.002)		(0.002)
Adj R^2	0.253	0.287	0.304	0.316	0.329	0.411
N	983,209	973,902	983,209	973,902	983,209	973,902
# of Firms	367,466	365,682	367,466	365,682	367,466	365,682
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y				
Firm FE			Y	Y	Y	Y
Industry Year Trend					Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. i stands for firm and t stands for year. Sample period is 2000-2006, the response variable is innovation, which is measured by the natural log of 1 plus number of patent applications. Variables are well defined in Table 4.3. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

B. Heterogenous Effects with Exporters to US

In previous section, the average negative effect of policy uncertainty on firm patenting has been established. However, firms with different characteristics may respond differently. Some firm's characteristics, including firm size, TFP, capital intensity, firm age, and exporter, that may affect its innovation activities have been discussed above. Besides those characteristics, one key concern is the heterogeneous response of exporters to U.S., compared with other firms because the U.S. is the most important export destination market for Chinese manufacturers and any uncertainty regarding the U.S. market may be transmitted to firms that export to the U.S. and firms that do not. Although non-exporting firms may benefit from reduced uncertainty through spillover externalizes, exporters are directly exposed to policy uncertainty, so they are expected to respond more to policy uncertainty shocks. Following the empirical specification in equation (4.44), this section adds U.S. exporter dummy to the baseline model. The estimation results are reported in Table 4.6.

The response variable is $lnPATENT$, which is measured by the natural log of 1 plus number of patent applications. Columns (1), (3), and (5) present the estimation results using policy uncertainty (TPU) only. Columns (2), (4), and (6) present the estimation results using all controls. All columns control for year fixed effect. Columns (1)-(2) control industry fixed effect additionally. Columns (3)-(4) control firm fixed effect while columns (5)-(6) control both firm and industry-year-trend fixed effect. The key explanatory variable is policy uncertainty, which is measured based on antidumping policies. The interaction term between policy uncertainty and exporters to the U.S. is introduced to each estimation. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

Similar to Table 4.5, the policy uncertainty estimation coefficient is negative and statistically significant at the 1% level, suggesting that domestic firms in high uncertainty climate experienced larger decrease in patent applications than firms in low uncertainty climate. More specifically, one percent increase in policy uncertainty is associated with roughly an average of 1.5 percent decrease in the number of patent applications by Chinese firms. One key regressor is the interaction term between TPU and exporters to the U.S. Specifically, the estimation coefficients of the interaction term are very close to 0 and not statistically significant even at the 10% significant level. My TPU measures are constructed with the antidumping duty that is product level based, as such, policy shock is not relevant for firms exporting to the US market as much we expected. The results imply that increases in policy uncertainty induces domestic innovation. However, no evidence was found that exporters to U.S. may have spillover effect on other firms. These results are different from previous research by Liu and Ma (2017) because they measure TPU uing the U.S. column 2 tariff. Since the policy shock is more relevant for firms exporting to the US market, it is expected that the TPU has stronger impact on exporters to U.S.

For other firm characteristics, similar to the baseline results, the estimation coefficients on the lagged TFP are all positive and statistically significant at the 1% level. Productive firms tend to be more actively engaged in innovation. One percent increase in productivity is associated with roughly 5 percent increase in the number of patent applications by Chinese firms. The effect of firm size is positive and statistically significant at the 1% level. Firms with bigger size in terms of larger employers are more likely to invest in innovation. Firms with intensive capital relative to labor appear to have more patent applications. Firm age has an negative effect on innovation. Chines exporters have more patent application comparing to firms which do no export.

C. Heterogenous Effects with Time-Varying Specifics

Table 4.5 and 4.6 have establish the average negative effect of policy uncertainty on firm patenting. This section examines heterogeneity in the impact of antidumping on innovation that are activist users of antidumping policy and foreign markets that, for the most part, rarely apply antidumping duties. The sample of firms in this section is identical to those in Table 4.5 and 4.6 but here I distinguish exporters which face active antidumping policy versus exporters that could face antidumping duties, but rarely or never do. Following the empirical specification in equation (4.45), this section adds active dummy to the baseline model. The estimation results are reported in Table 4.7.

The response variable is $lnPATENT$, which is measured by the natural log of 1 plus number of patent applications. Columns (1), (3), and (5) present the estimation results using policy uncertainty only. Columns (2), (4), and (6) present the estimation results using all controls. All columns control for year fixed effect. Columns (1)-(2) control industry fixed effect additionally.

Columns (3)-(4) control firm fixed effect while columns (5)-(6) control both firm and industry-year-trend fixed effect. The key explanatory variable is policy uncertainty, which is measured based on antidumping policies. The interaction term between policy uncertainty and non-active dummy is introduced to each estimation. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

Table 4.7: Policy Uncertainty and Innovation with Active Dummy, 2000-2006

Innovation Measures	lnPATENT					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TPU_{it-1}	-0.106***	-0.018***	-0.013***	-0.011***	-0.015***	-0.013***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
$TPU_{it-1} * NonAct_{it-1}$	0.041	0.032	0.058	0.053	0.050	0.046
	(0.042)	(0.040)	(0.028)	(0.028)	(0.028)	(0.028)
TFP_{it-1}		0.018***		0.005***		0.005***
		(0.001)		(0.001)		(0.001)
$lnkl_{it-1}$		0.034***		0.014***		0.013***
		(0.001)		(0.001)		(0.001)
$lnLabor_{it-1}$		0.048***		0.027***		0.025***
		(0.001)		(0.001)		(0.001)
$lnAge_{it-1}$		-0.018***		-0.014***		-0.010***
		(0.002)		(0.002)		(0.002)
$lnAge2_{it-1}$		0.005***		0.002***		0.001**
		(0.001)		(0.001)		(0.001)
$Exporter_{it-1}$		0.019***		0.008***		0.007***
		(0.001)		(0.002)		(0.002)
Adj R^2	0.326	0.381	0.304	0.336	0.319	0.421
N	983,209	973,902	983,209	973,902	983,209	973,902
# of Firms	367,466	365,682	367,466	365,682	367,466	365,682
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y				
Firm FE			Y	Y	Y	Y
Industry Year Trend					Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is 2000-2006, the response variable is innovation, which is measured by the natural log of 1 plus number of patent applications. Variables are well defined in Table 4.3. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

The policy uncertainty estimation coefficient is negative and statistically significant at the 1% level, confirms the results in Table 4.5 and 4.6 that domestic firms in high uncertainty climate experienced larger decrease in patent applications than firms in low uncertainty climate. More specifically, one percent increase in policy uncertainty is associated with roughly an average of 1.5 percent decrease in the number of patent applications by Chinese firms. The estimation coefficients of the interaction term are close to 0 and not statistically significant even at the 10% significant level. For firms that face not active antidumping duties, policy uncertainty is not a big concern for them and their expectation of antidumping duty changes would not change much. As such, exporters that fact non-active antidumping duties would not be affected by policy uncertainty change. Estimate results confirms the hypothesis that Chinese firms use information about policy changes and historical use of antidumping policy to update their beliefs about future trade policy changes.

For other firm characteristics, similar to the baseline results and the results in Table 4.6, the estimation coefficients on the lagged TFP are all positive and statistically significant at the 1% level. Productive firms tend to be more actively engaged in innovation. One percent increase in productivity is associated with roughly 5 percent increase in the number of patent applications by Chinese firms. The effect of firm size is positive and statistically significant at the 1% level. Firms with bigger size in terms of larger employers are more likely to invest in innovation. Firms with intensive capital relative to labor appear to have more patent applications. Firm age has an negative effect on innovation. Chines exporters have more patent application comparing to firms which do no export.

4.4.3.2 Entry and Exit under Policy Uncertainty

A.Baseline Results

Table 4.8 presents baseline estimates for the market entry behavior of manufacturing and trading firms that confronted a new antidumping measure somewhere in the world between 2000 and 2006.

The response variable is $Entry_{ijht}$, which is a dummy variable equal to to one if firm i enters foreign market h with a 6-digit HS product j at year t and 0 otherwise. Columns (1)-(3) present the estimation results using manufacturing firms only. Columns (4)-(6) present the estimation results using trading firms only. All columns control for year fixed effect. Columns (1)-(2) and (4)-(5)

control industry fixed effect additionally. Columns (3) and (6) control firm fixed effect. The key explanatory variable is policy uncertainty, which is measured based on antidumping duties. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

Table 4.8: Policy Uncertainty and Entry, 2000-2006

$Entry_{ijht}$	Manufacturing Firms			Trading Firms		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TPU_{ijht-1}	-0.033***	-0.034***	-0.032***	-0.035	-0.034	-0.033
	(0.006)	(0.006)	(0.006)	(0.024)	(0.024)	(0.024)
$Size_{it-1}$			-0.003***			-0.002
			(0.000)			(0.002)
$ln(GDP)_{ht-1}$		-0.000	-0.000		-0.006*	-0.006*
		(0.001)	(0.001)		(0.003)	(0.003)
$ln(RealExcahgne)_{ht-1}$		0.000***	0.000***		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Adj R^2	0.205	0.215	0.251	0.302	0.31	0.312
N	2,013,443	1,929,237	1,929,237	100,403	98,580	98,580
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y		Y	Y	
Country FE	Y	Y	Y	Y	Y	Y
Firm FE			Y			Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is 2000-2006, i stands for firm, j stands for 6-digit HS product, h stands for exporting destination. The response variable is $Entry_{ijht}$, which is a dummy variable equal to to one if firm i enters foreign market h with a 6-digit HS product j at year t and 0 otherwise. Variables are well defined in Table 3.3. Variable "Size" is defined as the logarithm of sales. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

Results in Table 4.8 show that increased uncertainty about the future tariff rate in destination h reduces participation in exporting activity. Entry into foreign markets declines as policy uncertainty increases. We see that there is a average of 3.3 percentage point decline in the entry for manufacturing firms and a average of 3.4 percentage point decline in entry for trading firms. Estimates of the tariff scare effect are slightly larger when we consider destination's characteristics in columns (2) and (5) and estimates are slightly smaller when we include firm size additionally in columns (3) and (6). Notably, the negative impact on entry is statistically different from zero at the 1% for manufacturing firms and is not statistically different from zero for trading firms. The impact of GDP growth in the destination has negative sign, but is imprecisely estimated. Firm size has a negative effect on firm entry. The estimated coefficient of firm size shows that there is a 0.3 percentage point decline in the entry for manufacturing firms and 0.2 percentage point decline in entry for trading firms if firm size increases by 1%. Larger firms need to cover higher cost to enter the foreign market and henceforth are less lightly to enter comparing to small firms.

In the estimation sample, the average probability of new market entry is 16.5 percent for manufacturing firms and 5.79 percent for trading firms. Thus, the threat of a tariff hike reduces the probability of entry by 20 percent (3.3/16.5) for manufacturing firms and 58.7 percent (3.4/5.79) for trading firms.

Table 4.9: Policy Uncertainty and Exit, 2000-2006

$Exit_{ijht}$	Manufacturing Firms			Trading Firms		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TPU_{ijht-1}	0.023***	0.023***	0.021**	0.043*	0.045*	0.043*
	(0.008)	(0.008)	(0.008)	(0.024)	(0.025)	(0.025)
$Size_{it-1}$			0.003***			0.004*
			(0.000)			(0.002)
$ln(GDP)_{ht-1}$		-0.000	-0.000		-0.004	-0.004
		(0.001)	(0.001)		(0.004)	(0.004)
$ln(RealExcahgne)_{ht-1}$		0.000	0.000		-0.001	-0.001
		(0.000)	(0.000)		(0.000)	(0.000)
Adj R^2	0.309	0.323	0.337	0.342	0.369	0.374
N	2,013,443	1,929,237	1,929,237	100,403	98,580	98,580
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y		Y	Y	
Country FE	Y	Y	Y	Y	Y	Y
Firm FE			Y			Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is 2000-2006, i stands for firm, j stands for 6-digit HS product, h stands for exporting destination. The response variable is $Exit_{ijht}$, which is a dummy variable equal to to one if firm i exits foreign market h with a 6-digit HS product j at year t and 0 otherwise. Variables are well defined in Table 4.3. Variable "Size" is defined as the logarithm of sales. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

Table 4.9 presents baseline estimates for the market exit behavior of manufacturing and trading firms that confronted a new antidumping measure somewhere in the world between 2000 and 2006. The response variable is $Exit_{ijht}$, which is a dummy variable equal to to one if firm i exits foreign market h with a 6-digit HS product j at year t and 0 otherwise. Columns (1)-(3) present the estimation results using manufacturing firms only. Columns (4)-(6) present the estimation results using trading firms only. All columns control for year fixed effect. Columns (1)-(2) and (4)-(5) control industry fixed effect additionally. Columns (3) and (6) control firm fixed effect. The key explanatory variable is policy uncertainty, which is measured based on antidumping duties. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

Results in Table 4.9 show that increased uncertainty about the future tariff rate in destination h increases exits from existing exporting market. Exit from existing foreign markets increases as policy uncertainty increases. We see that there is a average of 2.3 percentage point increase in the exit for manufacturing firms and a average of 4.3 percentage point increase in exit for trading firms. Estimates of the tariff scare effect are slightly larger when we consider destination's characteristics in column (5) and estimates are slightly smaller when we include firm size additionally in column (3). The positive impact of policy uncertainty on entry is statistically different from zero at the 1% level for manufacturing firms and is statistically different from zero at the 10% level for trading firms. The impact of GDP growth in the destination has negative sign, but is not statistically significant. Firm size has a positive effect on firm exit. The estimated coefficient of firm size shows that there is a 0.3 percentage point increase in the exit for manufacturing firms and 0.4 percentage point increase in exit for trading firms if firm size increases by 1%. Larger firms need to cover higher cost to enter the foreign market and henceforth are more lightly to exit comparing to small firms when hitting by shocks.

In the estimation sample, the average probability of market exit is 20.1 percent for manufacturing firms and 27.6 percent for trading firms. Thus, the threat of a tariff hike increases the probability of exit by 11.4 percent (2.3/20.1) for manufacturing firms and 15.6 percent (4.3/27.6) for trading firms. The impact of a tariff threat on market exit is substantial.

B. Heterogenous Effects with Time-Varying Specifics

Table 4.8 and 4.9 have establish the average negative effect of policy uncertainty on foreign market entry and positive effect on foreign market exit. Next, this section examines heterogeneity in the impact of antidumping on new market entry and market exit into foreign markets that are activist users of antidumping policy and foreign markets that rarely apply antidumping duties on imports from any origins for the most part. Table 4.10 reports the estimation results for manufacturing firms and trading firms new market entry. The sample of firms is identical to that in Table 4.8 but here I distinguish between entry into countries which actively use antidumping policy versus countries that could impose antidumping duties, but rarely or never did. Following the empirical specification in equation (4.47), this section adds active dummy to the baseline model.

Table 4.10: Policy Uncertainty and Entry with Time-Varying Heterogenous Effects, 2000-2006

$Entry_{ijht}$	Manufacturing Firms			Trading Firms		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TPU_{ijht-1}	-0.029***	-0.030***	-0.029***	-0.069***	-0.069***	-0.068***
	(0.010)	(0.010)	(0.010)	(0.019)	(0.019)	(0.019)
$TPU_{ijht-1} * NonAct_{ht-1}$	-0.007	-0.006	-0.005	0.332***	0.332***	0.333***
	(0.014)	(0.014)	(0.014)	(0.098)	(0.100)	(0.099)
$Size_{it-1}$			-0.003***			-0.002
			(0.000)			(0.002)
$ln(GDP)_{ht-1}$		-0.000	-0.000		-0.006*	-0.006*
		(0.001)	(0.001)		(0.003)	(0.003)
$ln(RealExcahgne)_{ht-1}$		0.000***	0.000***		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Adj R^2	0.349	0.347	0.375	0.415	0.433	0.458
N	2,013,443	1,929,237	1,929,237	100,403	98,580	98,580
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y		Y	Y	
Country FE	Y	Y	Y	Y	Y	Y
Firm FE			Y			Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is 2000-2006, i stands for firm, j stands for 6-digit HS product, h stands for exporting destination. The response variable is $Entry_{ijht}$, which is a dummy variable equal to to one if firm i enters new foreign market h with a 6-digit HS product j at year t and 0 otherwise. Variables are well defined in Table 4.3. Variable "Size" is defined as the logarithm of sales. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

The response variable is $Entry_{ijht}$, which is a dummy variable equal to to one if firm i enters foreign market h with a 6-digit HS product j at year t and 0 otherwise. Columns (1)-(3) present the estimation results using manufacturing firms only. Columns (4)-(6) present the estimation results using trading firms only. All columns control for year fixed effect. Columns (1)-(2) and (4)-(5) control industry fixed effect additionally. Columns (3) and (6) control firm fixed effect. The key explanatory variable is policy uncertainty, which is measured based on antidumping duties. The interaction term between policy uncertainty and non-active dummy is introduced to each estimation. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

The coefficient estimates on the measure of increased trade policy uncertainty are all negative. However, the coefficient estimates are smaller than those in Table 4.8 for manufacturing firms, and are larger than those in Table 4.8 for trading firms. For manufacturing firms, the probability of entry declines 2.9 percent into activist markets for a firm's existing products. For trading firms, the probability of entry declines 6.9 percent. For trading firms, since they are more active in foreign market and the policy uncertainty shock affect them more than manufacturing firms. As such, policy uncertainty shows a larger effect on trading firms. These estimates also show that Chinese firms use information about policy changes in market h and historical use of antidumping policy in other markets to update their beliefs about future trade policy changes in other markets. Firms then act on this updated information through their entry decisions.

The coefficient estimates of the interaction term between policy uncertainty and non-active dummy are not statistically significant different from 0 for manufacturing firms. This is consistent with the prediction in section 4.1.2. For manufacturing firms that face not active antidumping duties, policy uncertainty is not a big concern for them and their expectation of antidumping duty changes would not change much. As such, exporters that fact non-active antidumping duties would not be affected by policy uncertainty change. On the contrary, the coefficient estimates of the interaction term are all positive and statistically significant at the 1% level for trading firms. For trading firms, they are more active in international trade and not active antidumping policies provide them a relative stable climate. Increased policy uncertainty may force trading firms entering a market that are more stable and have non-active antidumping policies.

Table 4.11: Policy Uncertainty and Exit with Time-Varying Heterogenous Effects, 2000-2006

$Exit_{ijht}$	Manufacturing Firms			Trading Firms		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TPU_{ijht-1}	0.022***	0.022**	0.021**	0.064**	0.067**	0.066**
	(0.009)	(0.009)	(0.009)	(0.030)	(0.031)	(0.031)
EXP_{ijht-1}	-0.025***	-0.025***	-0.019***	-0.043**	-0.045**	-0.041**
	(0.003)	(0.004)	(0.004)	(0.019)	(0.020)	(0.021)
$TPU_{ijht-1} * EXP_{ijht-1}$	0.012	0.013	0.010	-0.035	-0.035	-0.036
	(0.022)	(0.023)	(0.023)	(0.032)	(0.032)	(0.032)
$Size_{it-1}$			0.002***			0.002
			(0.000)			(0.002)
$ln(GDP)_{ht-1}$		-0.000	-0.000		-0.004	-0.004
		(0.001)	(0.001)		(0.004)	(0.004)
$ln(RealExcahgne)_{ht-1}$		-0.000	0.000		-0.001	-0.001
		(0.000)	(0.000)		(0.000)	(0.000)
Adj R^2	0.314	0.313	0.335	0.686	0.674	0.697
N	2,013,443	1,929,237	1,929,237	100,403	98,580	98,580
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y		Y	Y	
Country FE	Y	Y	Y	Y	Y	Y
Firm FE			Y			Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is 2000-2006, i stands for firm, j stands for 6-digit HS product, h stands for exporting destination. The response variable is $Exit_{ijht}$, which is a dummy variable equal to to one if firm i exits foreign market h with a 6-digit HS product j at year t and 0 otherwise. Variables are well defined in Table 4.3. Variable "Size" is defined as the logarithm of sales. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

To further eximate differences in the propensity to exit foreign markets, I introduce firm's export market share into the baseline estimates. Table 4.11 reports the estimation results based on specification equation (4.48). Columns (1)-(3) present the estimation results using manufacturing firms only. Columns (4)-(6) present the estimation results using trading firms only. All columns control for year fixed effect. Columns (1)-(2) and (4)-(5) control industry fixed effect additionally. Columns (3) and (6) control firm fixed effect. The key explanatory variable is policy uncertainty, which is measured based on antidumping duties. The interaction term between policy uncertainty and export market share ($TPU_{ijht-1} * EXP_{ijht-1}$) is introduced to each estimation. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

Similar to Table 4.9, results in Table 4.11 show that increased policy uncertainty in export destination h increases exits from existing exporting market. The coefficients on lagged export market share are all negative and statistically significant for both manufacturing firms and trading firms. This evidence shows that firms with larger market shares are less likely to exit one produce than smaller market share firms. The coefficients on the interaction between the policy uncertainty and the firm's market share are positive for manufacturing firms and negative for trading firms. This indicates that the larger market share manufacturing firms are more likely to exit when trade policy uncertainty rises than smaller market share manufacturing firms, on the contrary, larger market share trading firms are less likely to exit when trade policy uncertainty rises than smaller market share trading firms.

The exit of smaller market share firms is consistent with Melitz (2003). Firms with smaller export market shares typically have higher marginal costs and would be less likely to participate in exporting if the expected tariff rises. Small market share firms appear to be operating with relatively high marginal production costs. In contrast, the larger market share firms appear to have production technologies characterised by increasing marginal costs.

4.5 Conclusion

This paper sheds light on a recurring debate about the impact of policy uncertainty on trade and innovation. Past literature emphasize that trade liberalization may stimulate innovation by expanding the market, intensifying competition, importing intermediate inputs that are complementary to indigenous R&D. Motivated by a set of facts on rising policy uncertainty, I assess the impact of trade policy uncertainty in a tractable open-economy general equilibrium framework with heterogeneous firms and trade to evaluate the impact of trade policies on innovation and firms entry and exit in foreign market. Firm innovation decisions in this model are motivated by defensive and expansionary innovation activities, as well as domestic and international business-stealing effect-

s. knowledge spillovers and decreasing returns to knowledge accumulation lead to cross-country convergence, productivity differences drive trade flows.

The theoretical analysis shows that in the static economy, increase openness benefits the fixed factor in final production by raising its compensation via higher-quality intermediate imports, and the impact on innovation is very positive, because trade liberalization lead to a large extent reduce market uncertainty, which translates into expected market growth and in turn leads to more innovation. In the dynamic sense, reduction policy uncertainty or increased openness, and thus foreign competition, encourages more domestic innovation through stronger incentives for defensive and expansionary R&D. Increased policy uncertainty or tariff leads to a reduction in foreign competition, and the impact on innovation is ambiguous. This is because, on the one hand, increased trade cost forces exporter exit the foreign market and also causes a reduction in firms entry to foreign market. These firms have lower incentive to innovate. On the other hand, domestic firms have incentive to innovate to gain more domestic market share as increased domestic competition.

To examine the link between increased policy uncertainty and firms' incentive to innovate, I use the imposition of antidumping duties in one market as a measure of rising trade policy uncertainty for the same product in other markets around the world. The empirical results show that the use of a contingent tariff in one market leads to a decrease in innovation measured by number of patent applications in home country. The effect of increase policy uncertainty on innovation is sizable, accounting for more than 1% decrease in patent filings.

Empirical results also show that increased policy uncertainty leads to a decline in new market entry by firms serving this market. There is also spillovers across firms that a firm which did not face a foreign tariff hike is less likely to enter foreign markets if a large share of its neighboring firms did face a foreign tariff hike. For firm exit, empirical results show that exit from a firm's existing destination markets rises when one of its existing markets hikes its import tariff. This is because an increase in trade policy uncertainty reduces the value to a firm of being an exporter in multiple destination for the same product.

This new dynamic model with policy uncertainty provides a useful framework for future research on the effect of policy uncertainty on firm dynamics. First, an intriguing question in this agenda is how uncertainty about export market conditions and trade policy interact with a firm's relative productivity across products to determine a firm's global trade pattern. Second, in regards to innovation policy, our framework can be used to analyze quantitatively the optimal policy design on innovation policies such as subsidy and intellectual right protection in open economies when policy uncertainty increases. Finally, the framework can shed new light on the design of optimal corporate tax policies in open economies, accounting for their broader dynamic implications on firms' innovation decisions.

CHAPTER 5. CONCLUSION

This dissertation fills the research gap in innovation, market valuation, trade, and policy uncertainty. Three emerging issues with respect to innovation were investigated in this dissertation, especially, how firms' productivity is related with the spectrum of the efficiency of innovation, such as technological categories associated with patents, innovation originality, and innovation generality, what impact do firms' innovative activities have on market value and stock returns, and how policy uncertainty affects firms' investment in innovation and exporting entry and exit decisions, respectively in each chapter.

Chapter 2 examines the empirical relationship between firm-level productivity and innovation from a variety of perspectives. First, this study investigates whether productive firms actively participate in innovation in terms of patents. Second, this study examines whether firms' patents are involved in a wide spectrum of technological categories (extensive innovation scope), and whether their innovative activities focus on inventing within a narrow set of fields (intensive innovation scope). Third, this study investigates whether, to successfully develop a patentable innovation in a certain technological field, productive firms cite patents across various related fields (extensive citation scope) or whether they only cite more patents from a narrow set of technological categories (intensive citation scope). Lastly, this paper explores how the novelty of invented patents is correlated with firm-level productivity. The empirical results reveal that: (i) productivity is positively correlated with the number of patents granted and the number of technological categories for these patents; and (ii) productivity is positive correlated with the number of citations per granted patent, and is also positively correlated with the number of technological categories for cited patents per granted patent.

Following, Chapter 3 examines the impact of innovation on firm's operating performance, market valuation, and stock returns, especially the role of Innovation Efficiency in predicting firm's future market valuation. How important are technologically related assets in driving firm's operating performance, such as future ROA, ROE, cash flow and profit margin, increase and in predicting future stock returns? How do investors respond to innovation information? Do they care only the quantity of inventive inputs or outputs, or do they value more about the quality of new innovations? Chapter 3 attempts to answer these questions by looking at the change of operating performances and market valuations affected by the changing value of corporate patentable assets measured by innovation quantity and efficiency. Empirically, this paper measures Innovation Efficiency by three different indexes that combining the breadth of knowledge used to innovate and R&D investments: number of granted patents per special technological fields scaled by R&D, number of granted patents per technological categories of non-self patents cited by a firm's patents scaled by R&D, and number of granted patents per technological categories of the citations received in the year before the forecast period by a firm's patents that were granted over the previous 5 years scaled by R&D. The empirical results show that: (i) firm's market valuation and excess returns increases are largely driven by the changing valuation of Innovation Efficiency, while innovation quantity, measured by patent intensity and R&D intensity, has a strong and significant negative effect; (ii) the positive effect of Innovation Efficiency became larger over time from 1950 to 2010 and for high-technology industries; (iii) high efficient innovation firms are able to achieve higher and more persistent profitability and better operating performance through the effect of productivity.

In Chapter 4, a benchmark model of innovation, policy uncertainty, and firms' exporting entry and exit model under open economy is constructed. Increasing trade negotiations and proposals result in an increase in uncertainty about the future and the outlook for international trade. In the past decades, there was limited uncertainty in trade policy and uncertainty has been trending upwards since President Trump's campaign was announced in 2015. Compared to history, trade policy uncertainty has reached a particularly high levels since 2015. The basic idea of the model is that policy uncertainty causes risks and loss in intermediate goods production and hence affects firms' profit. Firms reduce investment in innovation due to production profit deduction. Less R&D investment prohibits productivity progress and goods' quality improvements, and induces a larger decrease in innovation profit and production profit. Further more, entrants observe policy uncertainty and suspend their entry decision till policy is finally announced or withdraw. To compensate this risk spillover, firms increase prices and hire less skilled and unskilled labor. Welfare drops as wage decrease and price increases.Comparing to deterministic economy, policy uncertainty increases firm's option value of waiting. Only firms with high quality goods will choose to enter the foreign market because their option value of waiting is relatively lower than their entry value. Policy uncertainty also decrease foreign market competition and increasing markups. Increasing markups in turn allow less productive firms enter the domestic market,reallocating resources from exporter towards domestic surviving firms, increasing domestic firms' average size and aggregate productivity. Although exporting firms exit foreign market as policy uncertainty increases casing reduction in those firm's innovation, the increase number of surviving firms in domestic market stimulates cost-reducing innovation thereby leading to faster productivity growth. Finally, firm selection of exporting involves potential welfare losses since exit reduces the number of varieties available to consumers and more low productivity firms enter domestic market actually decreases the average productivity. Chapter 4 then embodies five major data sources to empirically investigate the impact of policy uncertainty on innovation and trade. For firms' innovation activities, the empirical results show that increased policy uncertainty significantly decreases patent applications. For entry, the empirical results show that increased uncertainty about the future tariff rate in destination country reduces participation in exporting activity. Entry into foreign markets declines as policy uncertainty increases. For firms' exit decisions, estimation results show that increased uncertainty about the future tariff rate in destination country increases exits from existing exporting market. Exit from existing foreign markets increases as policy uncertainty increases.

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APPENDIX A. ADDITIONAL DATA INFORMATION

A.1 Industries Classification Based on Technology

Table A.1: Industries Classification Based on Technology

Technology Level	Industries	ISIC Rev.3
High-tchnology	Aircraft and spacecraft	353
	Pharmaceuticals	2423
	Office, accounting and computing machinery	30
	Radio, TV and communciations equipment	32
	Medical, precision and optical instruments	33
Medium-technology	Electrical machinery and apparatus, n.e.c.	31
	Motor vehicles, trailers and semi-trailers	34
	Chemicals excluding pharmaceuticals	24 (no 2423)
	Railroad equipment and transport equipment, n.e.c.	352 + 359
	Machinery and equipment, n.e.c.	29
	Building and repairing of ships and boats	351
	Rubber and plastics products	25
	Coke, refined petroleum products and nuclear fuel	23
	Other non-metallic mineral products	26
	Basic metals and fabricated metal products	27-28
Low-technology	Manufacturing, n.e.c.; Recycling	36-37
	Wood, pulp, paper, paper products, printing and publishing	20-22
	Food products, beverages and tobacco	15-16
	Textiles, textile products, leather and footwear	17-19

Note: This table is based on Hatzichronoglou (1997), technology level is classified by the aggregate R&D intensities calculated after converting countries' R&D expenditures, value added and production using GDP PPPs. Data is from 12 OECD countries: United States, Canada, Japan, Denmark, Finland, France, Germany, Ireland, Italy, Spain, Sweden, United Kingdom.

A.2 Matching with CRSP by Decade

Based on Kogan et al. (2012), Table A.2 shows summary statistics for patents in the sample by decade. Column 2 shows the total number of patents, and column 3 shows how many patents are identified as having an assignee. Column 4 shows how many of those patents with assignees are matched to a company in CRSP. (The remaining assignees are either individuals, private companies, or the matching process was unable to identify the correct company.) Columns 5 and 6 show how many unique firms there are matched to patents or in CRSP.

Table A.2: Matching with CRSP by Decade

Years	Number of Patents			Number of Firms	
	Total	With Assignee	Matched to CRSP	Matched Firms	CRSP Firms
1950-1959	425,953	171,157	82,255	587	1,246
1960-1969	567,599	265,524	165,409	1,175	3,177
1970-1979	690,459	393,661	247,102	2,086	7,204
1980-1989	708,735	579,518	235,525	2,756	11,715
1990-1999	1,109,398	933,705	352,005	3,664	14,882
2000-2010	1,846,063	1,668,256	729,324	4,415	11,900
All Years	5,348,207	4,011,821	1,811,620	7,864	26,660

Note: This table is based on Kogan et al. (2012), column 2 shows the total number of patents, and column 3 shows how many patents are identified as having an assignee. Column 4 shows how many of those patents with assignees are matched to a company in CRSP. Columns 5 and 6 show how many unique firms there are matched to patents or in CRSP.

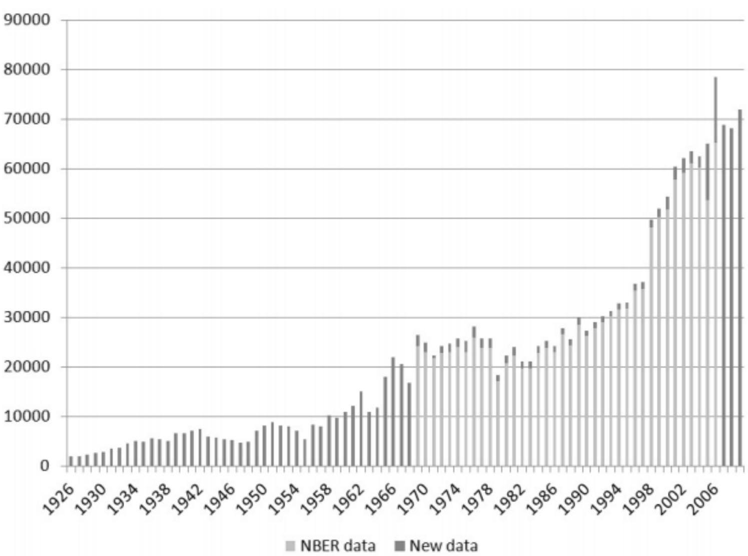

Figure A.1: Number of Patents with Matched Assignees

A.3 Comparing KPSS Patent Data with NBER Patent Data

Figure A.1 is from Kogan et al. (2012) and compares the number of patents matched to CRSP firms by year of patent grant for KPSS patent database and NBER patent database. Light shading denotes patents included in the NBER patent data set, while dark shading denotes patents that are new in our paper.

A.4 Comparing Cumulative Returns

Figure A.2 compares the cumulative returns of the sample and the S&P composite index. The green curve stands for the average cumulative returns of all firms in the sample, while the red dashed curve denotes the average cumulative returns of firms with patents in the sample. The bottom blue dashed curve is the cumulative returns of the S&P composite index.

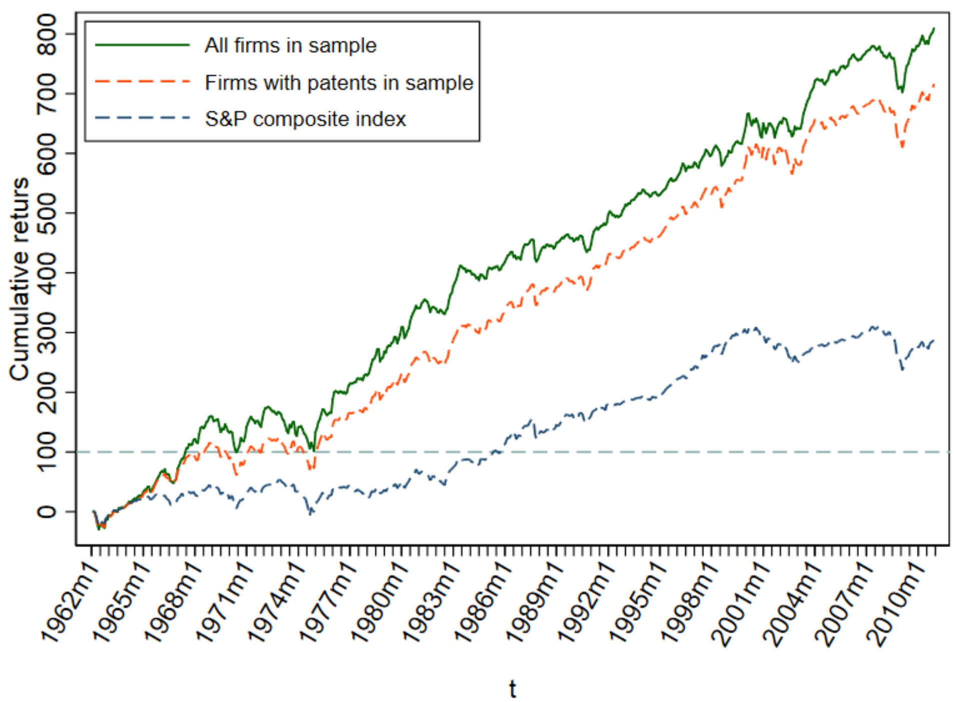

Figure A.2: Benchmarking Cumulative Returns Using the S&P Composite Index

APPENDIX B. ROBUSTNESS CHECKS FOR INNOVATION EFFICIENCY

B.1 Innovation Efficiency and Tobin's q: different IE quartiles

Table B.1 extends the estimations in Table 3.7. Similar to Table 3.5, firms are sorted into three groups (low, middle, and high) based on the third and two-thirds percentiles of the Innovation Efficiency measure $Nselftechs/RD$. Columns (1)-(3) present the estimation results using sample data of high-IE firms with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using sample data of middle-IE firms. Columns (7)-(9) are the panel fixed effect estimation results using sample data of low-IE firms. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

Table B.1: Innovation Efficiency and Tobin's q: different IE quartiles, 1950-2010

Industries	High-IE			Middle-IE			Low-IE		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IE Measure	Ptechs/RD	Nselftechs/RD	FCtechs/RD	Ptechs/RD	Nselftechs/RD	FCtechs/RD	Ptechs/RD	Nselftechs/RD	FCtechs/RD
L.IE	3.373***	3.160***	0.053**	0.221**	0.315***	-0.003	0.043**	0.024	-0.012
	(0.887)	(0.653)	(0.021)	(0.112)	(0.093)	(0.011)	(0.020)	(0.016)	(0.008)
L.PAT/ME	-0.063	-0.207	-0.180	-0.033	-0.008	-0.086	-0.096	-0.055	-0.052
	(0.145)	(0.144)	(0.138)	(0.165)	(0.171)	(0.160)	(0.076)	(0.075)	(0.073)
L.R&D/ME	-0.586***	-0.571***	-0.581***	-0.296***	-0.287***	-0.288***	-0.459***	-0.472***	-0.475***
	(0.091)	(0.090)	(0.091)	(0.067)	(0.067)	(0.067)	(0.102)	(0.103)	(0.103)
L.IE*(PAT/ME)	-19.308***	1.603	-0.166**	-0.723	-1.338**	0.016	0.064	0.019	0.031**
	(5.655)	(9.563)	(0.079)	(0.450)	(0.644)	(0.012)	(0.068)	(0.075)	(0.012)
L.lnAD	0.059***	0.057***	0.059***	0.036*	0.036*	0.035*	0.022	0.023	0.023
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.020)	(0.020)
L.lnCapEx	0.040	0.041	0.040	-0.031	-0.031	-0.031	0.014	0.015	0.015
	(0.032)	(0.033)	(0.032)	(0.031)	(0.031)	(0.031)	(0.039)	(0.040)	(0.040)
L.lnBTM	-0.257***	-0.257***	-0.258***	-0.294***	-0.294***	-0.295***	-0.345***	-0.345***	-0.345***
	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
L.(G=0)	0.087	0.095	0.074	-0.082	-0.075	-0.088	-0.083**	-0.084**	-0.090***
	(0.082)	(0.081)	(0.081)	(0.057)	(0.057)	(0.057)	(0.033)	(0.033)	(0.033)
R^2	0.500	0.503	0.501	0.470	0.470	0.470	0.501	0.501	0.500
N	11,458	11,458	11,458	11,113	11,113	11,113	10,724	10,724	10,724
# of Firms	1,269	1,269	1,269	2,352	2,352	2,352	3,100	3,100	3,100
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample is split into three panels high-IE firms, medium-IE firms, and low-IE firms. Sample period is from 1950 to 2010. The response variable is the natural log of Tobin's q. "IE" stands for Innovation Efficiency, measured by $Ptechs/RD$, $Nselftechs/RD$, and $FCtechs/RD$. Variables are well defined in Table 3.2. "L." stands for the lagged value. "IE*(PAT/ME)" denotes the interaction of Innovation Efficiency and patent intensity. $G = 0$ is non-patent firm dummy. Columns (1)-(3) present the estimation results using sample data of high-IE firms with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using sample data of middle-IE firms. Columns (7)-(9) are the panel fixed effect estimation results using sample data of low-IE firms. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

The estimation results are much close to the estimations in Table 3.7. On average, Innovation Efficiency has positive effect on subsequential Tobin's q, and this effect decreases as Innovation Efficiency level decreases. In contrast, patent intensity and R&D are negatively related to future Tobin's q. The negative effects do not change much among different Innovation Efficiency levels.

B.2 Alternative Innovation Efficiency Measure

Table B.2: Innovation Efficiency and Tobin's q, Alternative Measures (1950-2010)

IE Measures	Patents/RD			Nselfcitations/RD			FCitations/RD		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.IE	0.022***	0.015**	0.013	0.007	0.003	0.001	-0.029***	-0.027***	-0.030***
	(0.007)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
L.PAT/ME		-0.071	-0.128**		-0.034	-0.072		-0.058*	-0.071**
		(0.048)	(0.059)		(0.042)	(0.048)		(0.031)	(0.031)
L.R&D/ME		-0.450***	-0.444***		-0.454***	-0.451***		-0.439***	-0.438***
		(0.029)	(0.029)		(0.029)	(0.029)		(0.028)	(0.028)
L.IE*(PAT/ME)			0.035**			0.027*			0.029**
			(0.018)			(0.015)			(0.014)
L.lnAD	0.003	0.006	0.006	0.003	0.006	0.006	0.012	0.012	0.012
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.008)	(0.007)	(0.007)
L.lnCapEx	-0.029**	-0.003	-0.002	-0.032**	-0.006	-0.006	0.045***	0.049***	0.049***
	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.009)	(0.009)	(0.009)
L.lnBTM	-0.306***	-0.290***	-0.290***	-0.305***	-0.290***	-0.290***	-0.293***	-0.286***	-0.286***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
L.(G=0)	-0.039***	-0.038***	-0.040***	-0.041***	-0.041***	-0.042***	-0.026***	-0.031***	-0.032***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.007)	(0.007)
R^2	0.409	0.419	0.419	0.409	0.418	0.418	0.368	0.373	0.373
N	80,096	80,096	80,096	80,875	80,875	80,875	177,355	177,355	177,355
# of Firms	8,477	8,477	8,477	8,496	8,496	8,496	16,769	16,769	16,769
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is 1950-2010, the response variable is Tobin's q, which is measured by the natural log of Tobin's q. "IE" stands for Innovation Efficiency, measured by $Patents/RD$, $Nselfcitations/RD$, and $FCitations/RD$, as are denoted in Equation (B.1)-(B.3). Variables are well defined in Table 3.2. "L." stands for the lagged value. "IE*(PAT/ME)" denotes the interaction of Innovation Efficiency and patent intensity. $G = 0$ is non-patent firm dummy. Columns (1)-(3) present the estimation results using $Patents/RD$ measuring Innovation Efficiency and using panel data with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using $Nselfcitations/RD$ as the proxy of Innovation Efficiency. Columns (7)-(9) are the panel fixed effect estimation results using $FCitations/RD$ as the Innovation Efficiency measure. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

In this part, I use three alternative innovation measures to check the robustness of the empirical results. In Section 4, Innovation Efficiency is measured using the technology fields of patents or citations per patent scaled by R&D expenditures. Alternatively, in this part I use number of patents or citations scaled by R&D expenditures to measure Innovation Efficiency. Specifically, the three measures $Patents/RD$, $Nselfcitations/RD$, and $FCitations/RD$ are denoted respectively as:

$$\frac{Pcounts_{i,t}}{R\&D_{i,t-2} + 0.8 * R\&D_{i,t-3} + 0.8^2 * R\&D_{i,t-4} + 0.8^3 * R\&D_{i,t-5} + 0.8^4 * R\&D_{i,t-6}}, \tag{B.1}$$

$$\frac{Nselfcounts_{i,t}}{R\&D_{i,t-2} + 0.8 * R\&D_{i,t-3} + 0.8^2 * R\&D_{i,t-4} + 0.8^3 * R\&D_{i,t-5} + 0.8^4 * R\&D_{i,t-6}}, \tag{B.2}$$

$$\frac{\sum_{s=1}^{5} FCcounts_{i,t-s}}{R\&D_{i,t-3} + 0.8 * R\&D_{i,t-4} + 0.8^2 * R\&D_{i,t-5} + 0.8^3 * R\&D_{i,t-6} + 0.8^4 * R\&D_{i,t-7}}. \tag{B.3}$$

Table B.2 presents the estimation results based on Equation (3.15) using the these three alternative Innovation Efficiency measures. Most of the estimation coefficients keep the same signs as in Table 3.7, though the significance change a lot. Interestingly, the estimation coefficients on Innovation Efficiency measure $FCitations/RD$ are all negative and statistically significant at the 1% level. In contrast, the estimation coefficients on patent intensity and R&D intensity are all negative and most are statistically significant at the 1% level.

B.3 Alternative Productivity Measure

It has been shown that productivity plays a key role in explaining substantial increase of firm's productivity in Section4.3. Productivity is measured as total factor productivity (TFP) using the LP method proposed by Levinsohn and Petrin (2003) in Section4.3-4.4. Alternatively, in this part I use the OP procedure introduced by Olley and Pakes (1996) to calculate firm's TFP and do the robustness checks. Table B.3 presents the estimation results using the alternative TFP measure. Sample period is from 1950 to 2010 and the response variable is profit margin (PM). Columns (1)-(3) present the estimation results using $Ptechs/RD$ measure Innovation Efficiency with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using $Nselftechs/RD$. Columns (7)-(9) are the panel fixed effect estimation results using $FCtechs/RD$. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firms. Similar to Table 3.12, the coefficients on Innovation Efficiency increased a lot after introducing TFP, while the coefficients on patent intensity reverse signs and significance.

The coefficients on TFP are all positive and statistically significant. These results confirm the result that productivity plays a critical important role in explaining changing profitability.

Table B.3: Innovation Efficiency, Profit Margin, and Productivity (OP Method), 1950-2010

IE Measure	Ptechs/RD			Nselftechs/RD			Fctechs/RD		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.lnIE	0.383***	0.436**	0.452*	0.407***	0.371***	0.444**	0.086	0.018	-0.081
	(0.143)	(0.190)	(0.255)	(0.153)	(0.135)	(0.217)	(0.091)	(0.134)	(0.098)
L.ln(PAT/ME)		0.379***	0.507**		0.325**	0.484**		0.390***	0.542**
		(0.127)	(0.201)		(0.136)	(0.196)		(0.126)	(0.227)
L.ln(R&D/ME)		-0.776	-3.559***		-0.756	-3.626***		-0.881*	-3.925***
		(0.512)	(1.000)		(0.509)	(0.992)		(0.521)	(1.034)
L.lnIE*ln(PAT/ME)		-0.228	-0.200		-0.134	-0.170		-0.021	-0.026
		(0.166)	(0.281)		(0.175)	(0.290)		(0.056)	(0.068)
L.lnTFP			9.491***			9.677***			9.724***
			(0.733)			(0.727)			(0.730)
L.lnIE*lnPM	2.058***	2.082***	1.863***	0.855***	0.834***	0.620***	1.292	1.582	1.026
	(0.527)	(0.527)	(0.616)	(0.052)	(0.056)	(0.067)	(1.009)	(1.113)	(0.896)
L.lnSIZE	0.181***	0.149***	-0.068	0.180***	0.148***	-0.067	0.182***	0.148***	-0.074
	(0.023)	(0.032)	(0.050)	(0.023)	(0.032)	(0.049)	(0.023)	(0.032)	(0.048)
L.lnAD	-0.210***	-0.427***	-0.399***	-0.210***	-0.426***	-0.401***	-0.209***	-0.424***	-0.398***
	(0.063)	(0.089)	(0.088)	(0.063)	(0.089)	(0.088)	(0.063)	(0.089)	(0.088)
L.lnCapEx	-0.005	-0.087	0.637**	-0.004	-0.082	0.741**	-0.003	-0.081	0.771**
	(0.076)	(0.155)	(0.319)	(0.076)	(0.155)	(0.325)	(0.076)	(0.155)	(0.332)
L.lnBTM	0.163***	0.178***	0.142*	0.161***	0.174***	0.140*	0.163***	0.179***	0.151*
	(0.039)	(0.055)	(0.078)	(0.039)	(0.055)	(0.078)	(0.039)	(0.055)	(0.078)
L.(G=0)	-0.375***	-0.750***	-1.029**	-0.370***	-0.746***	-1.034**	-0.367***	-0.745***	-1.011**
	(0.126)	(0.171)	(0.509)	(0.127)	(0.171)	(0.509)	(0.127)	(0.171)	(0.508)
R^2	0.0396	0.0475	0.223	0.0387	0.0460	0.221	0.0378	0.0451	0.218
N	181,012	95,765	33,293	181,012	95,765	33,293	181,012	95,765	33,293
# of Firms	17,026	10,550	4,295	17,026	10,550	4,295	17,026	10,550	4,295
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is from 1950 to 2010. The response variable is profit margin (PM). "lnIE" stands for natural log of one plus Innovation Efficiency, measured by $Ptechs/RD$, $Nselftechs/RD$, and $FCtechs/RD$. "TFP" denotes firm's total factor productivity using the OP method (Olley and Pakes, 1996). "lnTFP" stands for natural log of one plus TFP. "ln(PAT/ME)" and "ln(R&D/ME)" stand for natural log of one plus patent intensity and R&D intensity, respectively. All the variables are well defined in Table 3.2. "L." stands for the lagged value. "lnIE*ln(PAT/ME)" denotes the interaction between log Innovation Efficiency and log patent intensity. "lnIE*PM" stands for the interaction between log Innovation Efficiency and profit margin. $G = 0$ is non-patent firm dummy. Columns (1)-(3) present the estimation results using $Ptechs/RD$ measure Innovation Efficiency with time, industry, and firms fixed effects. Estimation in columns (4)-(6) are by panel fixed effect using $Nselftechs/RD$. Columns (7)-(9) are the panel fixed effect estimation results using $FCtechs/RD$. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firms.

APPENDIX C. ROBUSTNESS CHECKS FOR POLICY UNCERTAINTY

This study conducts a series of robustness checks on alternative innovation measure, alternative policy uncertainty measure, and alternative model specifications.

C.1 Alternative Innovation Measure

Table C.1: Policy Uncertainty and Innovation using R&D, 2000-2006

Innovation Measures	lnRD					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TPU_{it-1}	-0.050**	-0.046**	-0.080	-0.068***	-0.043*	-0.043*
	(0.025)	(0.022)	(0.030)	(0.026)	(0.025)	(0.022)
$TPU_{it-1} * US_{it-1}$			-0.236***	-0.130*		
			(0.089)	(0.078)		
$TPU_{it-1} * NonAct_{it-1}$					-0.433**	0.363**
					(0.189)	(0.176)
TFP_{it-1}	0.146***	0.063***	0.146***	0.063***	0.146***	0.063***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
$lnkl_{it-1}$	0.322***	0.147***	0.322***	0.148***	0.322***	0.148***
	(0.003)	(0.007)	(0.003)	(0.007)	(0.003)	(0.007)
$lnlabor_{it-1}$	0.418***	0.278***	0.418***	0.278***	0.419***	0.278***
	(0.004)	(0.009)	(0.004)	(0.009)	(0.004)	(0.009)
$lnage_{it-1}$	-0.292***	-0.062***	-0.292***	-0.062***	-0.291***	-0.062***
	(0.013)	(0.018)	(0.013)	(0.018)	(0.013)	(0.018)
$lnage2_{it-1}$	0.094***	0.014***	0.094***	0.014***	0.094***	0.014***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
$Export_{it-1}$	0.135***	0.106***	0.135***	0.106***	0.136***	0.105***
	(0.007)	(0.011)	(0.007)	(0.011)	(0.007)	(0.011)
Adj R^2	0.190	0.015	0.190	0.015	0.190	0.015
N	715,308	715,308	715,308	715,308	715,308	715,308
# of Firms	321,968	321,968	321,968	321,968	321,968	321,968
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Industry Year Trend	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is 2000-2006, the response variable is innovation, which is measured by the natural log of 1 plus number of patent applications. Variables are well defined in Table 4.3. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

To test the robustness of the empirical results for innovation, I further use R&D as an alternative innovation measure to test the stability of the negative impact of increased policy uncertainty on innovation. The results are shown in Table C.1.

C.2 Poisson Method for Innovation

Table C.2: Policy Uncertainty and Innovation using Poisson Method, 2000-2006

Innovation Measures	lnRD					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TPU_{it-1}	-0.001	-0.019	-0.002	-0.041*	-0.012	-0.016
	(0.023)	(0.019)	(0.027)	(0.023)	(0.023)	(0.019)
ustpu			-0.005	-0.138*		
			(0.091)	(0.080)		
tpunonact					0.434***	0.306**
					(0.173)	(0.145)
tfp	0.080***	0.075***	0.080***	0.075***	0.080***	0.074***
	(0.004)	(0.007)	(0.004)	(0.007)	(0.004)	(0.007)
lnkl	0.392***	0.210***	0.392***	0.210***	0.392***	0.210***
	(0.004)	(0.011)	(0.004)	(0.011)	(0.004)	(0.011)
lnl	0.458***	0.384***	0.458***	0.384***	0.458***	0.384***
	(0.004)	(0.013)	(0.004)	(0.013)	(0.004)	(0.013)
lnage	0.025*	-0.006	0.025*	-0.005	0.026**	-0.006
	(0.013)	(0.025)	(0.013)	(0.025)	(0.013)	(0.025)
lnage2	0.018***	0.002	0.018***	0.002	0.018***	0.002
	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.006)
exp_dum	0.096***	0.087***	0.096***	0.087***	0.098***	0.087***
	(0.007)	(0.012)	(0.007)	(0.012)	(0.007)	(0.012)
Observations	715,308	147,026	715,308	147,026	715,308	147,026
Number of code	44,077	44,077	44,077	44,077	44,077	44,077
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Industry Year Trend	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is 2000-2006, the response variable is innovation, which is measured by the natural log of 1 plus number of patent applications. Variables are well defined in Table 4.3. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

Because the number of patents and the number of unique technological fields associated with patents are count data, the Poisson model is an alternative specification suitable to dealt with this type of data. The results are shown in Table C.2.

C.3 Alternative Measure of Policy Uncertainty

Table C.3: Policy Uncertainty and Entry using Intensity, 2000-2006

$Entry_{ijht}$	Manufacturing Firms			Trading Firms		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TPU_{ijht-1}	-0.004	-0.001	-0.001	0.051	0.053	0.024
	(0.008)	(0.008)	(0.013)	(0.043)	(0.043)	(0.044)
$Intensity_{ijht-1} * NonAct_{ht-1}$			0.001			0.324**
			(0.017)			(0.162)
$Size_{it-1}$		-0.003***	-0.003***		-0.002	-0.002
		(0.000)	(0.000)		(0.002)	(0.002)
$ln(GDP)_{ht-1}$	-0.000	-0.000	-0.000	-0.004	-0.004	-0.004
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
$ln(RealExcahgne)_{ht-1}$	0.000***	0.000***	0.000***	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	1,953,556	1,953,556	1,953,556	99,795	99,795	99,795
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is 2000-2006, i stands for firm, j stands for 6-digit HS product, h stands for exporting destination. The response variable is $Entry_{ijht}$, which is a dummy variable equal to to one if firm i enters new foreign market h with a 6-digit HS product j at year t and 0 otherwise. Variables are well defined in Table 4.3. Variable "Size" is defined as the logarithm of sales. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

To test the robustness of the empirical results for entry, I further use intensity as an alternative innovation measure to test the stability of the negative impact of increased policy uncertainty on innovation. The estimation results for entry are shown in Table C.3. Intensity is defined as

$$Intensity = \frac{count\ \ of\ \ products\ \ hit\ \ by\ \ antidumping\ \ policies}{count\ \ of\ \ firm\ \ exporting\ \ products}$$

The vast majority of prefecture-product-year observations are for prefectures in which no firm faces an antidumping duty so the value of intensity is zero. However, there are a large number of observations on prefectures in which a sizeable share of firms that export product were hit with an antidumping duty. Table C.4 presents the estimation results for exit.

Table C.4: Policy Uncertainty and Exit using Intensity, 2000-2006

$Exit_{ijht}$	Manufacturing Firms			Trading Firms		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
$Intensity_{ijht-1}$	-0.003	-0.006	-0.004	-0.125*	-0.127*	-0.005
	(0.011)	(0.011)	(0.011)	(0.067)	(0.067)	(0.074)
EXP_{ijht-1}			0.016***			0.053**
			(0.004)			(0.025)
$Intensity_{ijht-1} * EXP_{ijht-1}$			-0.000			-0.261***
			(0.031)			(0.081)
$Size_{it-1}$		0.003***	0.003***		0.004	0.001
		(0.000)	(0.000)		(0.002)	(0.003)
$ln(GDP)_{ht-1}$	-0.000	-0.000	-0.000	-0.003	-0.003	-0.004
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)
$ln(RealExcahgne)_{ht-1}$	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adj R^2	0.298	0.331	0.33	0.524	0.563	0.583
N	1,953,556	1,953,556	1,953,556	99,795	99,795	99,795
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is 2000-2006, i stands for firm, j stands for 6-digit HS product, h stands for exporting destination. The response variable is $Exit_{ijht}$, which is a dummy variable equal to to one if firm i exits foreign market h with a 6-digit HS product j at year t and 0 otherwise. Variables are well defined in Table 4.3. Variable "Size" is defined as the logarithm of sales. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

C.4 Logistic Method for Firm Entry and Exit

Because the entry and exit are binaries that each dummy variable with values of 0 or 1, the Logistic model is an alternative specification suitable to dealt with this type of data. Table C.5 presents the estimation results for firm entry using Logistic method. Similar to Table 4.10, the coefficient estimates on the measure of increased trade policy uncertainty are all negative. However, the coefficient estimates are much larger than those in Table 4.10 for both manufacturing firms and trading firms. These estimates confirms that Chinese firms use information about policy changes in market h and historical use of antidumping policy in other markets to update their beliefs about future trade policy changes in other markets. Firms then act on this updated information through their entry decisions.

Table C.5: Policy Uncertainty and Entry using Logistic Method, 2000-2006

$Entry_{ijht}$	Manufacturing Firms			Trading Firms		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TPU_{ijht-1}	-0.139***	-0.132***	-0.123***	-0.187	-0.180	-0.445**
	(0.027)	(0.027)	(0.044)	(0.167)	(0.167)	(0.175)
$TPU_{ijht-1} * NonAct_{ht-1}$			-0.015			1.627***
			(0.059)			(0.463)
$Size_{it-1}$		-0.012***	-0.012***		-0.015	-0.015
		(0.002)	(0.002)		(0.009)	(0.009)
$ln(GDP)_{ht-1}$	-0.001	-0.001	-0.001	-0.034	-0.033	-0.033
	(0.002)	(0.002)	(0.002)	(0.021)	(0.021)	(0.021)
ln(RealExcahgne)_ht-1	0.001***	0.001***	0.001***	0.001	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
N	1,953,556	1,953,556	1,953,556	99,795	99,795	99,795
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is 2000-2006, i stands for firm, j stands for 6-digit HS product, h stands for exporting destination. The response variable is $Entry_{ijht}$, which is a dummy variable equal to to one if firm i enters new foreign market h with a 6-digit HS product j at year t and 0 otherwise. Variables are well defined in Table 4.3. Variable "Size" is defined as the logarithm of sales. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

Table C.6 presents the estimation results for firm exit using Logistic method. Similar to Table 4.11, the coefficient estimates on the measure of increased trade policy uncertainty are all positive. However, the coefficient estimates are much larger than those in Table 4.11 for both manufacturing firms and trading firms. The coefficients on lagged export market share are all positive and statistically significant for both manufacturing firms and trading firms. This evidence is different from 4.11 and shows that firms with larger market shares are more likely to exit one produce than smaller market share firms. The coefficients on the interaction between the policy uncertainty and the firm's market share are positive for manufacturing firms and negative for trading firms.

Table C.6: Policy Uncertainty and Exit using Logistic Method, 2000-2006

$Exit_{ijht}$	Manufacturing Firms			Trading Firms		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
TPU_{ijht-1}	0.082**	0.075**	0.074**	0.211*	0.201*	0.252*
	(0.034)	(0.034)	(0.034)	(0.117)	(0.117)	(0.133)
EXP_{ijht-1}			0.086***			0.196*
			(0.016)			(0.102)
$TPU_{ijht-1} * EXP_{ijht-1}$			0.057			-0.073
			(0.104)			(0.169)
$Size_{it-1}$		0.011***	0.009***		0.021**	0.013
		(0.002)	(0.002)		(0.009)	(0.010)
$ln(GDP)_{ht-1}$	-0.001	-0.001	-0.001	-0.021	-0.022	-0.023
	(0.002)	(0.002)	(0.002)	(0.021)	(0.021)	(0.021)
$ln(RealExcahgne)_{ht-1}$	0.000	0.000	-0.000	-0.003	-0.003	-0.003
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
N	1,953,556	1,953,556	1,953,556	99,795	99,795	99,795
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Sample period is 2000-2006, i stands for firm, j stands for 6-digit HS product, h stands for exporting destination. The response variable is $Exit_{ijht}$, which is a dummy variable equal to to one if firm i exits foreign market h with a 6-digit HS product j at year t and 0 otherwise. Variables are well defined in Table 4.3. Variable "Size" is defined as the logarithm of sales. In all the regressions I use a cluster adjustment to estimate the standard errors assuming serial correlation within firm units.

APPENDIX D. ADDITIONAL DERIVATIONS FOR POLICY UNCERTAINTY

D.1 Expected Value of Exporting

To obtain the expected value of exporting, $\Pi^*(\tau_{c't}, \varphi_{ct})$, start from Equation (4.24), we can obtain

$$E\Pi^*(\tau'_{c't}, \varphi_{ct}) = E\pi^*(\tau'_{c't}, \varphi_{ct}) + \delta E\Pi^*(\tau'_{c't}, \varphi_{ct})$$

therefore,

$$E\Pi^*(\tau'_{c't}, \varphi_{ct}) = \frac{E\pi^*(\tau'_{c't}, \varphi_{ct})}{1-\delta}.$$

From Equation (4.24),

$$[1-\delta(1-\phi)]\Pi^*(\tau_{c't}, \varphi_{ct}) = \pi^*(\tau_{c't}, \varphi_{ct}) + \delta\phi E\Pi^*(\tau'_{c't}, \varphi_{ct}),$$

or

$$\Pi^*(\tau_{c't}, \varphi_{ct}) = \frac{\pi^*(\tau_{c't}, \varphi_{ct})}{1-\delta(1-\phi)} + \frac{\delta\phi}{1-\delta(1-\phi)} E\Pi^*(\tau'_{c't}, \varphi_{ct}).$$

Therefore,

$$\Pi^*(\tau_{c't}, \varphi_{ct}) = \frac{\pi^*(\tau_{c't}, \varphi_{ct})}{1-\delta(1-\phi)} + \frac{\delta\phi}{1-\delta} \frac{E\pi^*(\tau'_{c't}, \varphi_{ct})}{1-\delta(1-\phi)}.$$

D.2 Lemma 6 Proof

Guessing that the value function follows the form: $V_{G,ct}(\varphi_{ct}) = \varphi_{ct}^{\frac{1}{\beta}} v_{G,ct}$. Substituting this expression into Equation (4.23), we get:

$$\begin{aligned} r_{ct} v^L_{G,ct} \varphi_{ct}^{\frac{1}{\beta}} - \dot{v}^L_{G,ct} \varphi_{ct}^{\frac{1}{\beta}} = \max_{x^L_{G,ct}} \Big\{ & \pi(G;\tau_{c't}) \varphi_{ct}^{\frac{1}{\beta}} - (1-s_{ct}) w^L_{ct} \varphi_{ct}^{\frac{1}{\beta}} H(x^L_{G,ct}, \mu^L) \\ & + x^L_{G,ct} \sum_{g_{ct}=G+1}^{\bar{G}} f(g_{ct}, G)[\lambda^{g_{ct}-G} \varphi_{ct}^{\frac{1}{\beta}} v^L_{g,ct} - v^L_{G,ct} \varphi_{ct}^{\frac{1}{\beta}}] \\ & + \tilde{x}_{G,ct}[0 - v^L_{G,ct} \varphi_{ct}^{\frac{1}{\beta}}] + \xi[0 - v^L_{G,ct} \varphi_{ct}^{\frac{1}{\beta}}] \\ & + (x_{-G,c't} + \tilde{x}_{-G,c't}) \sum_{g_{ct}=-G+1}^{\bar{G}} f(g_{ct}, -G)[\lambda v^L_{-g,ct} \varphi_{ct}^{\frac{1}{\beta}} - v^L_{G,ct} \varphi_{ct}^{\frac{1}{\beta}}] \Big\}, \end{aligned}$$

where

$$\pi(G;\tau_{c't}) = \begin{cases} \pi + \pi^*(\tau_{c't}) & \text{if } G \geq G^E_{ct} \\ \pi & \text{if } G \in (G^I_{ct}, G^E_{ct}) \\ 0 & \text{if } G \leq G^I_{ct} \end{cases},$$

and

$$\pi^*(\tau_{c't}) = \frac{\pi^*(\tau_{c't})}{1-\delta(1-\phi)} + \frac{\delta\phi}{1-\delta} \frac{E\pi^*(\tau'_{c't})}{1-\delta(1-\phi)}.$$

Dividing all sides by $\varphi_{ct}^{\frac{1}{\beta}}$, we obtain the desired result.

D.3 Expected Waiting Value

Start from Equation (4.25), the expected value of exporting under policy uncertainty is

$$E\Pi^*(\tau'_{c't}, \varphi_{ct}) = \frac{E\pi^*(\tau'_{c't}, \varphi_{ct})}{1-\delta}.$$

From Equation (4.24), the conditional expected value of exporting given τ is

$$E[\Pi^*(\tau'_{c't}, \varphi_{ct}) | \tau'_{c't} \leq \bar{\tau}] = \frac{E[\pi^*(\tau'_{c't}, \varphi_{ct}) | \tau'_{c't} \leq \bar{\tau}]}{1-\delta(1-\phi)} + \delta\phi \frac{E[\Pi^*(\tau'_{c't}, \varphi_{ct})]}{1-\delta(1-\phi)}.$$

Combining the above two equations, then the conditional expected value of exporting is

$$E[\Pi^*(\tau'_{c't}, \varphi_{ct}) | \tau'_{c't} \leq \bar{\tau}] = \frac{E[\pi^*(\tau'_{c't}, \varphi_{ct}) | \tau'_{c't} \leq \bar{\tau}]}{1-\delta(1-\phi)} + \frac{\delta\phi}{1-\delta} \frac{E[\pi^*(\tau'_{c't}, \varphi_{ct})]}{1-\delta(1-\phi)}.$$

From Equation (4.31), the expected waiting value is

$$\Pi_w(\tau'_{c't}, \varphi_{ct}) = \frac{\delta\phi F(\bar{\tau})}{1-\delta(1-\phi F(\bar{\tau}))}[E(\Pi^*(\tau'_{c't}, \varphi_{ct})|\tau'_{c't} \leq \bar{\tau}) - K_e].$$

Substituting $E(\Pi^*(\tau'_{c't}, \varphi_{ct})|\tau'_{c't} \leq \bar{\tau})$ into the above equation we obtain the desired result.

D.4 Export Waiting Cutoff Condition

Using Equation 4.25), (4.32), and (4.33) we can get

$$\begin{aligned}\frac{\pi^*(\tau_{c't}, \varphi_{ct})}{1-\delta(1-\phi)} + \frac{\delta\phi}{1-\delta}\frac{E\pi^*(\tau'_{c't}, \varphi_{ct})}{1-\delta(1-\phi)} =& \frac{\delta\phi F(\bar{\tau})}{1-\delta(1-\phi F(\bar{\tau}))}\frac{E[\pi^*(\tau'_{c't}, \varphi_{ct})|\tau'_{c't} \leq \bar{\tau}]}{1-\delta(1-\phi)} \\ &+ \frac{\delta\phi F(\bar{\tau})}{1-\delta(1-\phi F(\bar{\tau}))}\frac{\delta\phi}{1-\delta}\frac{E[\pi^*(\tau'_{c't}, \varphi_{ct})]}{1-\delta(1-\phi)} \\ &+ \frac{1-\delta}{1-\delta(1-\phi F(\bar{\tau}))}K_e.\end{aligned}$$

Solve K_e then

$$K_e = \frac{\pi^*(\tau_{c't}, \varphi_{ct})}{1-\delta(1-\phi)} + \frac{\delta\phi}{1-\delta}\frac{E\pi^*(\tau'_{c't}, \varphi_{ct})}{1-\delta(1-\phi)} + \frac{\delta\phi F(\bar{\tau})}{1-\delta}\frac{\pi^*(\tau_{c't}, \varphi_{ct}) - E[\pi^*(\tau'_{c't}, \varphi_{ct})|\tau'_{c't} \leq \bar{\tau}]}{1-\delta(1-\phi)}.$$

Using Equation (4.18) and $\pi = \frac{\eta\beta}{1-\beta}\left[\frac{(1-\beta)^2}{\eta}\right]^{\frac{1}{\beta}}$, then

$$\begin{aligned}\varphi^U_{ct} = (\kappa + \tau_{c't})^{1-\beta}\left[\frac{(1-\delta)K_e}{\pi}\right]^{\beta} \times \Bigg[&\frac{1-\delta}{1-\delta(1-\phi)} + \frac{\delta\phi}{1-\delta(1-\phi)}E(\frac{\kappa+\tau'_{c't}}{\kappa+\tau_{c't}})^{-\frac{1-\beta}{\beta}} \\ &+ \frac{\delta\phi F(\bar{\tau})}{1-\delta(1-\phi)}(1 - E[(\frac{\kappa+\tau'_{c't}}{\kappa+\tau_{c't}})^{-\frac{1-\beta}{\beta}})|\tau'_{c't} \leq \bar{\tau}]\Bigg]^{-\beta}.\end{aligned}$$

Therefore

$$\varphi^U_{ct} = \varphi^D_{ct} \times \left[\frac{1-\delta(1-\phi\Gamma(\tau'_{c't}))}{1-\delta(1-\phi)}\right]^{-\beta},$$

where

$$\Gamma(\tau'_{c't}) = E\left(\frac{\kappa+\tau'_{c't}}{\kappa+\tau_{c't}}\right)^{-\frac{1-\beta}{\beta}} + F(\bar{\tau})\left(1 - E[(\frac{\kappa+\tau'_{c't}}{\kappa+\tau_{c't}})^{-\frac{1-\beta}{\beta}}|\tau'_{c't} \leq \bar{\tau}]\right).$$

D.5 Profit Loss Bound

$$\begin{aligned}
\Gamma(\tau'_{c't}) =& E\left(\frac{\kappa+\tau'_{c't}}{\kappa+\tau_{c't}}\right)^{-\frac{1-\beta}{\beta}} + F(\bar{\tau})\left(1 - E[(\frac{\kappa+\tau'_{c't}}{\kappa+\tau_{c't}})^{-\frac{1-\beta}{\beta}}|\tau'_{c't} \le \bar{\tau}]\right) \\
&= F(\bar{\tau})E[(\frac{\kappa+\tau'_{c't}}{\kappa+\tau_{c't}})^{-\frac{1-\beta}{\beta}}|\tau'_{c't} \le \bar{\tau}] + (1-F(\bar{\tau}))E[(\frac{\kappa+\tau'_{c't}}{\kappa+\tau_{c't}})^{-\frac{1-\beta}{\beta}}|\tau'_{c't} \ge \bar{\tau}] \\
&+ F(\bar{\tau})\left(1 - E[(\frac{\kappa+\tau'_{c't}}{\kappa+\tau_{c't}})^{-\frac{1-\beta}{\beta}}|\tau'_{c't} \le \bar{\tau}]\right) \\
&= (1-F(\bar{\tau}))E[(\frac{\kappa+\tau'_{c't}}{\kappa+\tau_{c't}})^{-\frac{1-\beta}{\beta}}|\tau'_{c't} \ge \bar{\tau}] + F(\bar{\tau}).
\end{aligned}$$

For $\tau'_{c't} \ge \bar{\tau}$,

$$E[(\kappa+\tau'_{c't})|\tau'_{c't} \ge \bar{\tau}] \ge E(\kappa+\tau_{c't}) = \kappa+\tau_{c't},$$

and

$$E[(\kappa+\tau'_{c't})^{-\frac{1-\beta}{\beta}}|\tau'_{c't} \ge \bar{\tau}] \le (\kappa+\tau_{c't})^{-\frac{1-\beta}{\beta}}.$$

Therefore,

$$E[(\frac{\kappa+\tau'_{c't}}{\kappa+\tau_{c't}})^{-\frac{1-\beta}{\beta}}|\tau'_{c't} \ge \bar{\tau}] \le 1,$$

and

$$\begin{aligned}
\Gamma(\tau'_{c't}) &= (1-F(\bar{\tau}))E[(\frac{\kappa+\tau'_{c't}}{\kappa+\tau_{c't}})^{-\frac{1-\beta}{\beta}}|\tau'_{c't} \ge \bar{\tau}] + F(\bar{\tau}) \\
&\le 1 - F(\bar{\tau}) + F(\bar{\tau}) = 1.
\end{aligned}$$