Three Essays on the Economics of Innovation

by

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Abstract

This study examines innovative activities of firms under environmental regulation and import competition. In particular, the first and the second chapters discuss the Porter Hypothesis, which suggests a positive link between stringent environmental regulation and firm innovation, from a theoretical and empirical perspective. The third chapter empirically investigates how import competition from low-wage countries affects firm innovation.

The first chapter compares equilibria in a duopoly with substitute goods, and obtains results consistent with predictions of the Porter Hypothesis. In this chapter I show that a binding minimum environmental quality standard can promote process innovation (i.e., cost reductions) and product innovation (i.e., increased environmental quality), and increase output and profits of both firms. This happens when between-firm spillovers in process innovation are sufficiently strong. The regulation can further raise consumer surplus and alleviate pollution, when environmental damage from production is mild and the marginal cost of process innovation exceeds a certain threshold. I demonstrate that these results are robust against changes in model specifications. Thus, a key finding of this paper is that environmental quality standards can benefit firms and consumers, by correcting not only for environmental externalities but also (as a by-product) for under-investment in process innovation.

The second chapter provides empirical support for the Porter Hypothesis in the context of a developing economy. In this chapter, I study the impact of a unique environmental regulatory policy called mandatory participation in Cleaner Production Audit (CPA) programs on firm innovation in China from 2001 through 2010. Using firm-level patent and CPA program enrollment data, I employ a difference-in-differences approach to examine the effect of CPA participation on Chinese listed companies, since the program's implementation in 2005. The analysis confirms that CPA participation enhanced firm innovation proxied by patent applications. I also find that this positive impact is stronger after substantial improvements were made to the program assessment framework in 2009, in eastern regions where stringent policy implementation was

combined with diversified financial incentives, and for larger companies with the resources needed to adapt to regulatory pressure. These results are robust to a variety of model specifications including models based on propensity score matching results.

The third chapter explores the impact of the surge in import competition from China on innovation in the U.S. manufacturing sector during the 1990–2001 period, using firm-level patent data. It finds evidence that Chinese import competition had a positive effect on U.S. innovation, as measured by patent applications weighted by citations. This positive effect persists when we use Chinese exports to the United Kingdom as an instrument, to address potential endogeneity. This chapter also finds that firms in less technologically advanced and less vertically differentiated industries, with high capital intensity and low labour productivity, have a greater incentive to innovate under import competition from China. These results are robust to a variety of measures for innovation and import penetration.

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List of Symbols – Chapter 1

CS	Consumer Surplus
D	Environmental Damage
R	Product R&D Invesment
U	Consumer Utility
W	Social Welfare
Y	Consumer Income
α	Process R&D Invesment Cost Parameter
β	Technology Spillover Parameter in Process Innovation
δ	Environmental Damage Parameter
γ	Product R&D Invesment Cost Parameter
μ	Product R&D Invesment Cost Parameter
π	Firm Profit
σ	Product Substitutability Parameter
c	Marginal Production Cost without Process Innovation
d	Marginal Cost Reduction / Process Innovation Output
e	Per Unit Environmental Damage without Product Innovation
p	Product Price
q	Environmental Quality of Products / Product Innovation Output
x	Production Output

List of Symbols – Chapter 2

α	Firm Fixed Effect
β	Industry-Year Fixed Effect
δ	Industry-Region-Year Fixed Effect
γ	Region-Year Fixed Effect
κ	Coefficient for Pseudo-CPA Participation Indicator
λ	Coefficient for Treatment Group Indicator
ϕ	Coefficient for Trend of Treatment Group Indicator
ρ	Coefficient for Other Firm Characteristics
θ	Coefficient for CPA Participation Indicator
ε	Error Term

List of Symbols – Chapter 3

M	Merchadise Import
Q	Value of Shipments
X	Merchadise Export
α	Constant Term
β	Coefficient for Import Penetration Ratio
γ	Coefficient for Other Firm Characteristics
ε	Error Term

Introduction

Economists consider innovation one of the main driving forces behind productivity and economic growth, as well as the resulting increase in social welfare. Since it was introduced in the classic work of Schumpeter (1942), the importance of innovation to the growth of modern economies has triggered numerous inquiries into how various factors, including firm characteristics, market structure and public policies, can affect innovation performance of firms, industries and the whole economy. In this thesis, I examine the impact of environmental regulation and import competition on firm innovation. Chapters 1 and 2 discuss the Porter Hypothesis, which suggests that strict environmental policies can stimulate firm innovation, from a theoretical and empirical perspective. Chapter 3 empirically investigates how firms' innovative activities respond to import competition from low-wage countries. This section briefly outlines the motivation, research questions, and findings of the three essays.

Environmental regulation, such as mandatory standards on environmental performance of firms or ecological quality of products, are often viewed as a burden to business activities, and thus detrimental to firm innovation and competitiveness. In a seminal paper, Porter and van der Linde (1995) challenged this idea and suggested that environmental regulation can, instead, stimulate innovation and enhance the profitability of regulated firms. This proposition has since become known as the *Porter Hypothesis*. Chapter 1 of the thesis, titled *Complementarity between Cost-reducing Innovation and Ecological Quality Improvement: the Porter Hypothesis and Beyond*, develops a novel theoretical model whose predictions are consistent with the Porter Hypothesis. In this chapter, I compare equilibria in Cournot and Bertrand duopoly with substitute goods. Prior to engaging in market competition, the model allows both firms to invest in process innovation, resulting in reduced production costs, and product innovation, resulting in improved product quality. I show that a binding minimum environmental quality standard can promote both types of innovation, and increase output and profits of both firms, provided that there exists a sufficiently strong between-firm spillover effect in process innovation. The regulation can further raise consumer surplus and alleviate pollution, when the environmental damage from production is sufficiently small and the marginal cost of process innovation exceeds a certain threshold. Thus, a key finding of this paper is that environmental quality standards can benefit both firms and consumers, by correcting not only for environmental externalities but also (as a by-product) for under-investment in process innovation.

Over the last few decades, many developing economies have been implementing more stringent environmental policies to address growing concerns over environmental deterioration. Consistent with Porter's statements in the 1990s, the governments of these economies sometimes indicate that environmental policies could boost innovation and competitiveness of the regulated industries. While previous studies have examined the impact of environmental policy on technological change in developed countries, research that examines this relationship in the context of developing economies is scarce. Chapter 2, titled *Environmental Regulation and Firm Innovation: Evidence from China*, provides empirical support for the Porter Hypothesis by showing a positive effect of environmental regulation on firm innovation in China. The chapter focuses on a unique environmental policy tool: mandatory participation in Cleaner Production Audit (CPA) programs in China. Using firm-level patent and CPA program enrollment data, I employ a difference-in-differences approach to examine the effect of CPA participation on Chinese listed companies, since the program's implementation in 2005. The analysis confirms that companies innovate more, as indicated by an increase in patent applications, when they are placed under stringent environmental regulation through CPA enrollment. I also find that this positive impact is more pronounced after substantial improvements were made to the program assessment framework in 2009, in eastern regions, where stringent policy implementation was combined with stronger financial incentives, and for larger companies that have the resources needed to adapt to regulatory pressure.

In recent years, the manufacturing sectors in developed economies, such as United States, have faced increasing import competition from low-wage countries, especially China. Does this competition hurt or help innovation? Chapter 3, *Firm Innovation under Import Competition from Low-wage Countries*, explores whether this surge in import competition from low-wage countries has spurred more innovation in the U.S. manufacturing sector during the 1990–2001 period. Using firm-level innovation and financial data, this chapter shows that a positive correlation between import competition from China and firms' innovation performance exists. The correlation persists when we use Chinese exports to the United Kingdom as an instrument to address the potential endogeneity problem. The empirical results also suggest that the impact of import competition varies across firms: those in low-tech and less-differentiated industries, with high capital intensity and low labour productivity, have a greater incentive to innovate when imports from low-wage countries increase.

In general, this thesis studies the economics of innovation from both a theoretical and an empirical perspective. The three chapters described in the introduction are self-contained, with their own introduction and conclusion sections. They are followed by concluding remarks and common reference section at the end of the thesis.

Chapter 1

Complementarity between Cost-reducing Innovation and Ecological Quality Improvement: the Porter Hypothesis and Beyond

1.1 Introduction

The *Porter Hypothesis*, developed by Porter (1991) and Porter and van der Linde (1995), suggests that "properly designed environmental standards can trigger innovation that may partially or more than fully offset the costs of complying with them" (Porter and van der Linde, 1995, p. 2). Jaffe and Palmer (1997) proposed a now generally accepted taxonomy that classifies Porter's argument into a weak and a strong version. The weak version suggests that firms subject to rigorous environmental regulation may invest more in research and development (R&D), which amplifies their chances to innovate. The results of the induced innovation *partially* offset the costs involved in pollution abatement and clean technology adoption. The strong version argues that the extra profits from innovation can *fully* offset, and even exceed, the costs associated with regulation. The latter makes it possible for firms to benefit from strict environmental policies.

In the last twenty years, a large literature has sought to provide theoretical foundations for the Porter Hypothesis.[1] One consensus among these studies is that, in order for environmental policies to benefit both consumers and producers, there must exist an additional market failure besides environmental externalities in the unregulated market. The market failures under consideration include information asymmetries, imperfect competition, and R&D spillovers. Previous models that use spillover effects find evidence for the weak version of the hypothesis, but fail to support the strong version. This paper presents a mechanism that leads to outcomes consistent with both the weak and the strong versions of the Porter Hypothesis, using inter-firm spillovers in process innovation as the additional market failure.

[1] This literature will be reviewed in Section 1.2.

I consider a three-stage game with two firms that first conduct process innovation, then product innovation, and finally compete in quantities or prices—market interaction can take the form of either Cournot or Bertrand competition.[2] Consumers view goods from different producers as imperfect substitutes, even if their quality is the same. I capture this feature of consumers' tastes by adopting a quality-augmented version of the standard quadratic utility function.[3] A spillover effect occurs at the process innovation stage. Specifically, I assume that investment by one firm lowers not only its own production costs, but, in part, also that of its rival. There is no spillover effect at the product innovation stage.[4]

The policy tool under consideration is a *minimum environmental quality standard (MQS)*. Such standards are found in many industries around the world; for example, exhaust emission standards are applied to new vehicle sales in virtually every country. I show that subjecting firms to an MQS can enhance consumer welfare as well as firm profits, because it stimulates innovative activities in production technology that would be undersupplied without the regulation. This is true even though the MQS is not, *per se*, designed to address the problem of underinvestment in process R&D. It merely ensures that the final product attains a certain minimum environmental quality.[5]

Given the structure and timing of the game, analysis in this paper applies to a mature manufacturing industry, in which technology breakthroughs occurred long time ago, and a small number of firms are currently focusing on cost reduction and incremental quality improvements to expand their market shares (see Adner, 2004; Malerba, 2007). The passenger automobile industry, for example, fits these descriptions and the characteristic that environmental quality is considered to be an important product feature. As an engine technology that improves fuel efficiency and reduce emissions, turbocharging was invented in early 1910s and first introduced in passenger cars in 1960s. However, turbochargers were widely used in passenger cars only after European countries tightened their emission standards and implemented carbon taxes in 1990s and 2000s. Automobile firms responded with investments for reducing production costs of turbocharged petrol engines, and thus made it profitable to equip non-premium models with this technology. In recent years, firms are continuing to improve their engines for better fuel economy and lower emissions, which corresponds to the incremental product innovation discussed in this paper.

[2] Although this paper uses duopoly models, the key factor driving the results is not the market structure but the spillover effect. One evidence is that firms expand their output and lower prices under regulation, instead of raising prices to pass along compliance costs to consumers, as described in Mohr and Saha (2008).

[3] Similar specification are used in Sutton (1997) and Symeonidis (2003).

[4] Previous empirical studies have found conflicting evidence on the relative magnitude and pervasiveness of spillover in process and product innovation. Using Spanish firm-level data, Ornaghi (2006) finds that technology diffusion in product innovation is stronger. de Faria and Lima (2012) finds the opposite result by applying a similar estimation strategy to Portuguese firm-level data. Using European Union industry-level data, Dietzenbacher (2000) finds spillover effect in process innovation to be larger, and a similar result is obtained by Chen et al. (2010) using Taiwanese industry-level data.

[5] The result that a MQS can raise consumer welfare and firm profits is robust when the order of process R&D and product R&D is reversed. Depending on the market under consideration, each timing assumption may be more realistic (see Utterback and Abernathy, 1975; Klepper, 1996; Adner and Levinthal, 2001; Adner, 2004; Malerba, 2007; Lambertini and Mantovani, 2010; Bacchiega et al., 2011).

Previous models that incorporate inter-firm spillover effects to generate the Porter Hypothesis do not simultaneously examine process and product innovation. As a result, they either generate only the weak version of the Porter Hypothesis (Mohr, 2002), or yield outcomes in which firms expand output but earn less profits (Greaker, 2006), or result in domestic firms benefiting at the expense of foreign competitors (Simpson and Bradford, 1996). The present paper contributes to this literature by showing that R&D spillover effects can also generate the strong version, provided that a complementarity between process and product innovation exists.

The remainder of this paper proceeds as follows. Section 1.2 presents a brief review of theoretical literature on the Porter Hypothesis. Section 1.3 introduces the basic settings of the model. Section 1.4 analyses the case in which producers are competing in quantities, whereas Section 1.5 considers the case involving Bertrand competition between firms. Section 1.6 shows the main propositions hold in spite of changes in model specifications. Section 1.7 concludes the paper, discusses interpretation of results and possible extensions.

1.2 Literature Review

Porter and van der Linde (1995) suggest that environmental regulation may lead to a "win-win" situation by fostering innovation that enhances efficiencies of regulated firms. This controversial idea soon found a ready audience among environmentalists and policymakers in 1990s, however, it also received plenty of criticisms from economists for its contradiction with the assumption of profit-maximizing firms (see Palmer et al., 1995). While several case studies are provided as evidence, the major proposition in Porter and van der Linde (1995) is presented in the absence of a formal economic model.

To provide a theoretical foundation for the Porter Hypothesis, over the last twenty years many researchers have studied the possible reasons for firms not being able to maximize profits, and how environmental policies may contribute to the correction of these deficiencies. Generally, these studies agree that a scenario consistent with Porter's predictions usually involves an additional market failure besides negative environmental externality in the unregulated market (see Mohr and Saha, 2008). The market failures investigated in previous literature, as summarized in Brännlund and Lundgren (2009) and Ambec et al. (2013), include information asymmetries, imperfect competition, and R&D spillovers.

In models that introduce agency considerations in innovation-related decision-making process, information asymmetry between owners and employees can prevent firms from profit maximization. Introduction of new technology may force managers and other workers to abandon previously established routines, in which they have accumulated specific experience. Besides that, adaptation to new routines usually incurs substantial learning costs. Since benefits to individuals from potential profit enhancement may not cover these private costs, employees have personal motives to resist technology adoption, or oppose investment in R&D for new technology. This type of deficiency is referred as "organizational failure" in Gabel and Sinclair-Desgagné (1998). If the profit-enhancing technologies are also environment friendly, regulators may achieve their environmental objectives through helping firms overcome the agency issues. Policy choices suggested by earlier studies include adoption subsidy to producers with "conservative" managers (Aghion et al., 1997), and a commitment to "distort production to the socially efficient level" (Ambec and Barla, 2002, p. 2).

Information asymmetry between producers and consumers can also reconcile the Porter Hypothesis with the assumption of profit-maximizing firms. Consumers may have a preference for products with higher environmental quality, but cannot easily distinguish them from average or even environmentally unfriendly goods, due to lack of credible information. This issue has been interpreted in different ways among literature. Rege (2000) suggests that by making false claims about environmental quality of their products, low-quality producers may earn excess profits while high-quality goods are under produced. In this case, more frequent inspections and higher penalties can increase the probability and cost of being caught cheating, and thus promote the production of high-quality products. Other studies argue that although consumers can choose to acquaint themselves with the environmentally friendly products, this process may take a considerable amount of time (Constantatos and Herrmann, 2011), and the information they obtain may be incomplete (Mohr and Saha, 2008). These obstacles can hold firms back from developing and introducing clean and productive technologies. Hence, environmental regulation in the form of emission tax, or force implementation of new technology, may address these issues and enhance firm profitability.

Another stream of literature investigates whether models with imperfect competition can generate outcomes consistent with the Porter Hypothesis. In a market with entry barriers, environmental regulation such as emission tax, can drive the existing firms to reduce output and raise product price. If the scarcity rents cannot fully offset the tax burden, firms may introduce cleaner but less productive technology to reduce pollution and achieve higher profitability. Although such models yield results in line with the Porter Hypothesis, Mohr and Saha (2008) indicate that the key factors driving the results are not innovation offsets but scarcity rents. Firms are able to earn more profits, mainly because they have transferred part of the regulation compliance costs to consumers. The duopoly models in André et al. (2009) and Lambertini and Tampieri (2012) fit this description—to comply with environmental standard, firms adopt less pollutive, but cost-inefficient technology and charge higher prices for their products.

Among the studies employing spillover effects as the additional market failure besides environmental externality, Greaker (2003) reaches the conclusion that an emission tax can promote process innovation, as indicated by reduced marginal cost, through the "intra-firm spillover effects." These effects are driven by economies of scale in pollution abatement. If this effect is so strong that per unit emission decreases with output, increasing the emission tax rate would lower firms' marginal production cost. In this case, it may be profitable for firms to produce more under stringent environmental regulation.

Other studies build their models on the basis of inter-firm spillover effects. Mohr (2002) assumes the productivity of firms that employ similar technology is determined by their collective production experience. A mandatory adoption of clean technology can benefit firms in the long term, as their productivity will grow faster compared with the pre-regulation period. Since the results are derives using a general equilibrium model, he does not distinguish between consumer and producer surplus, instead argues that the regulation brings short-term costs and long-term gains to the society. By introducing an upstream abatement equipment sector with free entry, Greaker (2006) shows that a lower emission quota reduces price of abatement equipment and increases export output of downstream industry, since the fixed cost of entering the upstream market decreases in the number of firms. However, total production cost rises despite of marginal cost reduction, so firms earn less profits even if environmental stringency enhances their "competitiveness," which is interpreted as "the ability to increase export market share" (Greaker, 2006, p. 2).[6] Simpson and Bradford (1996) specify a model with market structure similar to that employed in this paper. They assume that a domestic and a foreign firm compete in quantities in a third region's market, while process innovation by either firm may reduce the marginal production cost of its rival. Given certain specifications of the cost functions, they confirm that higher effluent tax imposed by domestic government can stimulate domestic R&D expenditure, and shift profits from the foreign firm to the domestic one.

As noted above, none of the studies that incorporate inter-firm spillovers generate results in line with the strong version of the Porter Hypothesis. This paper adds to the literature by proving that environmental regulation, in the form of a MQS, can stimulate innovation and benefit both consumers and producers in an oligopoly market, even if the policy is not targeting the exact phase of innovation where spillover occurs.

1.3 The Model

Consider a duopoly market where single-product firms indexed by $i = 1, 2$ supply products with ecological quality $q \in [0, Q]$ to a large number of identical consumers. The number of consumers is normalized to be 1. Firm i can invest R_i in developing environment-friendly production technologies and achieve a certain level of ecological quality $q_i = \gamma R_i^{\frac{1}{4}}$.[7] Hereafter I refer to R_i as product R&D input, while $\gamma > 0$ is a parameter that measures the cost of quality improvement.

Consumption of variety i entails damage to the environment, which is linearly decreasing in its ecological quality q_i, and linearly increasing in amount consumed. By denoting x_i as a representative consumer's

[6] This interpretation is in line with part of Porter's original statements, and is also adopted by some empirical studies on the hypothesis (see Costantini and Mazzanti, 2012).

[7] To examine the robustness of my results, I assume $q_i = \gamma R_i^{\mu}$ and allow $\mu \in (0, 1)$ in Section 1.6 and discuss whether this change alters the effectiveness of environmental regulation.

consumption of variety i, the total output of firm i is also equal to x_i when the market is cleared. Then environmental damage induced by consuming product i can be expressed as

$$D_i = \delta \cdot (e - q_i) \cdot x_i, \quad i = 1, 2, \tag{1.1}$$

where e represents emission per unit of output with zero product R&D input, and $\delta \geq 0$ is a parameter converting the actual amount of emissions into the monetary equivalent of pollution.[8]

Both firms start with a constant marginal production cost $c \in (0, 1)$. Through investing for process innovation, either firm can improve its own production efficiency and lower its marginal cost. However, firms may not be able to completely prevent the diffusion of the newly-developed manufacturing techniques. I use $\beta \in [0, 1]$ to capture the extent of technological spillovers, as $\beta = 0$ signals that firms are capable of keeping their process innovation completely private, and $\beta = 1$ suggests that the new technology can be immediately copied and applied by other producers without additional costs.

When $\beta = 0$, firm i must invest αd_i^2 in process R&D in order to lower its own marginal cost by d_i, where $\alpha > 0$ is a common cost parameter of process R&D for both firms. Note that the quadratic function indicates that process R&D investments, similar to those for product innovation, also yield diminishing returns. When $\beta \neq 0$, marginal production costs for firms 1 and 2 change into $c - d_1 - \beta d_2$ and $c - d_2 - \beta d_1$, given αd_1^2 and αd_2^2 as their respective process R&D investments.

The timing of the game is as follows:

Stage 1 Both firms simultaneously invest in process innovation.

Stage 2 Firms observe marginal cost reductions, and simultaneously invest in product innovation.

Stage 3 Firms observe product quality, and simultaneously choose quantities/prices to maximize profits.

Since both firms operate in the same industry, it is natural to assume that news of innovation in one firm travels to its competitor through various channels (employee turnovers, trade publications, etc.)—especially if the time passing between the stages is sufficiently long.[9] This means that firms generally have an idea about their competitors' overall production costs and product quality, even though they may not necessarily become immediately aware of each and every single investment a competitor makes into its production technology. Therefore, I assume both firms can observe production costs and product quality of itself and its competitor, before moving to the next stage in the model.

[8] Lombardini-Riipinen (2005) and Brécard (2013) take the difference between emissions without abatement effort and actual emissions ($e - e_i$) to represent the ecological quality of product i. Using q to directly represent the ecological quality serves better to connect this model with previous literature on imperfect competition with substitute goods.

[9] Taking the passenger automobile industry discussed in Section 1.1 as an example, development of new engines can take several years before models equipped with these engines reach the consumers.

Using p_i to represent the price of variety i, the profit maximization problem for firm i at Stage 3 is

$$\max_{x_i} \pi_i(x_i) = [p_i(x_i, x_j) - c + d_i + \beta d_j] \cdot x_i - \alpha d_i^2 - R_i, \quad i, j = 1, 2 \; and \; i \neq j,$$

in the Cournot case, where $p_i(x_i, x_j)$ represents its product price as a function of both firms' output in this stage; or

$$\max_{p_i} \pi_i(p_i) = [p_i - c + d_i + \beta d_j] \cdot x_i(p_i, p_j) - \alpha d_i^2 - R_i, \quad i, j = 1, 2 \; and \; i \neq j,$$

in the Bertrand case, where $x_i(p_i, p_j)$ represents its output as a function of both firms' product price in this stage.

The profit maximization problem for firm i at Stage 2 is

$$\max_{R_i} \pi_i(R_i) = [p_i^*(R_i, R_j) - c + d_i + \beta d_j] \cdot x_i^*(R_i, R_j) - \alpha d_i^2 - R_i,$$
$$i, j = 1, 2 \; and \; i \neq j,$$

where $p_i^*(R_i, R_j)$ and $x_i^*(R_i, R_j)$ represent its product price and output as a function of both firms' product investments in this stage.

Thus, at Stage 1, firm i is maximizing its profit π_i as follow:

$$\max_{d_i} \pi_i(d_i) = [p_i^*(d_i, d_j) - c + d_i + \beta d_j] \cdot x_i^*(d_i, d_j) - \alpha d_i^2 - R_i^*(d_i, d_j),$$
$$i, j = 1, 2 \; and \; i \neq j,$$

where $p_i^*(d_i, d_j)$, $x_i^*(d_i, d_j)$, and $R_i^*(d_i, d_j)$ represent its product price, output, and product R&D investment as a function of both firms' process investments in this stage.

On the demand side, consumers share a common utility function that is additively separable. [10] Hence a representative consumer's utility function takes the following form:

$$U = x_i + x_j - \frac{1}{2}\left(\frac{x_i^2}{q_i^2} + \frac{x_j^2}{q_j^2}\right) - \frac{\sigma x_i x_j}{q_i q_j} - p_i x_i - p_j x_j, \quad i, j = 1, 2 \; and \; i \neq j, \tag{1.2}$$

where $\sigma \in (0, 1)$ is a parameter that indicates the level of substitutability between varieties when $q_1 = q_2$.[11] As firms are symmetric in every aspect, in the following sections I focus on symmetric equilibria in which firms share the same marginal production cost and product quality. The value of σ can be a simple measure of substitutability in the remaining discussion, as $\sigma \to 0$ suggests the two varieties are consumed as two independent products even when they share the same quality, while $\sigma \to 1$ reflects that consumers consider them to be perfect substitutes in symmetric equilibria.

[10] I assume a representative consumer's income to be Y, then $Y - p_1 x_1 - p_2 x_2$ stands for an individual's remaining budget for everything else after consuming x_1 and x_2.

[11] Here I assume a representative consumer's utility depends on expenditure on the two products, which reflects the opportunity cost of forgone consumption of other products. Adding overall environmental damage to the utility function will not affect the results, as each individual consumer is quantitatively small and takes aggregate environmental damage as given. However, in the welfare calculations environmental damage is explicitly taken into consideration, and it drops as a result of environmental regulation.

Based on the utility function defined above, marginal utility from consuming variety i is $1 - (1/q_i) \cdot [(x_i/q_i) + (\sigma \cdot x_j)/q_j]$, which shows that a rise in quality of either variety can mitigate the negative utility induced by consumers' concerns on environmental damage. Since consumers' willingness to pay always matches the marginal utility gained, the inverse demand function for variety i is

$$p_i = 1 - \frac{x_i}{q_i^2} - \frac{\sigma x_j}{q_i q_j}, \quad i, j = 1, 2 \textit{ and } i \neq j. \tag{1.3}$$

I can easily define consumer surplus $CS = U$, then the corresponding social welfare function can be written as

$$W = CS + \pi_i + \pi_j - D_i - D_j, \quad i, j = 1, 2 \textit{ and } i \neq j. \tag{1.4}$$

Thus, an optimal strategy to increase social welfare is to raise both consumer surplus and firm profits, and lower environmental damages from production. The following sections show how these objectives can be simultaneously achieved by a MQS in markets with different structures.

1.4 Cournot Duopoly

1.4.1 Non-Cooperative and Cooperative Equilibria

I start with the case in which firms compete in quantities at the final stage, and solve for the subgame perfect equilibrium using backward induction. Taking marginal cost, product quality and R&D investments as given, firm i sets its production level x_i in the final-stage subgame to maximize profits. In the non-cooperative Cournot-Nash equilibrium, firm i produces

$$x_i^N = \frac{q_i}{4 - \sigma^2}[2q_i(1 - c + d_i + \beta d_j) - \sigma q_j(1 - c + \beta d_i + d_j)] \tag{1.5}$$

to achieve the optimal production level where $\partial \pi_i / \partial x_i = 0$. Note that the superscript N refers to the non-cooperative Nash equilibrium.

By setting $x_i = x_i^N$ and $q_i = \gamma R_i^{\frac{1}{4}}$, the profit function of firm i in the second stage can be expressed as

$$\pi_i(R_i) = \frac{\gamma^2}{(4 - \sigma^2)^2}[2R_i^{\frac{1}{4}}(1 - c + d_i + \beta d_j) - R_j^{\frac{1}{4}}(1 - c + \beta d_i + d_j)]^2 - \alpha d_i^2 - R_i. \tag{1.6}$$

Since I only consider the symmetric equilibria, the first order conditions $(\partial \pi_i / \partial R_i)\big|_{R_i = R_j} = 0$ yield the following optimal product R&D investments:

$$R_i^N = \frac{\gamma^4}{4 - \sigma^2}(1 - c + d_i + \beta d_j)^2[2(1 - c + d_i + \beta d_j) - \sigma(1 - c + \beta d_i + d_j)]^2. \tag{1.7}$$

The first-order derivatives $\partial R_1^N / \partial d_1$ and $\partial R_2^N / \partial d_2$ are positive when evaluated at $d_1 = d_2 = d^N$. Thus I come to the following lemma:

Lemma 1. *Suppose firms compete in quantities and the market is at a symmetric non-cooperative equilibrium. Growth of either firm's process R&D investment enhances product R&D investments and product quality of both firms, if the spillover effect in process innovation is sufficiently large.*

Proof. See Appendix A.1. □

By substituting Equation (1.7) into $\pi_i(R_i)$, the first order conditions in the first stage can be reorganized as

$$\frac{\partial \pi_i}{\partial d_i}\Big|_{d_i=d_j=d^N} = \frac{2\gamma^4[8-4(1+2\beta)\sigma+(1+3\beta)\sigma^2]}{(2-\sigma)^3(2+\sigma)^4}[1-c+(1+\beta)d^N]^3 - \alpha d^N = 0 \tag{1.8}$$

Since the coefficients on d^N are positive, I can infer that the above equation always has a unique solution $d^N \in (0, c/(1+\beta))$ that leads to a symmetric equilibrium, as long as the following constraint on α is met:

$$\alpha > \underline{\alpha}_1 = \frac{2\gamma^4(1+\beta)[8-4(1+2\beta)\sigma+(1+3\beta)\sigma^2]}{c(2-\sigma)^3(2+\sigma)^4}.$$

In order for d^N to be an interior maximum, $\partial^2\pi_i/\partial d_i^2$ must be negative when evaluated at $d_1 = d_2$. As pointed out by Henriques (1990), the condition $(\partial^2\pi_i/\partial d_i^2)(\partial^2\pi_i/\partial d_j^2) - (\partial^2\pi_i/\partial d_i d_j)(\partial^2\pi_j/\partial d_i d_j) > 0$ must also hold for a non-cooperative equilibrium with spillover effects to be stable, i.e., reaction curves in both output and R&D spaces must cross "correctly" to ensure that firms have no incentive to deviate from the equilibrium. A sufficient but not necessary condition for the second order and the stability conditions to hold simultaneously is $\alpha > \max\{\underline{\alpha}_2, \underline{\alpha}_3\}$.[12]:

Lemma 2. *Suppose firms compete in quantities, a uniform level of process innovation* $d^N \in (0, c/(1+\beta))$ *can lead to a unique and stable symmetric equilibrium, if the cost parameter α of process R&D is above a threshold value represented by* $\max\{\underline{\alpha}_1, \underline{\alpha}_2, \underline{\alpha}_3\}$.

Proof. See Appendix A.2. □

If the two competitors are able to cooperate at the process R&D stage and incorporate the spillover effects into their decision-making process, the joint profit function becomes

$$\pi^C = \frac{2\gamma^4}{(2-\sigma)(2+\sigma)^4}[1-c+(1+\beta)d^C]^4 - 2\alpha(d^C)^2 - 2R^C \tag{1.9}$$

since $d_1 = d_2 = d^C$, where the superscript C refers to the equilibrium with cooperation in process R&D. In this case, the first order condition that allows firms to maximize their joint profit is

$$\frac{\partial \pi^C}{\partial d^C} = \frac{2\gamma^4(1-\sigma)(1+\beta)}{(2-\sigma)^2(2+\sigma)^4}[1-c+(1+\beta)d^C]^3 - \alpha d^C = 0. \tag{1.10}$$

[12] The values of $\underline{\alpha}_2$ and $\underline{\alpha}_3$ are shown in Appendix A.2. Combining these conditions, I can now state the following lemma

In the same vein, the existence of a unique solution $d^C \in (0, c/(1+\beta))$ requires

$$\alpha > \underline{\alpha}_4 = \frac{2\gamma^4(1-\sigma)(1+\beta)^2}{c(2-\sigma)^2(2+\sigma)^4}.$$

The second order condition for the equilibrium with cooperation in process R&D can be rewritten as

$$\alpha > \frac{6(1-\sigma)(1+\beta)^2}{(2-\sigma)^2(2+\sigma)^4}[1-c+(1+\beta)d^C]^2 = \underline{\alpha}_5[1-c+(1+\beta)d^C]^2.$$

Therefore $\alpha > \max\{\underline{\alpha}_4, \underline{\alpha}_5\}$ is a sufficient but not necessary condition for the existence of a unique and stable interior maximum in this game.

The relationship between the two equilibria is of particular interest. By comparing Equation (1.8) with Equation (1.10), I come to the following lemma:

Lemma 3. *Suppose firms compete in quantities, they invest more for marginal cost reduction and earn higher profits in a symmetric equilibrium with cooperation in process R&D than in a symmetric non-cooperative equilibrium, if* $\beta \in (\sigma, 1]$ *and* $\alpha > \max\{\underline{\alpha}_4, \underline{\alpha}_5\}$.

Proof. See Appendix A.3. □

1.4.2 Minimum Quality Standard

Now I envisage a straightforward policy implemented by a regulator intending to alleviate environmental damage: firms have to meet a quality standard $\underline{q} = q(d^C)$ or they will be shut down completely. Suppose the market is at the symmetric non-cooperative equilibrium, the optimal response of either firm to this MQS would be adjusting its process R&D input in the first stage. The reason is that simply raising ecological quality in the second stage, without adjustments to process R&D investments, violates the first order condition in the first stage and necessarily diminishes profits.

With lower marginal production costs, firms have more incentives to invest for higher ecological quality. This positive link between the two types of innovation is confirmed in Lemma 1. If $\beta \in (\sigma, 1]$ and $\alpha > \max\{\underline{\alpha}_4, \underline{\alpha}_5\}$ are also satisfied, profits of both firms increase as a result of higher level of innovation activities.

To further examine if the MQS eventually leads to an increase in social welfare without hurting consumers, I rewrite the partial derivative of consumer surplus with respect to process R&D, when evaluated at a symmetric non-cooperative equilibrium, as

$$\frac{\partial CS}{\partial d_i}\Big|_{d_i=d_j=d^N} = \frac{2\gamma^4(1+\beta)(31+\sigma-16\sigma^2+2\sigma^4)}{(2-\sigma)(2+\sigma)^4}[1-c+(1+\beta)d^N]^3. \tag{1.11}$$

The above positive partial derivatives suggest that consumers can benefit from marginal cost reduction of either producer.

To ensure the regulator achieves her original objective through implementing the MQS, I need to check the impact of changes in process innovation on environmental damage. By evaluating the partial derivatives of aggregate environmental damage with respect to process innovation of firm i at symmetric equilibria, I obtain

$$\begin{aligned}\frac{\partial(D_i + D_j)}{\partial d_i}\Big|_{d_i=d_j=d^N} \propto & -\frac{2f_1(\beta,\sigma)}{(2-\sigma)^2}\left\{\frac{\gamma^2}{2+\sigma}\sqrt{\frac{1}{2-\sigma}}[1-c+(1+\beta)d^N]-e\right\} \\ & -\frac{\gamma^2(1+\beta)}{2+\sigma}\sqrt{\frac{1}{2-\sigma}}[1-c+(1+\beta)d^N]\end{aligned} \tag{1.12}$$

where

$$f_1(\beta,\sigma) = 10 + (2 - 7\sigma + 2\sigma^2)\beta - 5\sigma + \sigma^2 > 0.$$

Hence, the aggregate environmental damage is negatively correlated with process innovation of either firm as long as $e < \bar{e}_1 = \gamma^2/[\sqrt{2-\sigma}\cdot(2+\sigma)]$.

The above discussion can be summarized as the following proposition:

Proposition 1. *Suppose firms compete in quantities and the market is at a symmetric non-cooperative equilibrium. A binding MQS can increase social welfare by increasing consumer surplus, increasing profits, and reducing environmental damage, if the following conditions hold simultaneously:*

1. *The spillover effect in process innovation (β) is sufficiently large.*
2. *The process R&D cost efficiency ($1/\alpha$) is sufficiently low.*
3. *The initial marginal environmental damage from production (e) is sufficiently low.*

The first and the second conditions indicate that process innovation is quite expensive for either of the firms, and can be easily mirrored by its competitor. Therefore, neither firm is willing to unilaterally raise its own process R&D investment at a symmetric non-cooperative equilibrium. On the other had, a binding MQS can force firms to simultaneous increase process innovation and earn higher profits. Since product innovation boosts consumer demand, firms expand their output after complying with the MQS. The third condition ensures that the marginal environmental damage is substantially lowered by product innovation induced by regulation. Otherwise, the overall amount of environmental damage would increase as a result of output expansion, despite the improvements in the ecological quality of both varieties.

1.5 Bertrand Duopoly

1.5.1 Non-Cooperative and Cooperative Equilibria

Another scenario of interest is where the product market involves Bertrand competition. When firms compete in prices instead of quantities in the final stage, firm i now chooses p_i in the final-stage subgame to maximize

$$\pi_i(p_i) = \frac{q_i[(1-p_i)q_i - (1-p_j)q_j][p_i - 1 + c - d_i - \beta d_j]}{(1+\sigma)(1-\sigma)} - \alpha d_i^2 - R_i. \tag{1.13}$$

In the Bertrand-Nash equilibrium, the first order conditions that $\partial \pi_i / \partial p_i = 0$ yield

$$p_i^N = \frac{q_i[2(1+c-d_i-\beta d_j) - \sigma^2] - \sigma q_j(1-c+\beta d_i + d_j)}{(4-\sigma^2)q_i}. \tag{1.14}$$

Given Equation (1.14) and $q_i = \gamma R_i^{\frac{1}{4}}$, I can rewrite profit of firm i as a function of its product R&D input:

$$\pi_i(R_i) = \frac{\gamma^2}{(1-\sigma^2)(4-\sigma^2)^2}[(2-\sigma^2)(1-c+d_i+\beta d_j)R_i^{\frac{1}{4}} - \sigma(1-c+\beta d_i + d_j)R_j^{\frac{1}{4}}]^2 - \alpha d_i^2 - R_i. \tag{1.15}$$

Similar to Lemma 1, the following lemma applies to the Bertrand case:

Lemma 4. *Suppose firms compete in prices and the market is at a symmetric non-cooperative equilibrium. Growth of either firm's process R&D investment enhances product R&D investments and product quality of both firms, if the spillover effect in process innovation is sufficiently large.*

Proof. See Appendix A.4. □

Given Equation (1.15) and Equation (A.4), the first order conditions for firms to maximize their profits in the non-cooperative equilibrium and the equilibrium with cooperation in process R&D are

$$\begin{aligned} \frac{\partial \pi_i}{\partial d_i}\Big|_{d_i=d_j=d^N} &= \frac{\gamma^4(2-\sigma^2)f_2(\beta,\sigma)}{4(1-\sigma)(1+\sigma)^2(2-\sigma)^4(2+\sigma)^3}[1-c+(1+\beta)d^N]^3 - \alpha d^N = 0 \\ \text{and} \quad \frac{\partial \pi^C}{\partial d^C} &= \frac{\gamma^4(1+\beta)(2-\sigma^2)(2-2\sigma+\sigma^2)}{2(1+\sigma)^2(2-\sigma)^4(2+\sigma)^2}[1-c+(1+\beta)d^C]^3 - \alpha d^C = 0 \end{aligned} \tag{1.16}$$

respectively, where

$$f_2(\beta,\sigma) = 8 + (4\sigma^3 + 3\sigma^2 - 8\sigma)\beta + 2\sigma^4 + 2\sigma^3 - 7\sigma^2 - 4\sigma.$$

To ensure that both equations lead to positive solutions $d^N, d^C \in (0, c/(1+\beta))$, the condition that $\alpha > \max\{\underline{\alpha}_6, \underline{\alpha}_7\}$ has to be met, where

$$\underline{\alpha}_6 = \frac{\gamma^4(1+\beta)(2-\sigma^2)f_2(\beta,\sigma)}{4c(1-\sigma)(1+\sigma)^2(2-\sigma)^4(2+\sigma)^3}, \quad \underline{\alpha}_7 = \frac{\gamma^4(1+\beta)^2(2-\sigma^2)(2-2\sigma+\sigma^2)}{2c(1+\sigma)^2(2-\sigma)^4(2+\sigma)^2}.$$

Following procedures employed in the proof of Lemma 3, I can infer that $d^C > d^N$ and $\pi^C > \pi^N$ require $\beta \in (\underline{\beta}, 1]$, where

$$\underline{\beta} = \frac{\sigma(8 - 4\sigma^2 - 3\sigma)}{8 - 4\sigma - 7\sigma^2 + 2\sigma^3 + 2\sigma^4}$$

is always larger than $\sigma/(4 - \sigma - 2\sigma^2)$, and less than 1 when $\sigma \in (0, \sqrt{3} - 1)$.

Similar to Lemma 2, the second order condition and the stability condition for the non-cooperative equilibrium translate into the following lemma:

Lemma 5. *Suppose firms compete in prices, a uniform level of process innovation* $d^N \in (0, c/(1 + \beta))$ *can lead to a unique and stable symmetric equilibrium, if the cost parameter* α *of process R&D is above a threshold value represented by* $\max\{\underline{\alpha}_6, \underline{\alpha}_8\}$.

Proof. See Appendix A.5. □

On the other side, the second order condition for the equilibrium with cooperation in process R&D is satisfied when

$$\alpha > \underline{\alpha}_9 = \frac{3\gamma^4(1 + \beta)^2(2 - \sigma^2)(2 - 2\sigma + \sigma^2)}{2(1 + \sigma)^2(2 + \sigma)^2(2 - \sigma)^4}. \tag{1.17}$$

A straightforward simulation confirms $\underline{\alpha}_9 > \underline{\alpha}_8$ and $\underline{\alpha}_7 > \underline{\alpha}_6$, when β is set to be between $\underline{\beta}$ and 1. The previous discussion is summarized in the following lemma:

Lemma 6. *Suppose firms compete in prices, they invest more for marginal cost reduction and earn higher profits in a symmetric equilibrium with cooperation in process R&D than in a symmetric non-cooperative equilibrium, if* $\beta \in (\underline{\beta}, 1]$, $\sigma \in (0, \sqrt{3} - 1)$, *and* $\alpha > \max\{\underline{\alpha}_7, \underline{\alpha}_9\}$.

1.5.2 Minimum Quality Standard

When the market is at a non-cooperative symmetric equilibrium, a MQS $\underline{q} = q(d^C)$ would motivate firms to raise process R&D investments in the first stage, followed by investing more in product R&D in the second stage, as suggested by Lemma 4. Meanwhile, if all the conditions specified in Lemma 6 are also met, the two firms can earn more profits when complying with the MQS.

The impacts of marginal cost reduction on consumer surplus are indicated by the following derivatives:

$$\frac{\partial CS}{\partial d_i}\Big|_{d_i=d_j=d^N} = \frac{\gamma^4(1 + \beta)(2 - \sigma^2)[1 - c + (1 + \beta)d^N]^3}{(2 + \sigma)(1 + \sigma)^2(2 - \sigma)^4} > 0. \tag{1.18}$$

The overall influence of the MQS on environment is slightly more difficult to evaluate than in the Cournot case, since the partial derivatives are more complex in terms of their structure, as shown below:

$$\begin{aligned}\frac{\partial(D_i + D_j)}{\partial d_i}\Big|_{d_i=d_j=d^N} &\propto (1 + \beta)(1 - \sigma)(2 + \sigma)\Delta_2\Theta_2^{-\frac{1}{2}}\left\{2\gamma\Theta_2^{\frac{1}{4}}[1 - c + (1 + \beta)d^N] - e\right\} \\ &- 2[1 - c + (1 + \beta)d^N)][(1 + \beta)\Delta_2^{\frac{1}{2}} + \frac{1}{2}(1 + \beta)(1 - \sigma)(2 + \sigma)\Delta_2\Theta_2^{-\frac{1}{2}}] \\ &\cdot \left\{\gamma\Theta_2^{\frac{1}{4}}[1 - c + (1 + \beta)d^N] - e\right\}\end{aligned} \tag{1.19}$$

where

$$\Delta_2 = \frac{\gamma^4(2-\sigma^2)^2}{2(\sigma-1)(1+\sigma)^2(2-\sigma)^4(2+\sigma)^3} < 0, \quad \Theta_2 = \frac{\gamma^4(2-\sigma)^2}{4(1+\sigma)^2(2-\sigma)^4(2+\sigma)^2} > 0.$$

Since e must be greater than $q^N = \gamma\Theta_2^{\frac{1}{4}}[1-c+(1+\beta)d^N]$, the above derivatives are negative when

$$e \le \frac{2\gamma[1-c+(1+\beta)d^N][2-c+(1+\beta)d^N]\Theta_2^{\frac{1}{4}}}{3-2c+2(1+\beta)d^N} \le \frac{\sqrt{2}}{6}\gamma = \bar{e}_2.$$

In a sum, the MQS can help the regulator achieve her goal of pollution reduction, and benefit both consumers and firms through spurring process and product innovation.

Proposition 2. *Suppose firms compete in prices and the market is at a symmetric non-cooperative equilibrium. A binding MQS can increase social welfare by increasing consumer surplus, increasing profits, and reducing environmental damage, if the following conditions hold simultaneously:*

1. *The substitutability between the two varieties (σ) is sufficiently low.*
2. *The spillover effect in process innovation (β) is sufficiently large.*
3. *The process R&D cost efficiency ($1/\alpha$) is sufficiently low.*
4. *The initial marginal environmental damage from production (e) is sufficiently low.*

Compared with Proposition 1 drawn from the Cournot case, Proposition 2 needs an additional constraint to hold when firms compete in prices. The first condition is needed because if consumers consider the two varieties to be very close substitutes, firms may make plenty of investments in process innovation due to fierce competition. Their investments may exceed what they could have invested in a game with cooperation in process R&D. To keep the MQS implemented comparable in Cournot and Bertrand games, I restrain the substitutability between the two varieties to be not too large. A MQS with higher product quality can certainly lead to results in line with Proposition 2 without the constraint on product substitutability.

1.6 Alternative Model Specifications

Thus far, I have assumed that firms invest for marginal cost reduction before attempting to improve product quality, and focus the discussion on product substitutability and spillover effect through assigning a specific cost function for product innovation. In this section, I explore whether modelling changes, such as switching the sequence of process and product innovation, or specifying a more general product R&D cost function, would substantially alter the possibility for a MQS to lead to a win-win situation.

1.6.1 Product Innovation Prior to Process Innovation

In order to investigate if the timing of the game affects the effectiveness of a MQS, in this subsection I assume firms first conduct product innovation, then determine process R&D input, and compete in quantities in the third stage. Denote the marginal production cost that firm i expects in the first stage as C_i, the optimization problems for firm i at the first and the second stage now change into:

$$\begin{aligned} &\textbf{Stage 1} \quad \max \pi_i(R_i) = [p_i(R_i, R_j) - C_i(R_i, R_j)] \cdot x_i(R_i, R_j) - \alpha[d_i(R_i, R_j)]^2 - R_i, \\ &\textbf{Stage 2} \quad \max \pi_i(d_i) = [p_i(d_i, d_j) - c + d_i + \beta d_j] \cdot x_i(d_i, d_j) - \alpha d_i^2 - R_i, \\ &\qquad\qquad\qquad\qquad i, j = 1, 2 \; and \; i \neq j. \end{aligned}$$

To reduce analytical complexity of the optimization problems, I assume $\sigma = 1/2$, which suggests a medium level of substitutability between the two varieties. Through backwards induction, I can easily get the optimal level of output and marginal cost for both firms in the third and the second stages. When evaluated at symmetric equilibria, the partial derivatives $(\partial d_i^N/\partial R_i)\big|_{R_i=R_j}$ and $(\partial d_j^N/\partial R_i)\big|_{R_i=R_j}$ cannot simultaneously be positive. However, there still exists complementarity between process and product innovation in the following form:

$$\frac{\partial(d_i^N + d_j^N)}{\partial R_i}\Big|_{R_i=R_j} = \left(\frac{\partial d_i^N}{\partial R_i} + \frac{\partial d_i^N}{\partial R_j}\right)\Big|_{R_i=R_j} \propto \alpha\gamma^2(1-c)(4-\beta) > 0, \quad i, j = 1, 2 \; and \; i \neq j. \tag{1.20}$$

In other words, when the market is at a symmetric non-cooperative equilibrium, growth of either firm's product R&D investment contributes to a rise in the aggregate marginal cost reduction, while parallel increase of product quality also enhances process R&D input from both firms.

In order for making comparison between equilibria simpler, I assume firms do not only collaborate at the process R&D stage but also jointly determine their product quality in a R&D cooperative equilibrium. $R^N < R^C$ is necessary for a MQS to achieve results consistent with the predictions of the Porter Hypothesis. I first explore the constraint on R^N and R^C to narrow down the scope of discussion for the first order conditions in the first stage. An obvious fact is that marginal production cost cannot be less than zero in any equilbria, and this condition translates into

$$d^N < d^C < \frac{c}{1+\beta} \Leftrightarrow R^N < R^C < \bar{R}_1 = \frac{5625\alpha^2c^2}{16\gamma^4(4-\beta)^2(1+\beta)^2}. \tag{1.21}$$

Let $(\partial\pi_i/\partial R_i)\big|_{R_i=R_j=R^N} = F_N(R^N) - 1 = 0$ and $(\partial\pi^C/\partial R^C) = F_C(R^C) - 1 = 0$ denote the first order conditions for the non-cooperative and the R&D cooperative equilibria respectively. The second order condition suggests that in order for solutions to $F_C(R^C) - 1 = 0$ to result in a stable equilibrium, the values of R^C must be either below $\bar{R}_2$ or above $\bar{R}_3$, where

$$\bar{R}_2 = \frac{625\alpha^2}{144\gamma^4(1+\beta)^4}, \quad \bar{R}_3 = \frac{625\alpha^2}{16\gamma^4(1+\beta)^4}.$$

Therefore as long as $\bar{R}_1 > \bar{R}_2$, i.e. $\beta > (64 - 225c)/(16 + 225c)$, there always exists at least one R^C that leads to a symmetric R&D cooperative equilibrium.

Incorporating this information with the second order and the stability conditions for the non-cooperative game, simulation results confirm that when $\beta > 1/2$, a solution to $F_N(R^N) - 1 = 0$ can lead to a stable Nash equilibrium if it is less than $\bar{R}_2$.[13] Additional simulation shows that $F_N(R^N)$ is always less than $F_C(R^C)$ for any $R^N, R^C \in (0, \bar{R}_4)$, where $\bar{R}_4 = 16\alpha^2/[9\gamma^4(1+\beta)^4] < \bar{R}_2$.

$F_N(R^N)$ is strictly increasing with R^N for all $R^N \in (0, \bar{R}_4)$ if $\beta > 1/2$. Thus a sufficient but not necessary condition for $F_N(R^N) - 1 = 0$ to have a unique, positive solution below $\bar{R}_2$ is $\alpha > \underline{\alpha}_{10} = 2/[5\gamma^4(1-c)^2]$. This constraint on α also ensures the increasing function $F_C(R^C)$ to be greater than 1 when $R^C = \bar{R}_4$. Given the fact that $(64 - 225c)/(16 + 225c) < 1/2$ when $c > 1/6$, the above discussion can be summarized as:

Lemma 7. *Suppose firms compete in prices and the substitutability between products is at a medium level. Firms invest more for both process and product innovation, and obtain higher profits in a R&D cooperative equilibrium than in the non-cooperative equilibrium, if marginal production cost without innovation is sufficiently high, the spillover effect in process innovation is sufficiently large, and the marginal cost of process R&D rises sufficiently fast as investment grows.*

I next examine the conditions for a binding MQS $\underline{q} = q(R^C)$ to benefit consumers and the environment, through evaluating the partial derivatives of consumer surplus and aggregate environmental damage with respect to R_i at the symmetric non-cooperative equilibrium:

$$\begin{aligned} \frac{\partial CS}{\partial R_i}\Big|_{R_i=R_j=R^N} &\propto 75\alpha - 4\gamma^2(4-\beta)(1+\beta)\sqrt{R^N}, \\ \frac{\partial(D_i + D_j)}{\partial R_i}\Big|_{R_i=R_j=R^N} &\propto 75\alpha e - 150\alpha\gamma(R^N)^{\frac{1}{4}} + 4\gamma^3(4-\beta)(1+\beta)(R^N)^{\frac{3}{4}}. \end{aligned} \tag{1.22}$$

The first set of derivatives is positive when $R^N < 1/(c\bar{R}_1)$, while the second group is negative when $e < \bar{e}_3 = 2\gamma(R^N)^{\frac{1}{4}} - (4\gamma^3)/[75\alpha(4-\beta)(1+\beta)(R^N)^{\frac{3}{4}}]$.

Proposition 3. *Suppose firms compete in prices, the substitutability between products is at a medium level, and the market is at a symmetric non-cooperative equilibrium. A binding MQS can increase social welfare by increasing consumer surplus, increasing profits, and reducing environmental damage, if the following conditions hold simultaneously:*

1. *The initial marginal production cost (c) is sufficiently high.*

2. *The spillover effect in process innovation (β) is sufficiently large.*

3. *The process R&D cost efficient ($1/\alpha$) is sufficiently low.*

[13] It can be shown through simulation that for any $R^N \in (\bar{R}_2, \bar{R}_1)$, the second order condition and the stability condition cannot hold simultaneously.

4. *The initial marginal environmental damage from production (e) is sufficiently low.*

Similar to the additional constraint on product substitutability in Proposition 2, the first condition in Proposition 3 is needed because if the initial marginal production cost is too low, there may not be enough room for firms to adjust process innovation to comply with the MQS. In general, Proposition 3 shows that the change in timing of game does not compromise the effectiveness of a MQS.

1.6.2 Alternative Product Innovation Function

Throughout the derivation of Proposition 1 and Proposition 2, I assume the product innovation function takes a specific quartic form. In this subsection I reset it as $q = \gamma R^{\mu}$, where $\mu \in (0, 1)$ indicates product R&D input generates diminishing returns. To focus my discussion on μ I also assume firms compete in quantities and the substitutability parameter σ is fixed at $1/2$. Thus, the outcome of the third-stage non-cooperative subgame is no different from that in Section 1.6.1. The optimal product R&D investment of firm i in the second stage takes the following form:

$$R_i^N = \left(\frac{225}{32}\right)^{\frac{1}{2\mu-1}} \left\{\mu\gamma^2(1 - c + d_i + \beta d_j)[3(1 - c + d_i + \beta d_j) + (1 - \beta)(d_i - d_j)]\right\}^{\frac{1}{1-2\mu}} .$$

The partial derivatives of product R&D input with respect to marginal cost reduction are

$$\frac{\partial(R_i^N + R_j^N)}{\partial d_i}\Big|_{d_i=d_j} = \left(\frac{\partial R_i^N}{\partial d_i} + \frac{\partial R_i^N}{\partial d_j}\right)\Big|_{d_i=d_j} \propto 1 - 2\mu$$

when evaluated at symmetric equilibria. Hence there still exists complementarity between process and product innovation, if μ is between 0 and $1/2$.

Utilizing a derivation process similar to that employed in Section 1.4, I can show that innovation output and profits are both higher in the symmetric equilibrium with cooperation in process R&D than in the non-cooperative equilibrium, if the process innovation cost parameter α is above a threshold value to ensure the existence, optimality and stability of both equilibria. Without any additional constraint on the spillover effect parameter β, consumer surplus rises with process innovation at a symmetric equilibrium. When the environmental damage parameter e is sufficiently low, pollution by production activities is also lower in the symmetric equilibrium with cooperation in process R&D. In a sum, with variable μ in the product innovation function, it is still possible to identify scenarios in which a MQS yields results consistent with the weak and the strong versions of the Porter Hypothesis.

1.7 Conclusion and Discussion

Among studies using inter-firm spillover effect to generate results consistent with the Porter Hypothesis, this paper is the first to obtain results in line with the strong version of the hypothesis. More specifically, the paper provides theoretical evidence to both the weak and the strong versions of the hypothesis, by showing that stringent environmental regulation can motivate firms to innovate and enhance their profitability. The paper employs a duopoly model with substitute products, in which process innovation resulting in cost reduction, and product innovation resulting in quality improvement are both available to firms. Prior to engage in quantity or price competition, firms first simultaneously choose their process R&D investments, then simultaneously invest for ecological quality improvements of their products. Given the structure of this game, it is possible for firms to under-invest for innovation at a symmetric non-cooperative equilibrium, since they are unable to fully capture benefits generated from the inter-firm spillovers in process innovation. In this context, a MQS aiming to cut down pollution can stimulate process and product innovation of both firms, and promote social welfare through simultaneously raising profits and consumer surplus.

The positive effects of environmental regulation on innovation and social welfare persist with alternative model settings, such as switching the sequence of process and product innovation, and specifying a more general product R&D function (allowing the product innovation cost parameter to be variable instead of fixed to be $1/4$). In practice, it is also possible for firms to choose process and product R&D investments simultaneously instead of sequentially (see Rosenkranz, 2003). Given the spillover effect occuring in process innovation, complementarity between the two types of innovation may still hold, and thus firms are likely to under-invest for cost reduction and quality improvement. In this case, a minimum environmental quality standard can achieve similar results as discussed above.

Throughout this paper, I assumed that technology spillovers occur in process innovation but not in product innovation, and the policy tool employed is a MQS. These assumptions strengthen the policy implications of the main propositions—as a typical command-and-control measure not designed to address the under-investment issue in process innovation, a MQS can generate favourable results by correcting two market failures at once. Under different parameter constraints that ensure complementarity between the two types of innovation, similar results may be achieved through implementing market-based instruments such as emission taxes, or when spillover occurs in product instead of process innovation.

The results presented in this paper should be interpreted with caution. As noted earlier, the Porter Hypothesis does not suggest that environmental regulation necessarily leads to innovation, let alone profit enhancement. In fact, main propositions from the model indicate that it is not particularly easy for the profit-stimulating effect to come into play. The exact impact of a MQS on innovation and profits depend on several factors, including the marginal costs of process and product innovation, marginal environmental damage without abatement effort, and the magnitude of spillover effects. Therefore, these findings highlight the importance of information collection for policymakers before implementing environmental policies. Given the difficulties in practice to obtain comprehensive information on production costs and technology spillovers, policymakers may benefit from reviewing policies implemented elsewhere, and tightening environmental regulation in an incremental manner.

There are two important aspects of the Porter Hypothesis that are not covered in this paper, and can be explored in future research. The model abstracts from international competition, which is one of the starting angles of Porter's argument. In addition, the narrow version of the hypothesis emphasizes that performance-based environmental polices are more likely to trigger innovation that command-and-control measures. A comparison between the likelihood of achieving favourable results by using a MQS and other policy tools, such as an effluent tax or R&D subsidies, may shed new light on the discussion on environmental policy, innovation and growth (see Acemoglu et al., 2012).

Finally, the robustness of my main results can be further checked along two dimensions. Simpson and Bradford (1996) suggest that "relatively slight differences in the specification of the cost functions can lead to very different policy conclusions" (p. 14). Therefore, the generality of the propositions can be further improved, by adopting even more general cost functions for innovation and production. It also needs to be examined whether different market structure can lead to substantially different results. For example, it is likely that the magnitude of spillover effect increases with the number of firms in the market, while firm profits generated from market power are decreasing. Therefore, it should be of great interest to investigate how the number of firms affects the conditions for the Porter Hypothesis to hold.

Chapter 2

Environmental Regulation and Firm Innovation: Evidence from China

2.1 Introduction

In recent decades, developing economies, including China, have been tightening environmental regulations to address growing concerns over environmental deterioration. Regulatory efforts, such as the adoption of developed-country standards and the elimination of government subsidies for pollution-intensive industries, have led to substantial improvements in environmental performance (Dasgupta et al., 2002). In addition, these policies have also been said to boost innovation and competitiveness of the regulated industries. For example, an official document from the Chinese central government states that addressing environmental issues through regulation can facilitate technological improvements and promote innovation (see Chen, 2010). While previous studies have examined the impact of environmental policy on technological change in developed countries, research that examines this relationship in the context of developing economies is scarce.[1] This paper provides evidence for a positive effect of environmental regulation on innovation by Chinese firms.

Traditionally, environmental regulation has been viewed as a burden on business activities, and as detrimental to firm performance as measured by research and development (R&D) expenditures, sales, and profits (Iraldo et al., 2011).[2] However, the Porter Hypothesis, formulated by Porter (1991) and Porter and van der Linde (1995), argues that strict environmental regulation can foster innovation and, in addition, lead to improvements in commercial competitiveness. Jaffe and Palmer (1997) refine the hypothesis, by stating three different versions of it. First, the "weak" version posits that environmental regulation places additional constraints on firms' profit-maximizing decisions and encourages them to innovate as a response, although

[1] I will discuss the literature on environmental regulation and innovation in Section 2.2 below.

[2] This view is sometimes called the "Structure–Conduct–Performance" paradigm.

the resulting innovation may not necessarily be socially beneficial. Second, the "narrow" version suggests that only well-designed and well-enforced policies are likely to achieve this effect. Finally, the "strong" version states that innovation motivated by environmental regulation can not only facilitate environmental improvements but also increase firm competitiveness, measured by productivity or profitability. The vast majority of previous empirical studies cover the "weak" and the "strong" versions of the Porter Hypothesis (see Ambec et al., 2013). The findings in this paper support the "weak" and the "narrow" versions.

The paper focuses on a unique environmental policy tool: mandatory participation in Cleaner Production Audit (CPA) programs in China. Launched nationwide in 2005, the aim of CPA programs is to address environmental problems that accompany rapid industrial growth, through regulating pollution-intensive firms in various sectors. Each Chinese provincial-level government announces a list of companies within its jurisdiction as candidates for mandatory CPA participation every year.[3] The selection of candidates is based on either their past environmental performance or the inputs used in their production processes. Every company on the list is obligated to disclose its pollutant emissions,[4] conduct firm-wide CPA projects, and pass an assessment and an acceptance inspection conducted by local environmental agencies. Thus, firms participating in CPA programs face public supervision and regulatory pressure simultaneously.

I examine the impact of mandatory CPA participation on firm innovation from 2001 to 2010. To do so, I construct a new dataset containing information on patenting activity, CPA participation, and key financial indicators for 733 Chinese companies listed in Shanghai and Shenzhen stock exchanges. The dataset is constructed by using name-matching algorithms to combine information obtained from the Chinese Patent database, the Osiris database, and a series of lists of companies that passed CPA assessments and acceptance inspections, which was released by the Ministry of Environmental Protection of China. The Chinese Patent database covers more than 190,000 published patent applications by Chinese listed companies between 1990 and 2010 (He et al., 2013). The Osiris database contains up to 20 years of financial statistics on listed and major unlisted or delisted companies in more than 190 countries, including China. The MEP lists record the start and the end years of CPA programs participated in by 17,862 firms in 31 provincial-level regions between 2005 and 2012.[5]

I use a firm's number of patent applications as a measure of its innovative activities. Other firm-specific variables that potentially affect innovation are firm size, cash flow, capital intensity, and prior innovation. I then use a difference-in-differences (DID) approach to identify the average effect of mandatory

3 China also encourages companies to voluntarily participate in CPA programs. However, in regions where cleaner production was well enforced, the voluntary participation rates for firms with annual sales of more than RMB5,000,000 were all less than one-ninth of the mandatory participation rates in 2012 (Song et al., 2012). Thus, the present paper focuses on mandatory CPA participation.

4 These disclosures are through local media and not collected by environmental agencies. Therefore, a database containing firm-level information on both CPA participation and environmental performance is lacking.

5 These provincial-level regions, formally provincial-level administrative divisions, include: 22 provinces, such as Liaoning and Zhejiang; 5 autonomous regions, such as Guangxi and Xinjiang; and 4 municipalities, such as Beijing and Shanghai.

CPA participation on firm innovation. My results indicate that companies innovate more when they are placed under stringent environmental regulation through CPA enrollment. The confirmed positive effect of mandatory CPA participation is on overall innovation, instead of environmental innovation in other plant- or firm-level studies on the "weak" version of the Porter Hypothesis. Theoretical literature on the "weak" version of the hypothesis indicates that innovation triggered by regulation can be either environmentally friendly, or efficiency-enhancing, or both (see Brännlund and Lundgren, 2009; Ambec et al., 2013). Hence, this paper provides more general evidence for the "weak" version, through confirming the positive link between environmental regulation and firms' overall innovation performance.

Substantial changes were made to the CPA regulatory framework in 2009, when the audit was coupled with financial incentives to improve environmental performance in 11 eastern Chinese provincial-level regions. To capture the effect of these regulatory changes, I also divide CPA participation into two periods, 2005–2008 and 2009–2010. I find that the positive effect of CPA participation on firm innovation is more pronounced in 2009 and 2010, and mainly driven by firms in eastern China. Furthermore, the stimulative effect of CPA participation on innovation is stronger for larger companies with the resources needed to adapt to regulation. These findings lend support to the "narrow" version of the Porter Hypothesis, which emphasizes the importance of enforcement and flexibility for the effectiveness of environmental regulation. It argues that performance- or market-based instruments, such as tradable permits and pollution charges, are more likely to motivate innovation than command and control measures, such as emission standards and equipment specifications. In eastern China after 2008, the diversified financial incentives provided to CPA participants and strong performers make the regulatory scheme fall more toward the performance-based side. These government-funded subsidies and rewards allow firms to take a more flexible approach to meet the evaluation standards for CPA programs. In addition, higher environmental awareness has also driven local governments in eastern China to enforce CPA-related regulatory policies more stringently. Given these facts, I view CPA programs implemented in eastern China after 2008 as closer to a "strict but flexible" regulatory scheme as described in Porter and van der Linde (1995).

My empirical methodology has a number of advantages over previous estimates of the effect of environmental policy on innovation. First, measures of environmental regulation discussed in earlier studies include pollution abatement costs and perceived environmental stringency obtained from survey data.[6] Because these variables are self-reported, systematic measurement errors as well as potential endogeneity can bias the estimations. The measure for environmental regulation employed here—mandatory participation in CPA programs—is publicly available for verification and unlikely to be affected by individual firms. In this aspect, it is similar to measures of government monitoring activity (e.g., the number of government

[6] Jaffe and Palmer (1997), Brunnermeier and Cohen (2003), Yang et al. (2012), and Rubashkina et al. (2015) employ pollution abatement costs to measure environmental regulation. Arimura et al. (2007) and Lanoie et al. (2011) use perceived environmental stringency as an alternative measure. I will discuss these studies in Section 2.2 below.

on-site inspections) to capture the strength of regulation (see Berrone et al., 2013). However, government monitoring activities are performed only to ensure policy compliance, and thus fall into the category of command and control approaches. Mandatory CPA participation, as previously described, tends to be more performance-based, especially in eastern China after 2008.

A second potential endogeneity issue can arise if a firm's CPA enrollment status and innovation are both correlated with its environmental performance, which is not observed in my dataset. However, analyzing firm-level data throughout the period of 2001 to 2009, I find no systematic differences between the pre-regulation innovation patterns of listed companies that were later enrolled in CPA programs (CPA participants) and those that were not. I also perform a falsification test to show that innovation patterns of CPA participants did not differ from non-participants, even when the participants were soon to be enrolled in the programs. Finally, to eliminate the possibility that the selection of CPA participants is based on firm characteristics other than environmental performance, I use a propensity score matching approach to construct a sub-dataset, in which each CPA participant is matched with a financially similar firm that had never participated in any CPA program. Estimation results based on the sub-dataset confirm the main findings in this paper.

Findings from this study have policy implications worth considering, as China has been making remarkable efforts in recent years to reduce pollution, while striving to maintain economic growth driven by energy- and pollution-intensive industries. As a unique policy tool, mandatory participation in CPA programs has shown the determination of the Chinese central government to address this issue, since similar programs in other countries operate on a voluntary basis. This policy has shown its potential to improve environmental performance and stimulate firm innovation simultaneously, especially when combined with financial incentives to encourage compliance and enhance performance. As a policy currently in force, it may deserve stronger supportive measures, such as financial support from the central government instead of only being funded provincial and municipal governments, to extend its scope and strengthen its effectiveness.

The rest of the paper proceeds as follows. Section 2.2 reviews previous research on environmental regulation and innovation and locates this paper in the existing literature. Section 2.3 reviews the development of environmental regulation, and in particular the CPA programs, in China. Section 2.4 describes the empirical methodology employed in the analysis, including model specifications and identification strategy. Section 2.5 describes how the data were collected and consolidated, and the procedures taken to construct the key variables used in the estimation. Section 2.6 contains the main results and shows that effects of mandatory CPA participation are heterogeneous across regions and firms of different sizes. In Section 2.7, I conduct several robustness checks and show that the main results are not sensitive to a number of alternative model specifications. Section 2.8 concludes with a discussion on future work.

2.2 Related Literature on Environmental Regulation and Innovation

Since its formulation in the 1990s, the Porter Hypothesis has received plenty of criticisms for its contradiction with the assumption of profit-maximizing firms (see Palmer et al., 1995). To provide a theoretical foundation for the hypothesis, over the last twenty years researchers have investigated possible reasons for firms under-investing in innovation and not maximizing profits, and how environmental policies may contribute to the correction of these deficiencies. One consensus among these studies is that a scenario consistent with Porter's predictions usually involves an additional market failure besides negative environmental externalities (see Mohr and Saha, 2008).

The main additional market failures under discussion, as summarized in Brännlund and Lundgren (2009) and Ambec et al. (2013), include information asymmetries, imperfect competition, and R&D spillovers. Information asymmetry may prevent firms from investing in innovation and maximizing profits, since managers and other employees do not share the same objective functions with firm owners (Aghion et al., 1997; Gabel and Sinclair-Desgagné, 1998), or because consumers cannot easily distinguish "green" products from less environmentally friendly goods (Rege, 2000; Constantatos and Herrmann, 2011). In an oligopolistic market, environmental stringency can enhance the development of less-pollutive but cost-inefficient technology, when firms are able to reduce output and raise prices as a response to an increase in regulatory compliance costs (André et al., 2009; Lambertini and Tampieri, 2012). Models with economies of scale in environmental innovation, or inter-firm diffusion of technology developments can also generate results consistent with the "weak" version of the Porter Hypothesis (Simpson and Bradford, 1996; Mohr, 2002; Greaker, 2003). Innovation discussed in these studies may refer to environmental innovation, or overall innovative activities that may not have direct impacts on the environment.

Many researchers have also examined the Porter Hypothesis empirically. Studies testing the "weak" version generally fall into two categories: those exploring the impact of regulation on environmental innovation, and those investigating policies' effect on overall innovation. Most studies testing the "strong" version assess the changes in firm productivity under regulation, while a few researchers study the link between environmental stringency and firm profitability.[7] Research that tests the "narrow" version of the hypothesis is scarce.

Examining only environmentally related innovative activities, Popp (2003), Arimura et al. (2007), Lanoie et al. (2011), and Berrone et al. (2013) find a positive correlation with environmental policies by using plant- or firm-level data in the U.S. and other members of the Organisation for Economic Co-operation and Development (OECD); Brunnermeier and Cohen (2003) and Kneller and Manderson (2012) also show the positive relationship by using industry-level data in the U.S. and the United Kingdom (UK); Popp (2006) and

7 Rassier and Earnhart (2010), Lanoie et al. (2011), and Rexhäeuser and Rammer (2014) find that environmental regulation impairs firm profitability, although regulation-driven innovation can improve resource efficiency and offset part of the compliance costs.

Johnstone et al. (2010) provide country-level evidence for the positive link through analyzing data for OECD members. Findings from these studies confirm the effectiveness of environmental policies in promoting environmentally friendly new technologies.

Studies investigating the link between environmental regulation and overall innovation show mixed results. Using industry-level data for the U.S. manufacturing sector, Jaffe and Palmer (1997) find a positive relationship between pollution abatement costs and total R&D expenses. On the other hand, successful patent applications did not increase with environmental compliance expenditures. Subsequent studies, all using industry-level data for manufacturing industries in developed economies, continue to employ pollution control expenditures to measure environmental stringency. In a study covering both environmental and total R&D investments, Kneller and Manderson (2012) show that regulation-led environmental R&D investments crowded out investments for other types of innovation in the UK. Nevertheless, findings from other studies are in favor of the "weak" version of the Porter Hypothesis. Hamamoto (2006) and Yang et al. (2012) find environmental regulation to be positively correlated with R&D expenditures in Japan and Taiwan; Rubashkina et al. (2015) show the positive link between regulation and patent applications in 17 European countries, but find no evidence for a similar relationship with R&D expenditures.

Among the literature discussing the "weak" version of the Porter Hypothesis, Hamamoto (2006), Yang et al. (2012), and Rubashkina et al. (2015) also extend their analyses to explore the impact of environmental regulation on industry productivity. They all find that productivity rises with environmental stringency, which is in line with the "strong" version of the hypothesis. This finding is supported by Berman and Bui (2001) using plant-level data for the oil refinery industry in the U.S., and by Lanoie et al. (2011) using survey-based plant-level data for the manufacturing sector in seven OECD countries. However, some other studies find evidence against the "strong" version. Jaffe et al. (1995) review several earlier studies and conclude that they all support a negative link between environmental regulation and productivity, despite the strength of the link varying. Gray and Shadbegian (2003) echo this argument by showing that productivity for pulp and paper mills in the U.S. are negatively correlated with pollution abatement costs. Focusing on air quality regulations in the U.S., Greenstone et al. (2012) also suggest that these policies led to a 2.6% decline in total factor productivity (TFP) of manufacturing plants. One possible reason for these studies finding an adverse effect of regulation, as suggested by Jaffe et al. (1995) and Telle and Larsson (2007), is that the commonly used methods to compute productivity measures do not include emissions as inputs.

This paper adds to the literature in the following ways. First, this study provides evidence for the positive link between environmental policy and overall innovation at the firm level in a developing country. As reviewed above, all previous literature discussing the "weak" version of the Porter Hypothesis uses data for manufacturing industries in developed economies; moreover, all of the studies on regulation and overall innovation use industry-level data. Through adopting two firm-specific indicators—annual patent applications and CPA enrollment status—to measure innovation and environmental regulation in China, this paper examines the effect of environmental policy at a more micro level. It provides evidence against the argument that regulation-driven environmental investments crowd out investments for other types of innovation. The results support the effectiveness of environmental stringency in enhancing overall firm innovation in developing countries.

This paper is also one of the few to investigate the "narrow" version of the Porter Hypothesis. Only a few earlier studies, including Popp (2003) and Lanoie et al. (2011), have discussed this version and provided circumstantial evidence. My results show that the positive effect of CPA participation on innovation is strongest in eastern China after 2008. This fact highlights the importance of stringent policy enforcement supported with diversified financial incentives. Hence, this paper provides more direct evidence for the "narrow" version of the hypothesis, by showing that well-enforced and more performance-based regulatory regimes are more effective in terms of bolstering innovation.

2.3 Cleaner Production Policy in China (1993–2010)

Accompanied with rapid industrial growth and urban developments, environmental degradation in China became evident in late 20th century and early 21st century. Besides serious social issues, environmental problems had also induced substantial economic costs for the fast-growing economy. An official report of the Chinese central government estimates that the annual cost of pollution averaged about seven percent of the nation's annual Gross National Product (GNP) between 1981 and 1985 (National Environmental Protection Agency, 1990). Studies in subsequent years suggest that the economic burden of environmental degradation in China was between six and eight percent of the nation's Gross Domestic Product (GDP) in the early 1990s, and this ratio stayed above three percent in 2004 (Smil, 1997; Wang and Yu, 2006). To address the environmental issues, China started to put the cleaner production concept into practice in the 1990s. The success of pilot projects eventually led to nationwide implementation of CPA programs in 2005.

The development of cleaner production practices and CPA-related policies in China before 2010 can be divided into three main phases. The first phase (1993–2004) involved the Chinese central government identifying CPA as the main policy tool to implement cleaner production, and disaggregating pilot projects launched and supported by provincial-level governments. In the next phase (2005–2008), the central government clarified the implementation procedures and criteria that need to be met to pass the assessments and acceptance inspections (hereinafter, the "passing criteria") for CPA programs. However, provincial-level governments had not fully incorporated these guidelines and standards into their diversified local practices until the end of this phase. The last stage (2009–2010) involved provincial and municipal governments localizing the interpretation and execution of the improved regulatory framework.

With support from the World Bank and the United Nations Environmental Programme (UNEP), the first cleaner production project, "Cleaner Production Promotion in China," was carried out on 27 companies during the 1993–1996 period. Despite the success of this project and several other provincial-level pilot programs, the scope and impact of cleaner production in China was limited in the 1990s through the early 2000s, partly due to its incompatibility with the then-existing environmental practices that favor end-of-pipe treatments (Shi, 2003). One significant characteristic of the enforcement and promotion of cleaner production in China at this early stage is that both were carried out "almost entirely on a provincial or local level" (Hicks and Dietmar, 2007, p. 4).

The announcement of the "Cleaner Production Promotion Law" (CPPL) in June 2002 was the first substantial move by the Chinese central government to consolidate and normalize local policies. As the first law of its kind in the world, CPPL clearly defines cleaner production and its scope, and introduces CPA as the main instrument for its implementation. Although the word "mandatory" is not employed in the CPPL text, the law implies that implementing CPA programs is not merely optional for firms that exceed pollutant discharge quotas or do not meet pollution discharge standards ("Category 1 firms"). For firms using or discharging toxic or hazardous materials ("Category 2 firms"), CPA participation is not only required, but is required on a "periodical" basis.

After CPPL came into force in January 2003, more than 20 provincial-level regions (hereinafter, "regions") launched pilot projects. Hundreds of firms participated in demonstrative CPA programs as part of these pilot projects in 2003 and 2004. However, implementation procedures for CPA programs were not clearly specified until the central government released the "Interim Measures on Cleaner Production Audit" in August 2004. In December 2005, the central government released a similar but more detailed document, "Provisions on Procedures of Cleaner Production Audit of Key Enterprises" (the Procedures document). According to that document, every year each county- or district-level environment agency is responsible for reporting to its superior authority a list of companies that are candidates for mandatory CPA participation. The selection of candidates should be based only on environmental monitoring reports for Category 1 firms, and receipts or analytical reports of toxic or hazardous materials for Category 2 firms. After collecting reports from its subordinates, a provincial-level environmental agency is in charge of determining a final list of companies for mandatory CPA participation within its jurisdiction.

Within one month of being identified by any provincial-level list, a company is obligated to make its own pollutant emission information known to the public. The information to be disclosed includes but is not limited to pollutant names and intensities, emission types and destinations, overall amount of emissions, emission quotas assigned, and pollution charges paid to environmental agencies. Under public supervision, firms can choose between participating in CPA programs by themselves or cooperating with qualified external consulting agencies. Either way, they have to launch CPA projects within two months of the list release date, complete these projects within another 10 months and submit summary reports to local authorities.[8]

The Procedures document assigns provincial-level environmental agencies to assess effects of companies' CPA projects and conduct acceptance inspections upon receipt of summary reports. However, the document provides little information on passing criteria and implementation procedures for the two major steps. Hence, there were again inconsistencies and deficiencies in CPA practices at provincial level, which called for further clarification and consolidation efforts from the central government.

Between 2006 and 2008 the Chinese central government announced cleaner production standards for 41 industries. These standards dealt with the issue of unclear criteria. The release of the "Implementation Guide on Assessment and Acceptance Inspection of Cleaner Production Audit of Key Enterprises" in July 2008 (the Guide document) greatly alleviated the issue of inconsistent evaluation procedures across regions. The Guide document clearly indicates that within one month of submitting CPA summary reports, to qualify for government financial support firms need to pass assessments organized by local environment agencies. These assessments focus primarily on evaluating the performance of non- and low-cost cleaner production options that have been carried out, and the plausibility of medium- and high-cost options planned for future implementation. Within two years of completing CPA programs, firms are again obligated to apply for and pass final acceptance inspections. Different from assessments conducted with advices from environmental and industrial experts, acceptance inspections are performed solely by local environmental agencies and put more emphasis on verifying whether firms have implemented the medium- and high-cost options.

From late 2008 to early 2009, provincial-level governments released detailed local implementation rules for the Guide document. These rules established a multi-level regulatory system for CPA programs. Although they generally follow the structure of the Guide document, there is a disparity in interpretation and enforcement across regions; because the eastern regions are economically more developed, they have more detailed passing criteria, standardized implementation procedures, and diversified financial support for assessments and acceptance inspections.

One leading example of stringent policy enforcement is the local CPA regulatory policy introduced in Shanghai on January 1, 2009. In its official technical guide for CPA implementation, the Shanghai government adds an additional "pre-assessment" stage. This stage includes site investigations and expert discussions. For each stage of the CPA evaluation process, to ensure consistency, the Shanghai government document includes a standardized evaluation sheet with detailed subcategories. In addition to subsidies funded through pollution charges, the Shanghai government also arranges special subsidies for CPA-related expenses, half of which would be available at the launch of firms' CPA programs and half of which could be claimed upon passing assessments.

[8] This rule was not strictly applied in practice at least before 2012. Thus, there could be a lag as long as two years between the announcement date of a provincial list and the date when a company on the list actually launched its CPA projects.

Liaoning is another province with a relatively comprehensive regulatory system. The Liaoning government assigns the Liaoning Centre for Cleaner Production (LCCP), which was co-founded with the European Union (EU) in 1997, to take charge of CPA assessments. This differs from many other provincial authorities, which assign that responsibility to provincial environmental protection bureaus. Liaoning offers a unique type of financial support—subsidized loans from the €10 million Liaoning Cleaner Production Revolving Fund, co-funded by the EU—to firms implementing medium- and high-cost options in CPA programs.

Although a local regulatory and promotional framework for CPA programs had been in place in each region since 2009, efforts devoted to enforcing these policies differ greatly across regions. There is a great deal of variation in the amount of CPA assessment and acceptance inspection expenses covered by funding from the finance department in each region every year. The latest statistics released by the central government show that among the 10 regions reporting these expenses in 2010, three eastern provinces—Zhejiang, Jiangsu and Shandong—were ranked as the top three and accounted for nearly 70% of the total amount spent.[9] Regional characteristics are also reflected in various supportive policies. For example, to ensure that policies are effectively carried out, the vice governor of Liaoning in charge of economic development personally signs yearly agreements with all the regional mayors to set up targets for the number of companies that should be participating in CPA programs within each city (see Geng et al., 2010). The Guangdong government provides incentives as part of an approach to stimulate performance in CPA programs; it gives a RMB50,000 bonus to each firm that performs well in CPA programs, while one of its subordinate—the Dongguan government—gives an additional RMB300,000 to each qualified firm within its jurisdiction.

2.4 Empirical Methodology

The empirical models in this paper investigate the impact of mandatory CPA participation on innovation performance of Chinese listed companies. Since the status of CPA participation varies across individual firms and over time, I employ an individual fixed effects log-linear model and the difference-in-differences (DID) approach to identify the *treatment* effect of CPA enrollment on firms' patent applications. This section introduces the models and discusses the identification strategy.

2.4.1 Econometric Models

I first consider a *uniform impact* model, in which the level of innovative activities *innov* for a Chinese listed company i in industry s and region r at year t is given by

$$innov_{i,s,r,t} = \alpha_i + \beta_{s,t} + \gamma_{r,t} + \theta\, CPA_{i,s,r,t} + \rho\, X_{i,s,r,t} + \varepsilon_{i,s,r,t}. \tag{2.1}$$

[9] Due to lack of data for other regions and the pre-2007 period, this indicator cannot be used in the empirical analysis to reflect the disparity in policy enforcement across regions.

In the baseline regressions I employ the natural logarithm of the aggregate number of invention, utility model and design patent applications as the main indicator for innovation.[10] Since invention and utility model patents are usually considered as more valuable and innovative, I also include the logarithm of the aggregate number of these two types of patent applications as an alternative indicator to represent the level of firms' core innovative activities.[11]

The right-hand side of the model contains the firm fixed effects α_i to capture the potential impact from time-invariant and firm-specific factors. Note that firm fixed effects subsume industry and region fixed effects, which are correlated with firm characteristics such as core industry and headquarter location.[12] Since the patterns of innovation can differ significantly by industry and over time, the model contains industry-year fixed effects $\beta_{s,t}$ to control for such differences. Similarly, the trend of innovation can differ across regions because of China's considerable regional differences in economic development and innovation-related policies. The region-year fixed effects $\gamma_{r,t}$ control for the regional differences in development of innovation over time.

The key variable, $CPA_{i,s,r,t}$, measures whether firm i in industry s and region r was enrolled in a CPA program and thus facing stringent environmental regulation at year t. This binary variable takes the value 1 if the company was participating in a CPA program at year t, and 0 otherwise. $X_{i,s,r,t}$ represents a series of variables controlling for characteristics of firm i in industry s and region r at year t, including *size*, *cash flow*, *capital intensity* and *prior innovation*. The coefficient of interest is θ. It measures the impact of environmental regulation on firm innovation, by capturing the difference in the change of patent applications for firms participating in CPA programs and the change for those not regulated under the scheme.

Because the sample period is 2001 to 2010 and CPA programs were not implemented until 2005, I use contemporaneous independent variables in the model to utilize as many observations as possible. Nevertheless, to examine whether the main results still hold if environmental regulation and other firm characteristics are assumed to have a delayed impact on innovation, I also perform a sensitivity test in which the independent variables are lagged by one year. The corresponding estimation results presented in Section 2.7.1 are consistent with the main results.

The effect of mandatory CPA participation is assumed to be constant over the 2005–2010 period in the uniform impact model. However, the implementation and enforcement of CPA-related policies did vary over time. As outlined in Section 2.3, CPA programs started to be widely implemented in 2005; however, a comprehensive regulatory framework was not in place until 2009. Between 2006 and 2008, the

[10] The rationale of employing patent counts to measure firm innovation in China, as well as the definitions of the three types of patents are discussed in Section 2.5.1.

[11] I add one to each of the two patent variables when taking logarithms, since the number of patent applications can be zero for a listed company in a particular year. This method is arbitrary but in line with many previous studies including Bloom et al. (2012).

[12] As will be noted later, switching core industry or changing headquarter location usually signals reorganization or a take-over. These changes can alter the unobserved heterogeneity of a listed company. Thus, the main dataset employed in the subsequent analysis does not include any firm changing its core industry or the location of its headquarters (at the provincial level) during the sample period.

Chinese central government published cleaner production standards for 41 industries. These standards were part of a regulatory framework that the government was establishing. The framework was solidified when provincial-level governments released local implementation rules for the Guide document in late 2008 and early 2009. The less ambiguous standards and evaluation procedures detailed in these documents greatly reduced inconsistencies in the assessments and acceptance inspections of CPA projects, and thus improved the efficiency and effectiveness of CPA programs (Bai et al., 2012). In addition, financial incentives provided based on policies specified in these documents made mandatory CPA participation fall more toward a performance-based policy.

In recognition of the possible differences in environmental stringency and enforcement measures for companies participating in CPA programs at different stages of policy development, I also estimate a *differential impact* model as follows:

$$innov_{i,s,r,t} = \alpha_i + \beta_{s,t} + \gamma_{r,t} + \theta_1\, CPA\ 2005\text{–}2008_{i,s,r,t} + \theta_2\, CPA\ 2009\text{–}2010_{i,s,r,t} + \rho\, X_{i,s,r,t} + \varepsilon_{i,s,r,t}. \quad (2.2)$$

In the above equation, CPA enrollment status is reflected in two separate binary variables, *CPA 2005–2008* and *CPA 2009–2010*. The value of *CPA 2005–2008* is equal to 1 only if a listed company was participating in a CPA program at year t between 2005 and 2008. Similarly, the value of *CPA 2009–2010* is equal to 1 only if a company was regulated through mandatory CPA participation at year t in either 2009 or 2010. This model is also estimated using log-liner specifications, in which the coefficients θ_1 and θ_2 respectively capture the impact of CPA participation on innovation in the two periods.[13]

2.4.2 Identification

The coefficient of interest θ (and θ_1, θ_2) can be identified through the DID method under the assumption that after controlling for observed and unobserved heterogeneity, the patterns of innovative activities over time are similar among firms. In Equation (3.1) and Equation (2.2), the observed firm-level heterogeneity is controlled by variables in $X_{i,s,r,t}$. The firm fixed effects α_i capture systematic unobserved heterogeneity that is firm-specific and time-invariant. The industry-year fixed effects $\beta_{s,t}$ and region-year fixed effects $\gamma_{r,t}$ capture systematic unobserved fluctuations in innovation over time, assuming the impacts of these fluctuations are constant across firms in a given industry and a certain region respectively.

Once a listed company i in industry s and region r is required to participate in a CPA program at year t, the change in innovation between year t and year $t-1$ resulted form the status of being regulated and other regulation-independent factors can be expressed as

$$innov\,(CPA_{i,s,r,t} = 1) - innov\,(CPA_{i,s,r,t-1} = 0).$$

[13] Since the numbers of patent applications are non-negative integers, an alternative approach is to estimate both the uniform impact and the differential impact model using negative binomial specifications. The corresponding regression results are qualitatively consistent with the main results shown in Section 2.6.3 and are available upon request.

The counterfactual benchmark is

$$innov\,(CPA_{i,s,r,t} = 0) - innov\,(CPA_{i,s,r,t-1} = 0),$$

which is the difference in innovation between the two years if firm i had not participated in the CPA program. This benchmark is unobservable, but it can be approximated by a variation in the innovation of another listed company, j, which did not participate in any CPA program at either year t or year $t-1$. The observed difference between innovation of firm j in industry s and region r at year t and year $t-1$ captures only the change led by regulation-independent factors, and can be written as

$$innov\,(CPA_{j,s,r,t} = 0) - innov\,(CPA_{j,s,r,t-1} = 0).$$

Therefore, the coefficient, θ, can be identified by the following difference in differences:

$$[innov\,(CPA_{i,s,r,t} = 1) - innov\,(CPA_{i,s,r,t-1} = 0)] - [innov\,(CPA_{j,s,r,t} = 0) - innov\,(CPA_{j,s,r,t-1} = 0)],$$

which reflects the change in innovation between year t and year $t-1$ induced by CPA participation.

A potential endogeneity problem arises if mandatory CPA participation, as an environmental policy implemented by local governments, is linked to companies' innovation performance. CPA enrollment is mainly determined by prior environmental performance, which was disclosed at the time of program enrollment but not collected to be associated with each participant. Whether innovation is an advantage or a disadvantage for heavy polluters depends on the interaction between abatement costs, environmental innovation, and investments for other types of innovation in a particular industry. Further, the trend of environmental performance might be substantially different for pollution-intensive firms and other companies, as the top polluters within a region might choose to lower emissions to avoid CPA enrollment. Thus, not only the level but also the trend of innovation can differ systematically between pollution-intensive firms and others.

Selection of CPA participants based on the prior level of innovation does not lead to bias in the estimations, since firm fixed effects are included to eliminate the potential impact of this heterogeneity. On the other hand, selection based on differences in the trend of innovation would lead to bias in the estimated parameter θ, because firm fixed effects do not vary over time to reflect the trend heterogeneity. Although industry-year and region-year fixed effects are included in the models, they may not fully capture the differences in innovation patterns between CPA participants and other firms. In addition, endogeneity may also arise from reversed causality, as holding environmentally friendly patents may improve the environmental performance of a firm. Benefiting from the improvements in environmental performance, a firm may pass the acceptance inspection for a CPA program earlier than without innovation.

Generally, environmental innovation accounts for only a small fraction of granted patents. For example, of more than four million U.S. patents examined by Nameroff et al. (2004), only 3,235 were "green chemistry" patents. It is likely that the fraction of environmental innovation is even smaller for Chinese firms, as environmental concerns were not emphasized in Chinese industrial policy until very recently. This suggests that the link between innovation and environmental performance itself is likely very weak in the main dataset. However, I do not observe whether any given patent is a "green patent" or not. I employ a pre-treatment model to test for systematic differences in innovative activities across firms that participated in at least one CPA program from 2005 to 2010 (*CPA participants*) and those had not participated in any CPA program during the same period (*CPA non-participants*). For each year t_1 since 2005, I compare the patterns of innovation from 2001 to year $t_1 - 1$ between a group of firms that participated in at least one CPA program after t_1 ($Regulated_{i,s,r,t_1} = 1$, the *treatment* group at year t_1) and the group of CPA non-participants ($Regulated_{i,s,r,t_1} = 0$, the *control* group at year t_1). The following model reveals whether there were systematic differences in both the level and the trend of innovation between the two groups of firms from 2001 to year $t_1 - 1$:

$$innov_{i,s,r,t} = \delta_{s,r,t} + \lambda\, Regulated_{i,s,r,t_1} + \phi\,(t \cdot Regulated_{i,s,r,t_1}) + \rho\, X_{i,s,r,t} + \varepsilon_{i,s,r,t}. \tag{2.3}$$

The binary variable $Regulated_{i,s,r,t_1}$ is firm-specific and time-invariant between 2001 and year $t_1 - 1$. In the above equation, to avoid perfect collinearity, I replace firm fixed effects α_i, industry-year fixed effects $\beta_{s,t}$, and region-year fixed effects $\gamma_{r,t}$ with industry-region-year fixed effects $\delta_{s,r,t}$. Significant estimates of λ and ϕ would indicate that the level and the trend of innovative activities differed systematically between the two groups of firms. Although the difference in level can be accounted for by the inclusion of firm fixed effects in the models, the difference in trend signalled by a significant ϕ could impair the validity of the DID approach employed in the analysis.[14]

I also perform a falsification test to examine if innovation patterns of CPA participants and non-participants started to differ only a few years before CPA program enrollment. For each firm participated in its first CPA program at year t_2, I assume it had been in the program since year $t_2 - k$, where k is a positive integer. I only include observations from 2001 to year $t_2 - 1$ for each CPA participant in this falsification exercise. On the other hand, I include observations from 2001 to 2009 for each CPA non-participant. The following model indicates whether there were systematic differences in the trend of innovation between the two groups of firms from year $t_2 - k$ to year $t_2 - 1$:

$$innov_{i,s,r,t} = \alpha_i + \beta_{s,t} + \gamma_{r,t} + \kappa\, Pseudo\text{-}CPA_{i,s,r,t} + \rho\, X_{i,s,r,t} + \varepsilon_{i,s,r,t}. \tag{2.4}$$

[14] One may argue that environmental performance may be correlated with observable firm characteristics other than innovative activities, or the selection of mandatory CPA participation is based on firm characteristics other than environmental performance. As a result, the two groups of firms may systematically differ in other aspects. In Section 2.7.3, I employ a propensity score matching method to construct a sub-dataset, where observable characteristics of firms in the treatment group and the control group do not differ systematically. Estimation results for the universal impact and the differential impact models are similar to the main results presented in Section 2.6.3.

The binary variable $Pseudo\text{-}CPA_{i,s,r,t}$ takes the value 1 if firm i in industry s and region r participated in its first CPA program at year t_2, and the year t is between year $t_2 - k$ and year $t_2 - 1$. Significant estimates of κ would suggest a systematic deviation in innovation patterns appeared k years before companies participated in CPA programs. This pre-treatment deviation could also impair the validity of the DID approach.

2.5 Data and Descriptive Statistics

I combine several publicly available datasets to construct key variables measuring firm innovation, environmental regulation and other characteristics. The main data sources include the Chinese Patent database, which is constructed through the Chinese Patent Data Project (CPDP); a series of lists of companies that passed CPA assessments and acceptance inspections, which was released by the Ministry of Environmental Protection of China (the MEP lists); and the Osiris database, which is managed by the information provider Bureau van Dijk (BvD).

The Chinese Patent database covers more than 190,000 published patent applications by Chinese listed companies between 1990 and 2010. The MEP lists record the start and the end years of CPA programs participated by 17,862 firms in 31 regions between 2005 and 2012. The Osiris database contains up to 20 years of financial statistics on listed and major unlisted or delisted companies in more than 190 countries, including China. This section briefly introduces the three source databases, details the process to construct the indicators and the main dataset used in subsequent analyses, and provides summary statistics for the key variables.

2.5.1 Innovation

China's patent law was rescinded in 1963, reinstituted in 1985, and revised in 1992, 2000 and 2008. The three revisions progressively aligned the patent system with those in Europe, Japan and the U.S. (He et al., 2013) As the designated authority, China's State Intellectual Property Office (SIPO) grants the following three types of patents: invention patents granted for "technical innovations that are practical, inventive and new;" utility model patents granted for "technical solutions related to the shape or structure of an object;" design patents granted to "protect the shape, colour, or combination of both of an object" (Canadian Trade Commissioner Service, 2015, p. 1). To obtain invention and utility model patents, an applicant needs to demonstrate in her application that the product/process is novel, creative and applicable. On the other hand, one only needs to demonstrate the novelty a given design to obtain design patents. The Chinese patent system allows an applicant to request a substantive examination for patent grant within 3 years after the filing, or the application is considered withdrawn. The possibly long gaps between initial check and substantive examination makes SIPO's average grant lag comparable to patent grant lags in Europe but longer than those in the U.S. (Liegsalz and Wagner, 2013) Although earlier studies such as Hu and Jefferson (2009) questioned the correlation between R&D activities and patent applications in China, more recent studies confirmed the positive link between patent counts, R&D input and financial performance (Chen et al., 2015; Dang and Motohashi, 2015). Hence, I consider patent counts as meaningful indicators of firms' innovation performance in China.

I use the annual number of patent applications extracted from the Chinese Patent database, which became publicly available in 2013, to measure a listed company's innovative activities. The database includes more than 190,000 published patent applications that companies listed in Shanghai and Shenzhen stock exchanges filed with the State Intellectual Property Office (SIPO) of China between 1990 and 2010. For each firm year, the database records the numbers of applications for invention, utility model and design patents respectively. The Chinese patent database also distinguishes between patent applications filed by a listed company's head office and those filed by its majority- and minority-owned subsidiaries.[15]

I use the aggregate number of applications for invention, utility model and design patents by the headquarter and the majority-owned subsidiaries of a listed company as the main indicator of its innovation. This indicator exclude patent applications by a company's minority-owned subsidiaries to better capture the overall innovation output that is closely linked with its own R&D input. Since design patents are often viewed as less valuable and less strategic than the other two types, I include the aggregate number of applications for invention and utility model patents as an alternative indicator. Given the aforementioned revision of China's patent law in 2000[16] and the increase in coverage of the Chinese Patent database after 2000, I choose 2001 as the start year of the sample period and compute these two indicators for each year from 2001 through 2010.

One limitation of the Chinese Patent database is that it does not provide commonly-used indicators, such as citations that a patent received or a patent's family size (the number of countries in which this patent is protected), to reflect the heterogeneity in patent value. As SIPO required invention patent applicants to include citation information in their applications only between 1997 and 2003 and after 2007, it is impossible to create a consistent measure for tracking the citations that each patent received. The user documentation of the CPDP also confirms that very few Chinese listed companies filed applications with foreign offices during the sample period. Thus family size cannot be employed as an indicator of patent value.

The Chinese Patent database offers several indirect measures as potential candidates for indicating patent value. The database records how many of each company's invention patent applications had been granted by January 2012. The database also records the number of unique International Patent Classification classes assigned to the invention and the utility model patents. For each of the three types of patents, the database records the number of granted patents that had expired by January 2012. However, when it comes to

[15] Majority-owned subsidiaries are referred to as "subsidiary companies" and "sub-subsidiary companies" in annual reports of listed companies and the user documentation of the Chinese patent database. Minority-owned subsidiaries are referred to as "joint ventures" and "associated enterprises."

[16] This second revision confirmed for the first time the effectiveness of contracts between R&D staff and their employers on the attribution of patents. This reform greatly boosted patents applications in the subsequent years.

usefulness as a satisfactory indicator, none is as good as citations received. Therefore, I do not incorporate these statistics into the indicator of innovation. Instead, I only use simple patent counts as the dependant variable to produce the results shown in Section 2.6.

2.5.2 Environmental Regulation

I use a binary variable *CPA* to indicate whether a listed company is under more stringent environmental regulation. The value of *CPA* is equal to 1 when a company was participating in a CPA program, and equal to 0 otherwise.[17]

I rely on the MEP lists to determine the length of the period during which a specific firm was participating in CPA programs (the "enrolled period"). The MEP lists contain four variables regarding the timing of CPA programs: the "announcement year" (the year in which a company was identified by a provincial-level list for mandatory CPA participation), the "report year" (when summary reports of CPA projects were submitted), the "assessment year" (when the company passed the assessment organized by local authorities), and the "acceptance inspection year" (when the company passed the acceptance inspection conducted by local authorities).

As reviewed in Section 2.3, firms are obligated to disclose pollution information to the public within one month after being identified by any provincial-level list. Also, until they pass acceptance inspections, these firms are required to continuously devote efforts to the medium- and high-cost options to which they committed in their CPA summary reports. Thus I view firms as under regulation and public supervision from the "announcement year" until the "acceptance inspection year," and consider these two variables the start and the end years of the enrolled period respectively. In any case where the value of the "announcement year" is missing, I use, as the start year, the value of "report year." Similarly, I use the value of the "assessment year" as a substitute for the value of "acceptance inspection year" when the latter is not available.

2.5.3 Firm-specific Control Variables

I use financial statistics of Chinese listed companies extracted from the Osiris database to measure firm-specific characteristics that may affect their innovative activities. The Osiris industrial company dataset contains general information such as names, major stock changes and industries, and financial indicators such as assets, liabilities and net profits of more than 80,000 listed and delisted companies around the world. To keep the sample consistent with the Chinese Patent database, in the analysis I include any company for which the major stock exchange is either the Shanghai or Shenzhen exchange, or is listed in one of the

[17] It is conceivable that mandatory CPA participation may substantially change firms' innovation patterns in the long term. In this case, the estimated treatment effect on firm innovation may be statistically significant both during and after CPA participation. However, estimations with the value of *CPA* set to be 1 both during and after participating in a CPA program did not confirm this hypothesis, as the estimated coefficients were not significantly different from zero in general.

exchanges as well as in the Hong Kong Stock Exchange between 2001 and 2010.

Due to the inconsistent disclosure requirements from Chinese authorities, R&D expenditure—the most accurate measure of innovation input and thus highly correlated with its output—is not reported by most of listed companies in the sample.[18] Hence, I construct four other control variables—*size*, *cash flow*, *capital intensity* and *prior innovation*—to measure innovation-related firm characteristics. First, to represent a company's *size*, I use the natural logarithm of the number of employees. Second, to indicate a company's *cash flow*, I use the natural logarithm of the cash flow-to-revenue ratio, which is defined as the ratio of total cash flow to operating revenue. *Size* and *cash flow* are the two most thoroughly examined firm-level determinants of innovation in past decades. Economies of scale and scope may result in the former having a positive impact on innovation. The imperfection of capital markets and the uncertain nature of returns to R&D investment can jointly contribute to the importance of the latter (see Cohen, 2010a).

Third, to proxy *capital intensity*, I use the natural logarithm of capital to labour ratio, which is defined as the ratio of the book value of plants and machinery to the number of employees. Capital-intensive firms may be more likely to patent "strategically" to hold up their rivals with litigations, or "defensively" to increase bargaining power and make credible counter-threats (Hall and Ziedonis, 2001a; Bessen and Hunt, 2007). Fourth, to capture a company's *prior innovation* that reflects its ability to develop new patents, I use the natural logarithm of labour productivity, which is defined as the ratio of annual net sales to the number of employees. The ideal indicator for a company's *prior innovation* is suggested to be its patent stock—total number of granted patents since its establishment or in recent years (Berrone et al., 2013; Yanadori and Cui, 2013). However, this approach does not apply to the analysis in this paper, as the Chinese patent database covers patent applications mostly after 1999 due to information availability. Therefore, I choose labour productivity as an alternative indicator of *prior innovation*, as productivity growth reflects efficiency improvements and is closely linked with innovation.

2.5.4 Construction of the Main Dataset

The main dataset used in the empirical analysis contains statistics for innovation, environmental regulation, and other characteristics of 733 Chinese listed companies between 2001 and 2010. To construct the dataset, I first merged patent data from the Chinese Patent database with financial statistics from the Osiris database, since these two datasets are linked through unique stock codes assigned to listed companies. The joint dataset was then merged with the MEP lists through name matching, because the MEP lists are in Chinese and only record basic company information such as names, addresses, and sectors.

[18] Another source, the China Stock Market & Accounting Research Database, provides R&D investment after amortization that is recorded in a company's asset account. This indicator, which can at best serve as an approximate measure of actual R&D expenses every year, is only available for Chinese listed companies after 2007. Therefore I do not include this variable in the main dataset.

Following the mapping strategy described in the user documentation of the CPDP, I took three major steps to match company names in Chinese. First, I obtained the so-called "stem" names of listed companies in the Chinese Patent-Osiris joint dataset and the MEP lists, by removing all special characters, punctuation marks, and various designators such as "group," "inc." and "ltd." (all in Chinese) in the original company names.

Second, I calculated the following similarity score based on the Levenshtein edit distance between each pair of the stem names in the two datasets:

$$Similarity = 1 - Levenshtein\ Distance = 1 - \frac{n}{N_l + N_m}.$$

N_l and N_m in the above equation represent the length of the stem names in the Chinese Patent-Osiris joint dataset and the MEP lists respectively, and n is the minimum number of editing operations required to transform one stem name to the other (Levenshtein, 1966; He et al., 2013). In the calculation of the Levenshtein edit distance, I allowed all three types of edit operations, including insertion, deletion, and substitution of any single character.

After the 1,842 listed companies included in the Chinese Patent-Osiris joint dataset were matched with companies in the MEP lists, I then exported the top 10 matches according to the similarity score and manually checked these 18,420 name pairs to ensure that the merged dataset only included "true matches."[19] Since the MEP lists can record either the headquarters of a listed company or its local subsidiaries, or both, as the targets of CPA programs, I consider a company to be under stringent environmental regulations as long as its headquarters or any of its subsidiaries was participating in a CPA program.

To ensure that firms in the final dataset share similar innovation patterns, I excluded companies in industries with zero CPA participant between 2005 and 2010, based on the three-digit U.S. Standard Industry Classification (SIC) code assigned to each listed company in the Osiris database. In the same vein, I excluded companies in Hainan and Tibet—the two regions with zero CPA participant between 2005 and 2010.[20] I kept only firms operating in the three key sectors with detailed cleaner production standards: the mining sector (SIC 101–149), the manufacturing sector (SIC 201–399), and the public utilities sector (SIC 481–497). I also excluded companies that exited the stock market during the sample period, as their choices might be affected by innovation performance or environmental regulation, and this correlation could lead to potential endogeneity issues. Finally, I excluded any firm changing its core industry or the location of its headquarter (at the provincial level), as these changes are usually linked with substantial reorganization or takeovers, which may enhance or weaken unobserved firm-specific factors related to innovation.

[19] A typical company name in the MEP lists includes the name of the parent company, as well as the name of the subsidiary company. Therefore, it is straightforward to verify whether the matched pairs are "true matches." However, it is still possible for this strategy to miss some matches, because names of some subsidiary companies may not contain parent company names due to name changes or input errors.

[20] Only two listed companies were excluded in this step.

2.5.5 Descriptive Statistics

Among the 733 companies included in the main dataset, 617 filed at least one patent application between 2001 and 2010. As shown in Figure 2.1, the number of firms filing patent applications continuously increased from 44 (out of 122) in 2001 to 466 (out of 667) in 2010. Meanwhile, the average number of patent applications filed by these listed companies also rose dramatically from about 8 in 2001 to more than 42 in 2010, indicating the growing trend of attaching more importance to innovation and standardizing protection for innovation. Between 2005 and 2010, 217 listed companies in the main dataset had participated in at least one CPA program. The number of firms under regulation each year climbed from 30 (out of 576) in 2005 to 111 (out of 667) in 2010. On average, CPA participants applied for more patents than non-participants. Since the number of observations for CPA participants is limited in 2001 and 2002, the significant gap between the average numbers of patent applications by CPA participants and non-participants in these two years was driven largely by outliers. The gap remained relatively stable between 2003 and 2006, substantially narrowed in 2007 and 2008, then enlarged to about 17 in 2010. This fact suggests that there exists a stronger positive correlation between mandatory CPA participation and firm innovation after 2008.

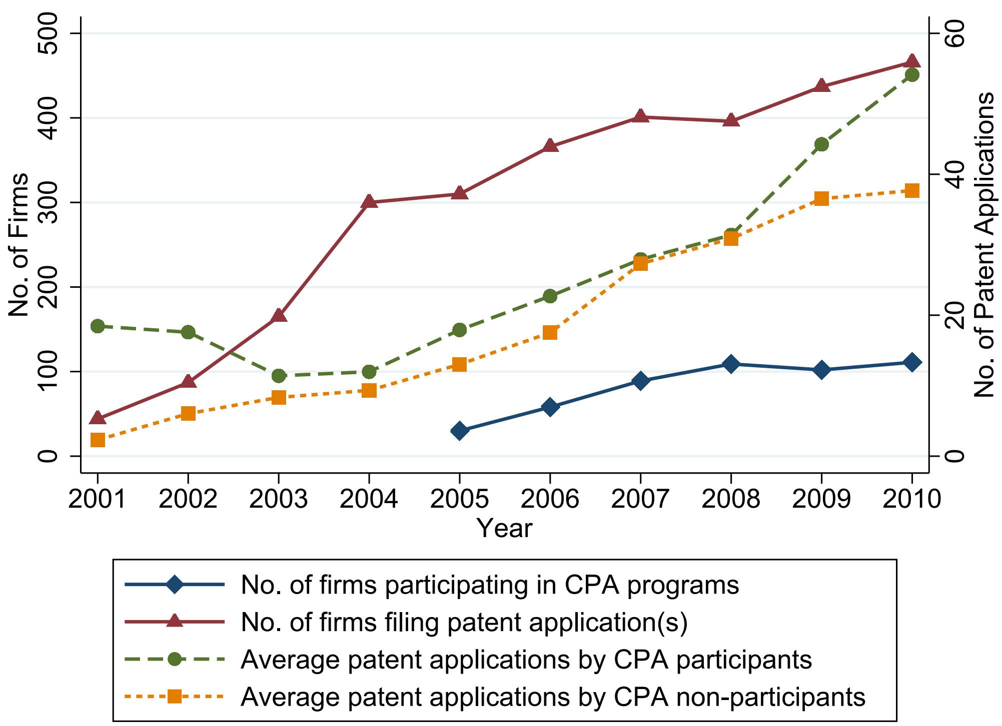

Figure 2.1: Mandatory CPA Participation and Patent Applications of Companies

Figure 2.2 reveals the distribution of CPA participants and non-participants by two-digit SIC industry in the main dataset. 646 companies in the main dataset operate in the manufacturing sector, 50 in the public utilities sector, and 37 in the mining sector. Over 29% of manufacturing companies had participated in at least one CPA program. The corresponding rate is 20% for companies in the public utilities sector, and 49% for those in the mining sector. The two-digit SIC industries containing over 100 listed companies are the chemicals and allied products industry (SIC 28), and the electronic and other electrical equipment and components except computer equipment industry (SIC 36). Other industries with at least 50 companies in the main dataset are the food and kindred products industry (SIC 20), the primary metal industries (SIC 33), the industrial and commercial machinery and computer equipment industry (SIC 35), the transportation equipment industry (SIC 37), and the electric, gas and sanitary services industry (SIC 49).

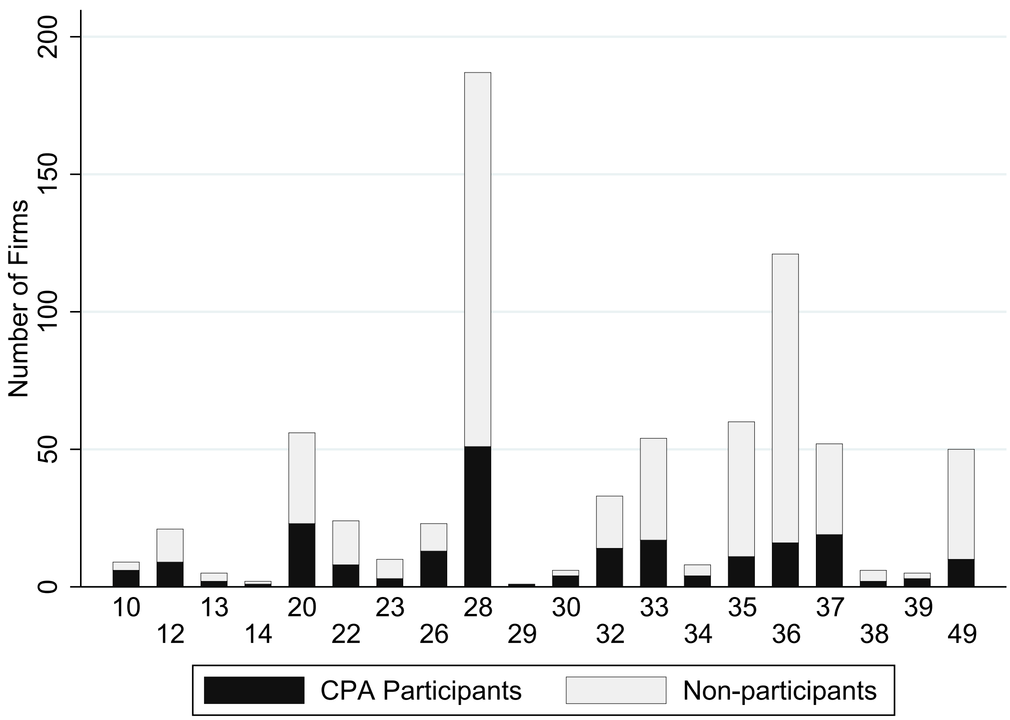

Figure 2.2: Number of CPA Participants and Non-participants by 2-digit SIC Industry

Table 3.1 presents the descriptive statistics, including the means, standard deviations, minimums, and maximums of the aforementioned variables across all 29 regions, 67 three-digit SIC industries for 10 years. In addition to the two innovation indicators listed in the table, it is worth mentioning that the mean of invention patent applications in the sample is 10.95. In other words, an average Chinese listed company in the main dataset applied for roughly 11 invention patents, 9 utility model patents and 4 design patents each year between 2001 and 2010. The value for *size* before log transformation averages 5,988 employees, reflecting that the main dataset is composed of large firms which could potentially yield a significant overall environmental impact.

Table 2.1: Descriptive Statistics

Variable	Mean	S.D.	Min	Max
Innovation				
All Patent Applications	24.55	156.23	0.00	5,284.00
Invention and Utility Model	20.17	148.2	0.00	5,035.00
Environmental Regulation				
CPA	0.10	0.30	0.00	1.00
Other Firm Characteristics				
Employment (thousand)	5.99	23.55	0.00	552.70
Cash Flow / Operating Revenue (%)	12.50	10.09	0.05	99.14
Capital Intensity (CNY million)	1.09	11.14	0.00	383.37
Labour Productivity (CNY million)	1.93	11.36	0.00	350.01

2.6 Empirical Results

In this section I present the estimation results for the pre-treatment model, the falsification test, the uniform impact and the differential impact models. I start with comparing the general pre-treatment innovation patterns between CPA participants and non-participants. Then I perform the falsification test to examine whether the innovation patterns of CPA participants systematically deviate from others only when they were soon to be regulated. After showing that innovation patterns of CPA participants did not differ from non-participants before participating in CPA programs, I present the main results showing that mandatory CPA participation increased firms' patent applications. I find that the effect is stronger after improvements in the regulatory system had been made. Sub-sample estimation results show that the positive effect is more significant in eastern China than in other regions. Estimations with the policy indicators interacted with firm size show that larger companies innovate more than smaller ones when facing environmental regulation.

2.6.1 Pre-treatment Innovation Patterns

Before the Chinese central government released the "Interim Measures on Cleaner Production Audit" in August 2004, the efforts devoted by local governments to promote cleaner production were largely lacking. An official report from the central government appraised the work of five provincial-level governments, and criticized others for not launching demonstrative CPA programs and sticking with policies favoring end-of-pipe treatment (State Environmental Protection Administration, 2004). Thus, before 2005, environmental pressure was not sufficiently strong to induce Chinese listed companies to alter their environmental performance, let alone innovative activities. However, since the nationwide implementation of CPA programs in 2005, companies that had yet participated in CPA programs might adjust its innovation strategy to avoid being selected, or prepare for upcoming mandatory enrollment.

To examine whether the level and the trend of patent applications differed systematically between CPA participants and non-participants before mandatory CPA participation, I perform a pre-treatment analysis as specified in Equation (2.3). For each year t_1 between 2005 and 2009, a listed company in the main dataset must belong to one of the three following groups: firms that had participated in CPA programs before year t_1, firms that participated in CPA programs for the first time at or after year t_1 (the treatment group at year t_1), or firms that had not participated between 2001 and 2010 (the control group at year t_1).[21] If the pre-treatment trend of innovation did not differ significantly between firms in the treatment and the control groups at each year between 2005 and 2009, the DID approach detailed in Section 2.4 should identify the effect of mandatory CPA participation on firm innovation.

The results of the pre-treatment analysis are reported in Table 2.2, in which columns (1) through (5) show the regression results using the number of all patent applications as the measure of innovation, while columns (6) through (10) contain the results for invention and utility model patents. Columns (1) and (6) present the results for firms in the treatment and the control groups in 2005, using observations from 2001 to 2004. Similarly, columns (2) and (7), (3) and (8), (4) and (9), (5) and (10) report the results, respectively, for firms in the treatment and the control groups in 2006, 2007, 2008, and 2009. Results in all columns are produced by models with firm characteristics including *size*, *cash flow*, *capital intensity* and *prior innovation* to control for observable factors that may affect firm innovation. The models also include industry-region-year fixed effects to control for unobservable factors that differ across industries and regions, and over time. Standard errors are reported in parentheses and are two-way clustered by three-digit SIC industry and year. This approach corrects for industry-wide and year-specific technology and policy shocks uncorrelated with the independent variables, which allows variations in innovative activities of firms to be correlated both within industry and in the same year.[22]

[21] There are only 35 firms in the treatment group in 2010. I do not perform the pre-treatment analysis for these firms and those in the control group in 2010, since the results could be driven by outliers and cluster-robust standard errors could not be computed.

[22] I have also experimented with other two-way clustering strategies, including by region and year, and by industry and region. The patterns of coefficient significance remain consistent in the pre-treatment estimation results and results presented in other sections.

Table 2.2: Pre-treatment Innovation Patterns

	All Patent Applications					Invention and Utility Model				
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Regulated_{2005}$	−0.033					−0.227				
	(0.393)					(0.465)				
$Trend \times Regulated_{2005}$	0.066					0.129				
	(0.081)					(0.101)				
$Regulated_{2006}$		−0.141					−0.041			
		(0.367)					(0.489)			
$Trend \times Regulated_{2006}$		0.066					0.046			
		(0.082)					(0.109)			
$Regulated_{2007}$			−0.228					−0.078		
			(0.414)					(0.476)		
$Trend \times Regulated_{2007}$			0.068					0.029		
			(0.086)					(0.099)		
$Regulated_{2008}$				0.159					0.245	
				(0.350)					(0.513)	
$Trend \times Regulated_{2008}$				−0.025					−0.045	
				(0.071)					(0.103)	
$Regulated_{2009}$					−0.175					−0.049
					(0.222)					(0.166)
$Trend \times Regulated_{2009}$					0.017					−0.004
					(0.048)					(0.043)
No. of Firms	626	644	637	617	579	626	644	637	617	579
Observations	1,215	1,712	2,195	2,607	2,871	1,215	1,712	2,195	2,607	2,871

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Industry-region-year fixed effects and firm characteristics including size, cash flow, capital intensity, and prior innovation are included to generate results but omitted from reporting. Standard errors are two-way clustered by industry and year.

Coefficient estimates for *Regulated* and *Trend* $\times$ *Regulated* are not statistically significant at the 10% level in any year. These results indicate that, after controlling for industry-region-year fixed effects and firm characteristics, Chinese listed companies later enrolled in CPA programs did not systematically innovate more (or less), or experience higher (or lower) variations in innovation than those did not participate. Since the selection of CPA participants is based on firms' prior environmental performance, it is likely for firms in the treatment and the control groups differ substantially in this aspect. However, the results of the pre-treatment analysis confirm that these differences did not significantly affect either the level or the trend of firm innovation, even after the nationwide implementation of CPA programs in 2005. Hence, mandatory CPA participation can be treated as independent from firm innovation, and the DID approach should correctly identify the impact of this policy.

2.6.2 Falsification Test

Analyses in Section 2.6.1 assume that innovation patterns of CPA participants and non-participants were stable during the pre-treatment period. However, a company might only adjust its environmental performance and innovative activities when management believed that mandatory CPA participation would be likely in the foreseeable future. It is also possible that when selecting candidates for mandatory CPA participation, environmental agencies put more emphasis on recent environmental performance and chose heavy polluters in the past few years. In these cases, the validity of the DID approach depends on whether innovation patterns differ systematically between CPA participants and non-participants in a several-year period before mandatory CPA enrollment.

I perform a falsification test as specified in Equation (2.4) to examine if the trend of innovation for CPA participants differed from non-participants between year $t_2 - k$ and year $t_2 - 1$, where t_2 is the year in which participants were enrolled in CPA programs for the first time. In this analysis I only include observations from 2001 to year $t_2 - 1$ for each CPA participant, and observations from 2001 to 2009 for each non-participant. Since the average length of CPA programs in the main dataset is about 2.4 years, I set the value of k to be 2 and 3 and perform two sets of falsification exercises.

Table 2.3 reports estimates of the coefficients in Equation (2.4). Columns (1) and (3) show results of the model assuming CPA participation to be two years earlier than the actual enrollment year, while columns (2) and (4) contain the results of the model assuming CPA participation to be three years earlier. All coefficients for the imaginary CPA participation indicator, *Pseudo-CPA*, are statistically insignificant at the 10% level. This fact indicates that innovation patterns of CPA participants and non-participants did not differ significantly from each other, even when CPA participants would be facing environmental regulation within two to three years. Thus, the results of the falsification test provide further support to the argument that the selection of CPA participants is independent from firm innovation, and the DID approach would identify the effect of mandatory CPA participation.

Table 2.3: Pseudo-CPA Participation in Pre-treatment Periods

	All Patents		Invention and Utility	
Independent Variable	(1)	(2)	(3)	(4)
Pseudo-CPA	0.152	0.152	0.129	0.120
	(0.096)	(0.104)	(0.084)	(0.099)
Size	0.432***	0.432***	0.411***	0.412***
	(0.055)	(0.055)	(0.050)	(0.050)
Cash Flow	0.004	0.003	0.021	0.021
	(0.028)	(0.028)	(0.020)	(0.021)
Capital Intensity	0.121***	0.121***	0.133***	0.133***
	(0.024)	(0.024)	(0.028)	(0.028)
Prior Innovation	0.184***	0.184***	0.163***	0.163***
	(0.062)	(0.063)	(0.060)	(0.060)
No. of Firms	689	689	689	689
Observations	3,801	3,801	3,801	3,801

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Firm, industry-year and region-year fixed effects are included to generate results but omitted from reporting. Standard errors are two-way clustered by industry and year.

2.6.3 Main Results

Given the results of the pre-treatment analysis and the falsification test, I now employ the DID approach to investigate the impact of mandatory CPA participation on firm innovation. Table 3.2 presents log-linear fixed effects estimates of the coefficients in Equation (3.1) and Equation (2.2). Note that columns (1) and (3) show the regression results for the uniform impact model, while the results for the differential impact model are presented in columns (2) and (4). The coefficients for three of the four control variables fit predictions from previous literature: larger firms, firms with more fixed assets, and more productive firms perform better in innovation. The coefficient estimate for the indicator of cash flow is insignificant, suggesting that innovative activities of Chinese listed companies may not be substantially liquidity constrained.

In columns (1) and (3), the coefficients for *CPA* are both positive and significant at the 10% level or above, indicating that on average, mandatory CPA participation stimulates innovation. More specifically, these coefficients suggest that CPA participation can raise all patent applications of a Chinese listed company by 11.6%, and this effect increases slightly to 14.2% for invention and utility patent applications. Using the means of these two innovation indicators for listed companies in the main dataset, I can infer that on average, CPA enrollment could lead to approximately 3 more invention and utility model patent applicaitons by a firm each year.

The results in columns (2) and (4) show that coefficient estimates for *CPA 2005–2008* are insignificant

Table 2.4: Main Results: Patent Applications and Mandatory CPA Participation

	All Patents		Invention and Utility	
Independent Variable	(1)	(2)	(3)	(4)
CPA	0.116*		0.142**	
	(0.068)		(0.058)	
CPA 2005–2008		0.014		0.052
		(0.052)		(0.047)
CPA 2009–2010		0.244**		0.256***
		(0.097)		(0.083)
Size	0.481***	0.478***	0.442***	0.440***
	(0.053)	(0.054)	(0.047)	(0.048)
Cash Flow	–0.004	–0.004	0.006	0.006
	(0.022)	(0.023)	(0.019)	(0.019)
Capital Intensity	0.125***	0.123***	0.128***	0.126***
	(0.030)	(0.030)	(0.030)	(0.030)
Prior Innovation	0.200***	0.199***	0.169***	0.169***
	(0.045)	(0.045)	(0.041)	(0.042)
No. of Firms	733	733	733	733
Observations	5,002	5,002	5,002	5,002

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Firm, industry-year and region-year fixed effects are included to generate results but omitted from reporting. Standard errors are two-way clustered by industry and year.

while those for *CPA 2009–2010* are significant at the 5% level or above. This discrepancy suggests that, in their early stages, CPA programs did not have a stimulative effect on firm innovation. However, a positive link between environmental regulation and innovation appeared after substantial improvements were made to the evaluation standards and procedures for CPA projects in 2009. The coefficients for *CPA 2009–2010* are more significant, and larger, than those for *CPA*. They indicate that CPA participation in 2009 and 2010 raised all patent applications and invention and utility patent applications of a listed company by 24.4% and 25.6% respectively. The average positive impact of mandatory CPA participation on firms' patent applications is largely driven by the positive interaction between environmental regulation and innovation since 2009.

2.6.4 Heterogeneous Effects of CPA across Regions

As discussed in Section 2.3, the Chinese central government delegates to each provincial-level government the enforcement and promotion of cleaner production within its own jurisdiction. When it comes to implementation of CPA programs, local governments are not only responsible for identifying the key sectors and announcing the lists of firms required to participate in each year, but also for specifying detailed implementation procedures and supportive policies, and for organizing assessments and conducting acceptance inspections for completed projects. Due to China's significant regional differences in both economic development and environmental awareness, it is not uncommon for regulations, incentives, and enforcement strategies to differ substantially from region to region.

In general, the economically more developed eastern regions are in the lead to have tighter environmental standards. For example, Shanghai's CPA evaluation process incudes an additional "pre-assessment" stage, during which site investigations are conducted and expert discussions are held.[23] Shanghai is also one of the leading regions to use online monitoring devices, in combination with periodic inspections conducted by technicians, to monitor effluent and exhaust gas from heavy polluters. The automated monitoring systems have enhanced the accuracy of pollution statistics, and thus facilitated the enforcement of CPA evaluation process. Finally, the Shanghai government provides special subsidies for CPA expenses to firms, of which half are available at the launch of CPA programs. The other half can be claimed after assessments are passed. Similar financial incentives are also provided by the Guangdong government in the form of a RMB50,000 bonus to firms that performed well in assessments, while one of its subordinates—the Dongguan government—pays an additional RMB300,000 to qualified firms within its jurisdiction. The argument that environmental regulation is better enforced in eastern regions is also supported by case studies of the Liaoning and Zhejiang provinces (Hicks and Dietmar, 2007; Geng et al., 2010), and the fact that three eastern provinces—Zhejiang, Jiangsu and Shandong—accounted for nearly 70% of CPA assessment and acceptance inspection expenses covered by government funding in 2010.[24]

To examine if stricter regulations, stronger incentives, and better enforcement in eastern regions stimulate more innovation, I classify the 31 Chinese provincial-level regions into two groups: Eastern China and Other Regions. To do so, I follow the approach proposed in the seventh five-year plan of China (1986–1990) and also adopted in the tenth five-year plan (2001–2005). The following 11 regions comprise a group that called Eastern China: Beijing, Tianjin, Shanghai, Liaoning, Hebei, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong, and Hainan. The remaining 20 regions belong to the group of Other Regions. I then divide the data into two sub-samples—one containing companies in Eastern China, and the other containing companies in Other Regions. I estimate the uniform impact and the differential impact models using separate observations from each of the sub-samples.[25]

Estimation results for both models on the two sub-samples are presented in Table 2.5. Again, results for the uniform impact model are shown in columns (1) and (3), while the results for the differential impact

[23] See "Provisions on Procedures of Cleaner Production Audit of Key Enterprises in Shanghai," which was released by the Shanghai Environmental Protection Bureau in 2008, for details on the CPA evaluation process.

[24] The 70% share is calculated based on the available statistics reported by 10 provincial-level regions. Due to lack of data for other regions and the pre-2007 period, this indicator cannot fully capture the environmental stringency in different regions. See Section 2.3 for a more detailed discussion.

[25] An alternative approach is to restrict the link between other variables and innovation to be the same across the two groups of regions, and estimate models with a dummy for Eastern China interacted with the policy indicators. Since the economic structure and innovation policies implemented differ greatly between Easter China and Other Regions, I split the sample to allow for differences in links between firm characteristics and innovation across regions.

model are in columns (2) and (4). There are substantial differences in coefficient estimates across the two sub-samples, suggesting that the environmental policy was not equally effective in all regions. The results in columns (1) and (3) indicate that if mandatory CPA participation is viewed as homogeneous across the 2005–2010 period, the effect of this policy is insignificant in either Eastern China or Other Regions. However, the estimates for *CPA 2005–2008* and *CPA 2009–2010* in columns (2) and (4) reveal that only firms participating in CPA programs in eastern regions after 2008 innovated significantly more. These results suggest that the details of the design and enforcement of environmental policies play an important role in encouraging firm innovation.

Table 2.5: Heterogeneous Effects of CPA Participation across Regions

	All Patents		Invention and Utility	
Independent Variable	(1)	(2)	(3)	(4)
	Panel A: Firms in Eastern China			
CPA	0.087		0.131	
	(0.097)		(0.082)	
CPA 2005–2008		–0.068		–0.010
		(0.065)		(0.067)
CPA 2009–2010		0.295**		0.320***
		(0.117)		(0.093)
No. of Firms	401	401	401	401
Observations	2,770	2,770	2,770	2,770
	Panel B: Firms in Other Regions			
CPA	0.145		0.156	
	(0.128)		(0.120)	
CPA 2005–2008		0.084		0.120
		(0.121)		(0.115)
CPA 2009–2010		0.213		0.197
		(0.153)		(0.141)
No. of Firms	332	332	332	332
Observations	2,232	2,232	2,232	2,232

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Firm, industry-year and region-year fixed effects, and firm characteristics including size, cash flow, capital intensity, and prior innovation are included to generate results but omitted from reporting. Standard errors are two-way clustered by industry and year.

2.6.5 Heterogeneous Effects of CPA across Firms of Different Sizes

The effectiveness of mandatory CPA participation may depend not only on the details of the regulatory framework, but also on the characteristics of the regulated firms. One potentially important such characteristic is firm size. Due to scale effects, larger companies may have lower compliance costs per unit of output. These companies may also be better able to allocate resources to innovative activities, including environmental R&D investments (Bartel and Thomas, 1987; Thomas, 1990; Sanchez, 1997). Thus, it is possible that small and large firms differ in their responses to environmental regulations.

To explore whether mandatory CPA participation provides stronger innovation incentives for larger companies, I add an interaction variable, *Size* × *CPA*, to the right-hand side of the uniform impact model. This variable is equal to *CPA* times the natural logarithm of the number of employees in a company. Similar interaction terms (*Size* × *CPA 2005–2008* and *Size* × *CPA 2009–2010*) appear on the right-hand side of the differential impact model.

Table 2.6 contains estimation results for the above specifications. Results for the uniform impact model with the interaction variable *Size* × *CPA* are reported in columns (1) and (3), while the results for the differential impact model with the interaction variables *CPA 2005–2008* and *CPA 2009–2010* are in columns (2) and (4). Compared with the main results of Section 2.6.3, a notable difference is that all estimates for the policy indicators are now statistically significant at the 5% level or above, although significance is still weaker for *CPA 2005–2008* than for *CPA 2009–2010*. The positive coefficients for all three interaction terms suggest that larger companies innovate more as a result of CPA participation than smaller companies. Based on an average firm size of 7.76 (measured in log employees) in my sample, the results in Table 2.6 imply that mandatory CPA participation stimulates annual patent applications by 6.0%. The effect becomes significant and more pronounced after 2008, when its magnitude increases to 16.1% for all patent applications and 15.3% for invention and utility model patent applications.

2.7 Sensitivity Tests and Robustness Results

This paper has shown so far that mandatory CPA participation enhanced the innovation performance of Chinese listed companies, and that the effectiveness of this policy varied over time, across regions, and across firms of different sizes. In this section, I perform sensitivity tests to demonstrate that these findings are robust against changes in model specifications.

2.7.1 Delayed Impact of Environmental Regulation

Given the complex and uncertain nature of innovation, it is reasonable to presume that environmental pressure, financial performance, and other firm characteristics may have a delayed instead of immediate impact on patent applications. Nevertheless, I use contemporaneous independent variables to produce the main results in Section 2.6.3, since the sample period 2001 to 2010 for the main dataset is relatively short, and the regulatory framework for CPA programs improved substantially after 2008. Lagging the independent variables for one year would not only cut down the number of observations but also make it difficult to

Table 2.6: Heterogeneous Effects of CPA Participation across Firms of Different Sizes

	All Patents		Invention and Utility	
Independent Variable	(1)	(2)	(3)	(4)
CPA	–0.713***		–0.641**	
	(0.266)		(0.251)	
Size × *CPA*	0.100**		0.094***	
	(0.040)		(0.037)	
CPA 2005–2008		–0.443*		–0.164
		(0.249)		(0.257)
Size × *CPA 2005–2008*		0.056		0.027
		(0.037)		(0.036)
CPA 2009–2010		–0.762***		–0.941***
		(0.271)		(0.297)
Size × *CPA 2009–2010*		0.119***		0.141***
		(0.040)		(0.040)
Size	0.475***	0.472***	0.437***	0.433***
	(0.053)	(0.054)	(0.047)	(0.048)
Cash Flow	–0.004	–0.005	0.005	0.005
	(0.022)	(0.022)	(0.018)	(0.019)
Capital Intensity	0.126***	0.124***	0.128***	0.127***
	(0.030)	(0.030)	(0.029)	(0.030)
Prior Innovation	0.198***	0.197***	0.167***	0.166***
	(0.044)	(0.045)	(0.041)	(0.041)
No. of Firms	733	733	733	733
Observations	5,002	5,002	5,002	5,002

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Firm, industry-year and region-year fixed effects are included to generate results but omitted from reporting. Standard errors are two-way clustered by industry and year.

analyze the heterogeneity in policy effectiveness over time, as the observations for *CPA 2009–2010* would be cut down by more than half.

In this subsection I lag all the independent variables for one year and re-estimate the uniform impact and the differential impact models to check the robustness of the main results. Table B.1 presents the estimation results for the uniform impact model in columns (1) and (3), and the results for the differential impact model in columns (2) and (4). Compared with the main results reported in Table 3.2, the number of firms included in the analysis decreases only slightly, from 733 to 723. However, the number of observations drops over-proportionally, by about 14%, as the annual number of observations in the main dataset increases over time. The coefficient estimates for *CPA* are positive and significant at the 5% level. The coefficients for *CPA 2005–2008* are insignificant, while those for *CPA 2009–2010* are positive and significant at the 1% level. These patterns are in line with findings in Section 2.6.3, except that mandatory CPA participation is suggested to have a delayed, more significant average impact on firm innovation under this specification.

2.7.2 Firms in the Manufacturing Sector

The main dataset used in previous analyses covers the three key sectors with at least one firm participating in CPA programs between 2005 and 2010. Figure 2.2 shows that about 88% of companies in the main dataset operate in the manufacturing sector. Firms' innovation patterns may be more similar to each other within this sector, than comparing with innovative activities of firms in the mining and the public utilities sectors. Therefore, a DID analysis on companies in the manufacturing sector may better capture the effect of mandatory CPA participation on firm innovation.

In this subsection I restrict the sample to companies operating in the manufacturing sector, and present the estimation results for the models in Table B.2. Columns (1) and (3) contain results for the uniform impact model, and columns (2) and (4) report the results for the differential impact model. By excluding companies in other sectors, the numbers of firms and observations included in the estimations both reduce by about 12%. The coefficient estimates for *CPA* are positive and significant at the 10% level or above. The coefficients for *CPA 2005–2008* are insignificant, while those for *CPA 2009–2010* are positive and significant at the 5% level or above. The coefficients for *CPA* and *CPA 2009–2010* are smaller than those presented in Section 2.6.3, indicating a slightly weaker positive effect of mandatory CPA participation in the manufacturing sector.

2.7.3 DID Analysis based on a Propensity Score Matching Approach

The validity of a DID analysis can greatly benefit from the similarity of patterns in the treatment and the control groups, as well as from the elimination of potential selection bias related to individual characteristics. To utilize to the greatest extent the information contained in the main dataset, in Section 2.6 I include in the control group 516 Chinese listed companies that had not participated in any CPA program between 2001 and

2010. I also employ a pre-treatment analysis and a falsification test to show that both the level and the trend of CPA non-participants' innovation did not differ from participants.

In this subsection, using a propensity score matching (PSM) approach, I construct a sub-dataset with 165 listed companies that later enrolled in CPA programs and 107 firms that never participated during the sample period. The PSM approach, which was developed by Heckman et al. (1997) and widely employed in DID analyses, matches the groups of firms that had similar observable characteristics in 2004, and thus shared a likelihood of being regulated in the following years. The group of non-participants selected through this approach could constitute a better control group for companies participating in CPA programs. Estimation results on this sub-dataset may better capture the effect of mandatory CPA participation, as it further alleviates the endogeneity issue arising from pre-treatment selection potentially based on firm characteristics other than prior environmental performance.

Following the implementation procedures detailed in Debaere et al. (2010) and Cozza et al. (2015), I use three steps to apply DID estimations based on a PSM approach. First, I estimate a probit model for all the listed companies in the main dataset, to predict the probability of being regulated (during the 2005–2010 period) in 2004. The firm characteristics that are assumed to be linked with the probability include *size*, *cash flow*, *capital intensity*, and *prior innovation* in 2004. The right-hand side of this model also includes industry dummies to control for industry-specific environmental performance that could lead to a higher or lower chance of being identified for CPA participation, and region dummies to take account of heterogeneity in local policies that may affect a firm's possibility of being regulated.

Second, I compute propensity scores based on the probit estimation results, and pair each later-participated firm with the most similar never-participated firm in terms of propensity score. These paired, listed companies constitute the new sub-dataset, while firms with scores higher than the maximum or lower than the minimum are dropped (see Leuven and Sianesi, 2003). I perform a balancing test to examine whether the distributions of observable characteristics are similar across the later-participated and the never-participated companies. Following Sianesi (2004), I compare the differences in means of the firm characteristics between the two groups, and the *pseudo* R^2 of the probit model, predicting the possibility of being regulated before and after matching. Results of the t-tests are presented in Table B.3. They suggest that the means of all four characteristics for firms that never participated in a CPA program do not differ significantly from those did. A substantial reduction in *pseudo* R^2 reflects that the performance of the probit model improved after matching. These facts confirm that the sub-dataset can be considered well-balanced after matching.

Finally, I estimate both the uniform impact and the differential impact models on the sub-dataset, which contains observations for 272 listed companies between 2004 and 2010. The results are presented in Table B.4. The coefficients for *CPA* in columns (1) and (3), and those for *CPA 2009–2010* in columns

(2) and (4) are positive and significant at the 5% level or above. These facts also indicate that mandatory CPA participation fostered patent applications by Chinese listed companies, and that the impact is stronger after 2008. These results are qualitatively consistent with the main results discussed in Section 2.6.3. This consistency further strengthens the robustness of the main results.

2.8 Conclusion and Discussion

The impact of environmental regulation on firm innovation has long been under discussion, even before the Porter Hypothesis was proposed in the early 1990s. Previous studies generally confirm the promotional effect of strict environmental policies on environmental innovation, but show mixed results for overall innovative activities. This paper uses firm-level data in China to provide evidence for the positive link between environmental stringency and overall innovation, which is advocated by the "weak" version of the Porter Hypothesis. This stimulative effect is found to be stronger after a multi-level regulatory system was finally established, and in regions where regulations were better enforced and supported by plenty of financial incentives. This finding makes this paper one of the few to discuss and support the "narrow" version of the Porter Hypothesis, which emphasizes the importance of policy implementation and flexibility. This paper also adds to the literature by confirming the positive effect of environmental policies on innovation at a more micro level in a developing economy.

Despite its contributions, this paper has at least three limitations. First, the main dataset lacks some information closely related to either innovation or environmental regulation, such as R&D expenses and the environmental performance of the listed companies. Although innovation can be attributed to other firm characteristics, and the sample selection issue is addressed by the pre-treatment analysis and the propensity score matching approach, the persuasiveness of estimation results would greatly benefit from a more comprehensive dataset. Second, the measures of innovation in this paper do not distinguish environmental patents from other types of patents, and do not reflect differences in the value of patents. A comparison between environmental and non-environmental innovative activities under regulation would provide more insights into the mechanisms of environmental policy's effect. However, an analysis reflecting the heterogeneity in patent value cannot be performed as long as citation statistics are not available for Chinese patents. Third, this paper does not discuss the "strong" version of the Porter Hypothesis. Given the fact that various financial data are available for listed companies, future research based on the main dataset of this paper should examine whether innovation triggered by environmental regulation enhances firm competitiveness.

Chapter 3

Firm Innovation under Import Competition from Low-wage Countries

3.1 Introduction

In recent decades, many developed economies, including the United States, experienced dramatic growth in manufacturing imports from developing countries. China led the wave of expansion in international merchandise markets, with an annual increase in manufacturing exports of more than 18% during the past two decades. Figure 3.1 shows the the rising share of manufacturing imports into the U.S. from low-wage countries[1] has increased from 4.6% in 1990 to 12.2% in 2001, thanks to a substantial contribution by commodities exported from China.

As this trend of rising import competition from low-wage countries in the U.S. manufacturing sector continues, it is important to understand its impact on firm performance such as innovative activities. Innovation is considered a fundamental driving force of economic growth (Romer, 1990; Aghion and Howitt, 1992), while manufacturing firms generates more than two-thirds of both U.S. research and development (R&D) spending and corporate patents. Since the seminal work presented in Arrow (1962), a substantial body of theoretical literature reveals that more intensive competition can contribute to growth of firm innovation. A number of trade models also indicate that increasing imports may stimulate domestic innovation through inter-industry, intra-industry, or within-firm reallocation of resources. These studies and their predictions will be reviewed in more detail in Section 3.2.

This paper examines whether the surge in imports from low-wage countries, especially China, has led to increased innovation by U.S. manufacturing firms, as measured by firm-level patent data. Our findings confirm the positive impact of Chinese import competition on firm innovation, and indicate that the effect is stronger for firms in low-tech and less-differentiated industries, and those with high capital intensity and

[1] Bernard et al. (2006) define low-wage countries as those with a per capita GDP of less than 5 % of U.S. per capita GDP during the period of 1972 to 1992. This approach has also been adopted in Mion and Zhu (2013) and Bloom et al. (2016) to calculate the share of imports from low-wage countries.

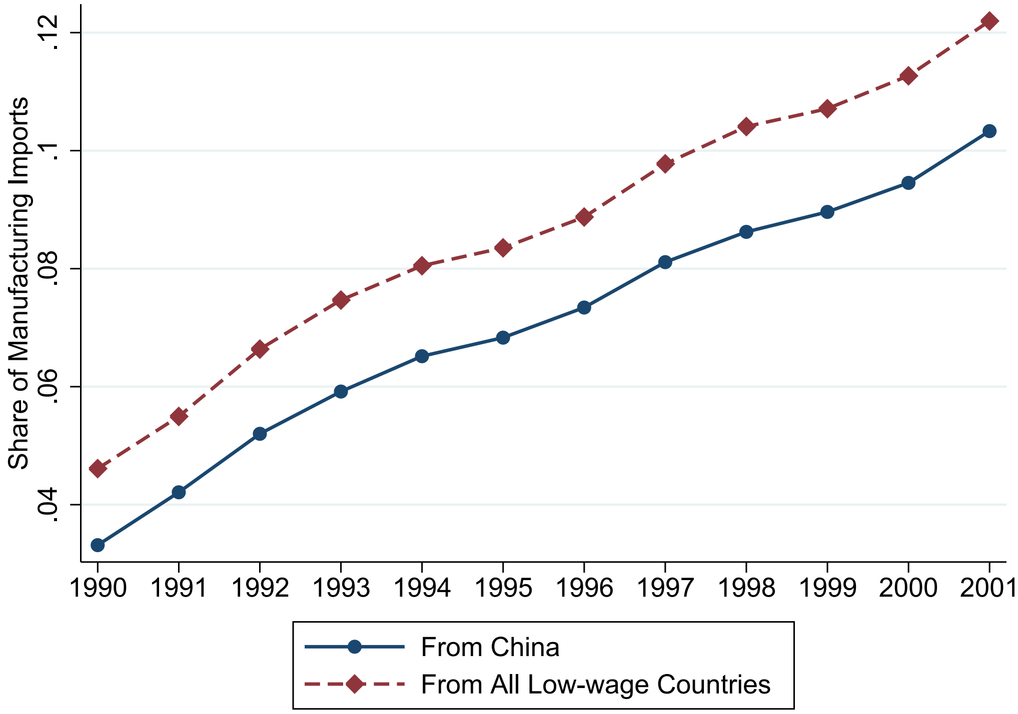

Figure 3.1: Share of Manufacturing Imports in the U.S. from China and All Low-wage Countries

low productivity. Our main finding is that there exists a robust positive relationship between exposure to imports from China and innovation of firms measured by citation-weighted patent applications. Besides baseline models with firm characteristics and fixed effects to control for other factors impacting innovation, we also employ the instrumental variable (IV) approach to deal with the potential endogeneity issues associated with adopting import penetration ratios to measure import competition from China. For example, unobserved technology shocks or policy changes can affect firms' production input, and thus change the amounts of intermediate products that they purchase from Chinese suppliers. In the same vein, technological advancements of U.S. companies can enhance their product quality or motivate them to lower prices. These favorable changes can encourage consumers to buy more domestic products instead of imported Chinese goods. Hence, the coefficient estimates from the baseline models adopting the ordinary least squares (OLS) method can be biased.

We use import penetration ratio of China to the United Kingdom (UK) as an instrument to tackle the potential endogeneity problem, since industry-level Chinese exports to the U.S. and the UK both reflect Chinese producers' competitiveness of in the particular industry, and thus strongly correlated with each other. On the other hand, the above-mentioned unobserved factors, which can affect import penetration ratios of China in the U.S., are unlikely to change UK producers' production input or alter UK consumers' preference between products made in China and elsewhere. Our IV estimation results confirm that the positive correlation between import competition from China and firm innovation persists, after the potential endogeneity problem has been addressed.

Our results also suggest that the impact of Chinese import competition varies across firms. We find that U.S. firms in low-tech and less-differentiated industries innovate more under import competition from China. These companies cannot easily differentiate their products from their competitors with lower wage costs, and thus face more intensive competition than those operate in high-tech or highly differentiated industries, even if the *measured* import penetration ratios are similar. We also find that U.S. firms with high capital intensity and low labour productivity innovate more when facing import competition from China. These companies may react faster to rising imports from low-wage countries, either due to their advantages in reallocating resources towards innovation, or because they are hit harder as less efficient domestic producers (Bloom et al., 2014).

There is a large literature suggesting that trade liberalization bolsters innovation by exporting firms (see Costantini and Melitz, 2008; Atkeson and Burstein, 2010; Lileeva and Trefler, 2010). However, it is not clear whether lowering trade barriers to import competition promotes or hinders innovation by domestic firms. Our empirical results support the argument that rising import competition from low-wage countries enhances innovation in high-wage countries. This finding is in line with a series of recent empirical studies investigating this relationship, at both the extensive and intensive margin. Higher exposure to imports from low-wage countries may reduce the relative size of labour-intensive industries (the inter-industry reallocation effect), enlarge the performance gap between high- and low-productivity firms within the same industry (the intra-industry reallocation effect), and encourage firms to produce more capital- and skill-intensive products (the within-firm reallocation effect) (Bernard et al., 2006). The inter-industry reallocation effect that favors R&D-intensive sectors is also identified by Federico (2013). Through employing data on export unit values in Italian manufacturing sectors, he shows that product quality rises as imports from low-wage countries increase in highly differentiated industries.

Both of the intra-industry and within-firm reallocation effects are further supported by plant- and firm-level evidence. For example, more productive Mexican firms are found to face less pressure to shrink under import competition from China, and are less likely to discontinue production of their core products (Iacovone et al., 2013). Focusing on Chinese import competition in Belgium, Mion and Zhu (2013) find that within-firm skill upgrading in low-tech industries, reflected by increasing shares of non-production workers and workers with tertiary education, can be attributed to growth of imports from China. Proxying innovation by the adoption of key operations management techniques, Iacovone et al. (2011) provide evidence on the intra-industry reallocation effect of Chinese import competition. They show that innovation by more productive firms has risen in response to the "China trade shock," while less productive firms innovate less.

Bloom et al. (2016) perform a more comprehensive examination of the link between Chinese import competition and innovation, based on European firm-level data. They employ a broad range of indicators including patents, total factor productivity, R&D expenses, computers per worker, and management practices, to capture firm innovation. They find that increased import competition from China does not only enlarge the performance gap in terms of employment and survival rate between high- and low-tech firms, but also contributes to the rise of innovation within surviving firms between 2000 and 2007. Their results provide evidence for the intra-industry reallocation effect of Chinese import competition that favors high-tech firms, and the positive effect on innovation at the intensive margin.

This paper is closely related to Bloom et al. (2016) in the sense that we also use patents as the main indicator of innovation, and the emphasis of our analysis is on the within-firm effect of import competition from China. However, one key difference between our work and the previous literature on this issue, including Bloom et al. (2016), is that we combine several widely recognized data sets covering firms in the United States, while others are based on either non-U.S. or more aggregated data. Although Bernard et al. (2006) also employ U.S. manufacturing plant data, they only observe plant characteristics in each census year, and industry switching can only be considered an indirect measure of the within-firm effect of import competition. Since the United States is generally considered to be one of the main technological leaders around the world, our dataset containing information on patents and financial statistics of U.S. manufacturing firms should be of particular interest. Further, we incorporate citation statistics into the computation of innovation measures, benefiting from the richness of the U.S. patent data. Through weighting patent applications by citations received in subsequent years, our approach to measure innovation takes account the fact that not all innovation is equally valuable, and thus offers another perspective to investigate the correlation between Chinese import competition and firm innovation.

The rest of this paper proceeds as follows. In Section 3.2 we briefly review theoretical literature investigating the relationship between import competition and innovation. Then we introduce the variables involved and describe the data in Section 3.3. Section 3.4 presents our empirical strategy and reports the main results, some extensions, and robustness results. Section 3.5 offers our conclusion and discussion for future work.

3.2 Theoretical Review

There are multiple models of how increase in imports from low-wage countries can stimulate firms in high-wage countries to innovate. One possible explanation to this positive correlation is that more intensive competition on domestic market, as a result of rising imports, can provide more incentives for firm innovation through amplifying the net benefit of innovation or reducing agency cost.

The other possible explanation is derived from trade models. These studies indicate that expanding imports from low-wage countries can trigger resource reallocation in high-wage countries. This mechanism encourages firms to invest in R&D, and favors growth of capital-, skill- or technology-intensive products, firms and industries.

3.2.1 Competition and Innovation

The presence of imports from abroad, including from low-wage countries such as China, is one of many forms of competitive pressure. Although the overall influence of competition on innovation is still under debate, there is a large stream of theoretical literature advocating that competition can promote innovation through two distinct channels: rise in net profits of innovation and reduction in agency cost.

3.2.1.1 Rise in Net Profits of Innovation

Arrow (1962) highlights for the first time the argument that compared with an incumbent monopolist, a firm in a competitive industry has stronger incentives to invest for cost reduction. With exclusive intellectual property rights, a competitive firm and a monopolist can realize the same amount of profits from an invention. However, the net profits of innovation are higher for the competitive firm, since it has zero legacy flow of profits generated by its market power.

The idea that new technologies partially "displace" monopoly profits and weaken monopolists' motive to innovate, which is often referred as the "replacement effect" in related literature, also contributes to the "inverted-U" relationship between competition and innovation illustrated in Aghion et al. (2005). With product market competition captured by the share of technological leader's profits attained by the follower, they prove that the incremental profits from innovation is increasing with competition, when both firms are at a similar technology level. They refer this promotional effect of competition on innovation in a neck-by-neck industry as an "escape-competition effect". With a low initial degree of competition, the transition dynamics of their model show that the industry is most likely to be in the leveled state, since the return to innovation is too low to attract investments in R&D. Therefore, increasing competition results in a faster average innovation rate under this scenario, thanks to the "escape-competition effect". On the other hand, the relationship is reversed if the product market competition is intense at the beginning.

Competition can also increase net profits from innovation through lessening opportunity cost, if adoption of new technologies involves substantial adaptation costs for employees, suppliers or clients (Holmes et al., 2012). Firms encountering these "switchover disruptions" may experience a temporary fall in output, and the foregone revenue collected from sales of these "lost" products can be viewed as additional costs of innovation. With the presence of such switchover costs, firms in a more competitive industry have greater incentive to innovate, since they face less opportunity costs due to lower product prices.

3.2.1.2 Reduction in Agency Cost

Development and adoption of new technologies often require managers to invest their personal efforts. These private costs are usually difficult to measure, and thus may not be observable by firm owners. The potential under-compensation for personal efforts may hinder managers' enthusiasm towards innovation, resulting firms under-invest in R&D.

This problem is mitigated when competition threatens firms' survival. If a firm is to be liquidated, its manager may suffer a utility loss since she loses her firm-specific human capital, and would need to incur search costs for a new job (Schmidt, 1997). When vigorous competition reduces a firm's profitability and heightens the probability of bankruptcy, the manager has to invest more for cost reduction, in order to keep the firm afloat and save her job.

Another scenario where this "threat-of-liquidation" effect of competition can stimulate innovation is when the vast majority of managers are highly impatient. With present-biased preference, these managers mainly care about keeping firms solvent and operational in the short term, and would seek to delay any costly innovation. Through the mechanism of agency cost reduction similar to that in Schmidt (1997), competition can serve as a "discipline device" to invoke technology adoption, when the market is populated by non-profit-maximizing firms controlled by "conservative" managers (Aghion et al., 1999).

Intensifying competition can also alleviate the under-investment problem, through inspiring firm owners to provide more managerial incentives for innovation. Raith (2003) shows that in an oligopolistic industry with substitutive goods, rising competition as a result of increasing product substitutability, leads to larger output of surviving firms, and thus magnifies the profit gains from marginal cost reduction. With the promising prospect, firm owners would be willing to offer managers higher compensation for firms' better performance in process innovation.

3.2.2 Trade and Innovation

It is generally accepted that trade liberalization can trigger resource reallocation and improves economic efficiency. When it comes to the impact of rising imports from low-wage countries, innovative activities in high-wage countries can be boosted through inter- and intra-industry, and within-firm reallocation effects.

3.2.2.1 Inter- and Intra-industry Reallocation Effect

The classical Heckscher-Ohlin model implies that in North-South trade, the developed countries mainly import labour-intensive products from less-developed economies. With high exposure to import competition from low-wage countries, firms in labour-intensive industries have a lower likelihood of survival than those in capital- and technology-intensive industries (see Bernard et al., 2006). Due to the fact that capital- and technology-intensive industries have generally greater R&D intensity, expansion of these industries can result in higher overall level of innovation in developed economies.

The intra-industry reallocation effects of trade liberalization introduced in Melitz (2003) and Bernard et al. (2003) also shed light on this topic. The main implication of their models is that within a single industry, firms with higher productivity have better chances to enter export markets. Through a similar selection process to determine players in the domestic market, increased exposure to import competition can also eliminate the less productive firms (see Holmes and Stevens, 2014). The industry average innovation rate is raised as a result of increasing competition from low-wage countries, since the more productive firms survive and they are more likely to innovate.

3.2.2.2 Within-firm Reallocation Effect

It is common for firms to produce a large variety of products that are different and even unrelated. These multi-product firms can be considered as being operating in multiple disaggregated industries. When numerous goods from low-wage countries flow into domestic market, these firms may alter their product mix towards technologically more advanced products to avoid the rapidly ascending competition (see Bernard et al., 2006, 2011). As firms switch to skill- and technology-intensive industries, the heightened importance of advanced technology motivates them to innovate.

The opportunity cost of this within-firm resource reallocation can be substantial, when manufacture of old products requires specific know-how that is difficult to transfer to other fields. The high adjustment cost hinders firms to reallocate factors to new product development. However, a surge in imports of goods similar to the old products can change the situation. If the old products become unprofitable due to import competition, firms will be more willing to shift resources into developing and producing new products (Bloom et al., 2014).[2]

The innovation-enhancing reallocation can also be achieved for firms in high-wage economies, through outsourcing the labour-intensive procedures in the production process. Rising import competition from low-wage countries often accompanies a fall in trade costs, such as a decline in transport costs or a reduction in import tariffs. Observing that, firms in high-wage countries can save costs through offshoring more low-skill tasks to these trade partners, or using cheaper, labour-intensive intermediate inputs. With the higher revenue led by cost reduction, the return to innovation goes up if marginal return to productivity gains increases with firm revenue. Then firms are motivated to incur a fixed R&D cost (Bøler et al., 2012), or to release the resources that can be reallocated for innovative activities (see Glass and Saggi, 2001; Naghavi and Ottaviano, 2009). This so-called "productivity effect" of outsourcing may induce R&D intensity in high-wage countries

[2] Calibration results of the model in Bloom et al. (2014) indicate that integration with low-wage countries contributes to additional 0.4 percentage of annual growth rate of the OECD countries during 1997 to 2006.

to increase, while the same indicator is decreasing in low-wage countries (Rodríguez-Clare, 2010). As this trend develops further, multinational production may eventually lead to a scenario in which firms in developed countries specialize in innovation, while firms in less-developed economies undertake production (Arkolakis et al., 2013).

3.3 Data and Variables

We combine several publicly available datasets, including the NBER patent and citation dataset (see Hall et al., 2001), the Standard and Poor's Compustat North America database, and the U.S. Manufacturing Exports and Imports dataset (see Schott, 2010) to construct our key variables. The NBER patent and citation dataset covers a substantial part of patents awarded to U.S. listed companies between 1976 and 2006. Patents in the NBER dataset were granted by the United States Patent and Trademark Office (USPTO) to single or multiple assignees, which can be linked with listed companies in the Compustat North America database. We also extract annual financial indicators of these publicly held companies from Compustat, since each of them is assigned with a unique identifier in the database. In addition to an illustration of the data, in the last subsection we provide sample statistics of these key variables and other firm specific factors potentially related to innovation.

3.3.1 Innovation

We use annual number of patent applications as the main indicator of firm innovation. To reflect the heterogeneity in significance (or "quality") of innovation, we weight every patent by the number of citations it receives (Griliches, 1990). In order for our work to be comparable with previous studies such as Bloom et al. (2016), we also include the unweighted patent application counts as an additional indicator.[3]

For each recorded patent, the NBER patent and citation dataset provides detailed information including application and grant year, Compustat identifier(s) of the assignee(s), as well as citations made and received. By employing the NBER dataset, we are able to calculate the citation-weighted and unweighted counts of patent applications by each patent assignee, in every year during the 1990 to 2001 period.[4] Note that we set 1990 as the start year due to the availability of data on import penetration ratio of China in the UK, which are used to construct our instrumental variable and will be discussed later. On the other hand, the end year has to be set as 2001. The reason is that the NBER patent and citation dataset ends in 2006, while we assume there exists a two-year lag between application and granting of each patent, and collect citations received

[3] Another interesting perspective is to study the impact of import competition on the "basicness" of firm innovation, using measures such as generality indices proposed in Trajtenberg et al. (1997) and Hall and Ziedonis (2001b). Liu and Rosell (2013) employed this strategy and found a negative correlation between import competition and innovation basicness.

[4] It is possible for USPTO to assign one patent application to multiple assignees. We follow common practice and attribute patents with multiple listed inventors to the principal assignee and ignores the others. This approach limits the coverage of the dataset but avoids double-counting of patents.

within three years after the granting year of cited patents. We make these assumptions because that the gaps between the application and the granting years of patents in the NBER dataset average about two years (Hall et al., 2001), and because we compare citations received in a relatively short time window to keep our sample period longer than a decade.[5]

3.3.2 Import Competition from China

To measure import competition from China faced by U.S. firms, we follow the generally adopted approach in Bernard et al. (2006), and construct import penetration ratio of China in industry j at year t as below:

$$ImportPen_{j,t} = \frac{M_{j,t}^{C}}{Q_{j,t} + M_{j,t} - X_{j,t}},$$

where $M_{j,t}^{C}$ represents the value of imports from mainland China to the U.S. in industry j at year t, $M_{j,t}$ represents the value of imports from all countries including China, $Q_{j,t}$ stands for the value of shipments produced domestically, and $X_{j,t}$ represents the value of exports in industry j at year t.

We extract data on imports, exports and shipments from the U.S. Manufacturing Exports and Imports dataset, which can be downloaded from Peter Schott's International Economics Resource Page. The latest version of this dataset tracks U.S. bilateral trade statistics between 1972 and 2005. The export and import data are available for each partner country at the four-digit 1987-version U.S. Standard Industry Classification (SIC87 codes 2011 through 3999) industry level. The dataset also includes value of domestic shipments for each industry and GDP per capita for each trading partner during the same period. Since each firm in the Compustat database is assigned with one four-digit U.S. SIC87 industry code, it is straightforward to derive the firm-level import penetration ratio of China from the above industry-level index. Given that the manufacturing sector consists of 342 four-digit SIC87 industries, there exist sufficient variations across industries for us to explore the correlation between import penetration ratios and firm performance.

As shown in Figure 3.2, import competition from China has increased remarkably from 1990 to 2001. The average import penetration ratio of China across all 4-digit SIC87 U.S. manufacturing industries was only less than 1.3% in 1990, while by 2001 this figure had almost quadrupled to over 5.0%. The three industries with most intensive import competition from China in 2001 are dolls and stuffed toys (with an import penetration ratio of 89%), footwear except rubber (78%), and rubber and plastic footwear (68%). Meanwhile, Chinese import penetration ratios are close to zero in many industries, such as natural, processed and imitation cheese, wood pallets and skids, truck and bus bodies, etc.

5 Because our sample period is limited to 1990–2001, we minimize the truncation issue discussed in Lerner and Seru (2015), which is sometimes associated with using the NBER patent and citation dataset. The other issues discussed in Lerner and Seru (2015), such as the disparity in patent filings across industries and regions, are addressed though including firm and year fixed effects in our estimations.

On the other hand, the three industries with largest rise in the indicator from 1990 to 2001 are footwear except rubber (72 percentage-point increase), leather and sheep-lined clothing (62 percentage-point increase), waterproof outerwear (48 percentage-point increase). More generally, ten of eleven industries that have experienced more than 30 percentage-point increase in Chinese import penetration fall within the textile and toy sector. On average, there are about 868 firms applying for approximately 17,658 patents each year, while the average of citation-weighted number reduces to about 15,871 annually.

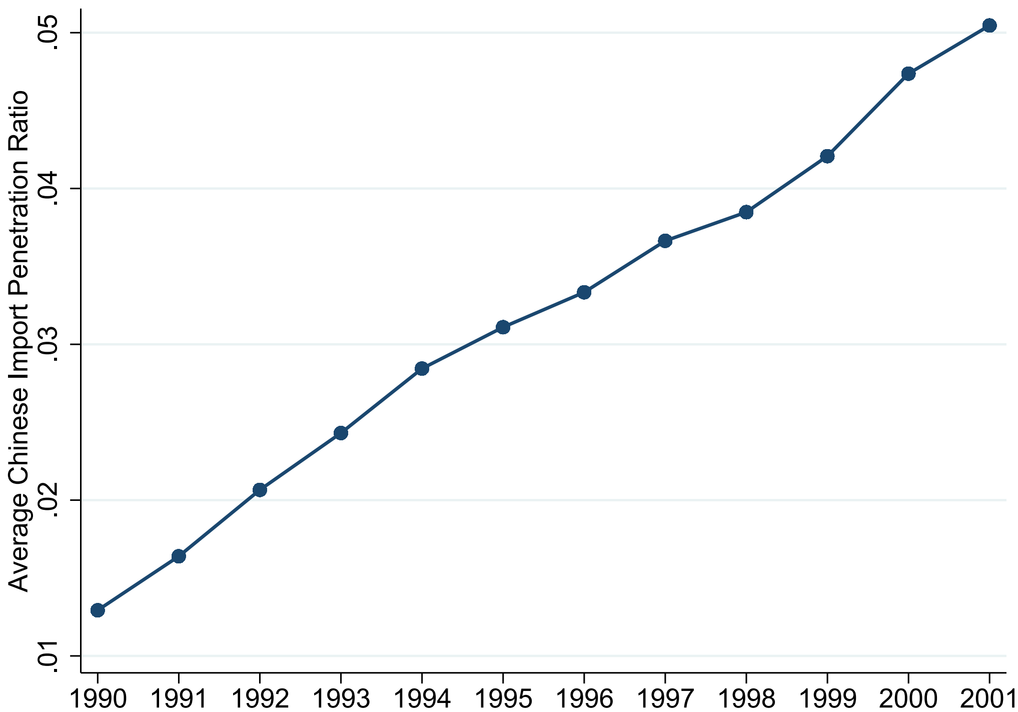

Figure 3.2: Average Import Penetration Ratio of China across U.S. Manufacturing Industries

3.3.3 Other Firm Specific Variables

As summarized in Cohen (2010b), empirical studies on innovation usually link innovation performance with size and other firm-specific characteristics. Following Link and Long (1981), Link (1982), Hall and Ziedonis (2001a), and Yanadori and Cui (2013), we attribute firms' R&D intensity, prior innovation performance, size, capital intensity and profitability as five factors other than import competition to affect firm innovation. We extract R&D expenditure for each firm directly from the Compustat North America database, then divide it by annual net sales to compute R&D intensity. Firms' prior innovation performance is represented by their patent stocks, computed by summing up their patent applications in the past five years in the NBER patent dataset.[6] Firm size and profitability are proxied by the number of employees and the net operating income respectively. We define capital intensity as the ratio of the value of plants, property and equipments to the number of employees. The last three firm-specific variables are also constructed through using financial statistics in the Compustat database.

3.3.4 Descriptive Statistics

We link firms in the Compustat database to the NBER patent data, following the procedures described in the "Matching Patent Data to Compustat Firms" file provided by the NBER Patent Data Project. With this file we can compute the number of patent application counts for each listed company, by matching patent assignee numbers in the NBER patent and citation dataset with firm identifiers in the Compustat database.. In our baseline model, we consider two sets of Compustat firms. The *narrow* sample only contains firms that were granted at least one patent between 1976 and 2006. The *main* sample includes firms in the narrow sample, and those identified not being granted any patent during the same thirty-year period by the NBER Patent Data Project.

We present the basic descriptive statistics of our main sample in Table 3.1. Our matched firms are large public U.S. firms. The size of these firms is indicated by their average number of employees and profits. They also invest large amounts in R&D and on average they applied for about 23 patents per year between 1990 and 2001.

The number of unweighted patent applications increased steadily from 14,393 in 1990 to 26,087 in 2001, while the number of citation-weighted patent applications in 2001 also peaked at 21,919, more than twice as many as the number in 1990. Based on the means and stand errors of the key variables, as presented in Table 3.1, we can tell that the firms in our main sample show plenty of heterogeneity in innovation performance and financial statistics. Given the characteristics of these firms it is clear that we can only speak to how imports affect the innovation activity of typically large, publicly traded companies. This has been a common caveat of studies using the Compustat/NBER dataset (e.g. Bloom et al., 2010). However, because these firms are very active in innovation, these data allow us to infer what happens to a large segment of R&D activity and the majority of successful patent applications.

3.4 Empirical results

Our empirical models investigate the relationship between import competition from China and firm innovation proxied by patent applications. The baseline regressions examine the overall within-firm effect of import

[6] As suggested by theoretical studies including Melitz (2003), productivity can be an important factor for innovation, and is thus strongly correlated with firms' prior innovation performance. I also experimented using labour productivity, defined as sales over the number of employees, to replace patent stocks in the main specifications and obtained similar results.

Table 3.1: Descriptive Statistics

Variable	Obs	Mean	S.D.	Min	Max
Innovation					
Patent Applications	10,419	22.84	94.42	0	2350
Citation-weighted Patent Applications	10,419	18.28	75.77	0	1376
Import Competition					
Import Penetration Ratio of China	10,419	0.02	0.05	0	0.89
Firm Characteristics					
R&D Intensity	10,419	0.05	0.06	0	1.45
Patent Stock (past five years)	10,419	96.63	381.05	0	6406
No. of Employees (thousands)	10,419	9.38	32.57	0	761.4
Capital Intensity (US$ millions)	10,419	50.25	87.39	0.2	3277
Net Operating Income (US$ millions)	10,419	243.67	1,007.55	0	21658

competition from China, while the heterogeneous responses across industries and firms are discussed in the subsequent analyses. We start with introducing the empirical modeling strategy employed in the baseline regressions, and presenting the main empirical results from the fixed effects and the instrumental variable (IV) specifications. Then we explore several dimensions in which the effect of import competition on innovation may differ, and present these estimation results in addition to our main findings. We also show that our findings are robust against various changes to the baseline specifications.

3.4.1 Baseline Model

We consider the level of innovative activities conducted by firm i in industry j at year t to be

$$\ln Innovation_{i,j,t} = \alpha + \beta\, ImportPen_{j,t-1} + \gamma X_{i,t-1} + \sum_{Firm} \phi_{Firm}\, I(Firm) + \sum_{Year} \phi_{Year}\, I(Year) + \varepsilon_{i,j,t}. \quad (3.1)$$

In our baseline regressions we use the natural logarithm of unweighted and citation-weighted patent application counts to index *Innovation*. [7] $ImportPen_{j,t-1}$ represents Chinese import penetration ration in industry j at year $t-1$, and thus measures the level of import competition from China that firm i experiences at year $t-1$. $X_{i,t-1}$ controls for firm characteristics that are related to innovation performance. As detailed in Section 3.3, these control variables include $R\&D\ Intensity_{i,t-1}$, the log levels of $Patent\ Stock_{i,t-1}$, $Number\ of\ Employees_{i,t-1}$, $Capital\ Intensity_{i,t-1}$, and $Net\ Operating\ Income_{i,t-1}$. We lag the independent variables by one year to reflect the fact that import competition from China, along with other firm-specific factors, do not hold an contemporaneous impact on innovation. We also experiment alternative lag-lengths,

[7] Since the numbers of patent applications are non-negative integers, an alternative approach is to estimate the main model using negative binomial specifications. The corresponding regression results are qualitatively consistent with main results generated from the log-linear specifications. In addition, the counts of patent applications are two variables with many zeros. Thus we add one to the value of each variable when we are taking natural logarithms. This method is in line with the previous literature such as Bloom et al. (2016).

such as using contemporaneous and two-year lagged independent variables. The corresponding robustness results presented in Section 3.4.5 are consistent with our main findings.

To eliminate any potential impacts of time-invariant and firm-specific characteristics on innovation, we add a set of dummy variables $\{I(Firm)\}$ to our baseline equation. Consequently, we only explore within-firm variation to examine the relationship between Chinese import competition and innovation. We also control for time-varying and year-specific effects that are homogeneous across firms, by adding the set of dummy variables $\{I(Year)\}$. These dummy variables are needed to control for general changes in the economy or the patent system that affect measured innovative activities. The coefficient of interest in Equation (3.1) is β, since previous literature reviewed in Section 3.2 predicts a positive correlation between import competition from China and firm innovation.

3.4.2 Baseline Results

Table 3.2 presents the OLS estimates of coefficients in Equation (3.1), with all columns controlling for firm and year fixed effects. To correct for industry-wide and year-specific shocks uncorrelated with the error term $\varepsilon_{i,j,t}$ and other right-hand-side (RHS) variables, standard errors in in Table 3.2 are two-way clustered by 4-digit SIC87 industry and year. Coefficient estimates with unweighted patent applications as the dependent variables are shown in columns (1) and (2), while citation-weighted patent counts are used as the dependent variables to generate results in columns (3) and (4). The results can also be grouped according to sample type: columns (1) and (3) show results for the narrow sample, which only includes firms awarded at least one patent between 1976 and 2006; results for the main sample, which covers firms with and without successful patent applications during the same period, are listed in columns (2) and (4).

When all patents are viewed as equally valuable, as in columns (1) and (2), the coefficient estimates suggest that Chinese import competition seems to have an insignificant impact on firm innovation. However, the coefficients of import penetration ratios turn positive and significant at 5% level, after patents are weighted by the number of citations received. In particular, the coefficients for the main sample suggest that a 1 percentage point increase in import penetration from China raises citation-weighted patent applications of a firm by 1.35%, while this effect increases to 1.56% if only patenters between 1976 and 2006 are included in the analysis. Overall, these baseline results provide support to the argument that import competition from China fosters innovation by U.S. manufacturing firms, when innovation is weighted by its influence.

Different from Bloom et al. (2016), which finds a consistent positive relationship between Chinese import penetration and firm innovation, our baseline results indicate that the effect may be different for different types of innovation. Through comparing the estimation results on unweighted and citation-weighted patent applications, we find that the positive impact of Chinese import competition on firm innovation biases towards those with higher influence and market value.

Table 3.2: Baseline Results: Patent Applications of Firms and Import Penetration from China

	Unweighted		Citation-weighted	
Independent Variables	(1) Narrow Sample	(2) Main Sample	(3) Narrow Sample	(4) Main Sample
Import Penetration	0.912	0.755	1.563**	1.351**
	(0.711)	(0.611)	(0.774)	(0.669)
R&D Intensity	0.804***	0.784***	0.777**	0.669**
	(0.298)	(0.285)	(0.342)	(0.298)
Patent Stock	0.160***	0.163***	0.133**	0.136**
	(0.061)	(0.061)	(0.056)	(0.056)
Log(*No. of Employees*)	0.159***	0.149***	0.172***	0.151***
	(0.052)	(0.049)	(0.055)	(0.049)
Log(*Capital Intensity*)	0.130***	0.118***	0.134***	0.122***
	(0.046)	(0.043)	(0.048)	(0.045)
Log(*Net Operating Income*)	0.057***	0.055***	0.062***	0.058***
	(0.017)	(0.015)	(0.016)	(0.015)
Number of Firms	1,136	1,228	1,104	1,228
Observations	7,435	7,844	7,248	7,844

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. All regressions include firm and year fixed effects. Standard errors are clustered by industry and year.

3.4.3 Endogeneity

A problem with adopting Chinese import penetration to measure import competition is its potential endogeneity. For example, unobserved technology or policy shocks can affect firm innovative activities, and motivate them to produce goods requiring more (or less) intermediate input from China. Improvements of product quality or price drops due to technological advancements of U.S. firms can encourage consumers to buy more domestic products, and thus reduces imports from China. The coefficient estimates from the OLS regressions can be biased with the presence of these issues.

We consider the instrumental variable (IV) approach to deal with the endogeneity issue, and choose Chinese import penetration to the UK as a plausible instrument following Lu and Ng (2013). Our contention for implementing this strategy is that import penetration ratios of China in the U.S. and the UK in a similar industry tend to fluctuate in the same direction, since they both reflect the commercial competitiveness of Chinese producers in that particular sector. Meanwhile, the unobserved factors correlated with market share of Chinese goods in the U.S. market, such as unobserved technology and policy shocks in the U.S., are unlikely to alter consumers' choice between Chinese and non-Chinese products in the UK market.

We denote the import penetration ratio of China in UK industry j at year t as $ImpUK_{j,t}$ and construct it as below:

$$ImpUK_{j,t} = \frac{M^C_{j,t}}{Q_{j,t} + M_{j,t} - X_{j,t}}.$$

Similar to their counterparts in $ImportPen_{j,t}$, $M^C_{j,t}$ in the above equation represents the value of imports from mainland China to the UK in industry j at year t. $M_{j,t}$, $Q_{j,t}$ and $X_{j,t}$ represent the values of overall import, domestic production and overall export of UK in industry i at year t.

Similar to how we obtain Chinese import penetration ratios in the U.S., we construct $ImpUK_{j,t}$ for each 2-digit U.S. SIC87 industry between 1990 and 2001, by substituting export, import and domestic production data from the Structural Analysis (STAN) database into the above equation. A noticeable fact is that the simple correlation between $ImportPen_{j,t}$ and $ImpUK_{j,t}$ is approximately 0.41.

The coefficient estimates generated by the two-stage least squares (2SLS) approach are given in Table 3.3. Results presented in columns (1) and (2) indicate that Chinese import penetration has insignificant impact on simple count of firms' patent applications, after the potential endogeneity issue is being addressed. Columns (3) and (4) show that coefficients on import penetration ratio of China are positive and significant at 10% level, when citation-weighted patent counts are employed as the measure of firm innovation. These results are consistent with the fixed effects results, and also imply that import competition from China stimulates firms to conduct innovation of greater influence and market value.

Coefficient for the main sample shown in column (4) suggests that a 1 percentage point increase in import penetration from China raises citation-weighted patent applications of a representative firm by

6.71%. Compared with the baseline fixed effects results, the coefficients on import penetration turn to be significantly larger in the results from the IV specifications. This increase in magnitude of the IV coefficient estimates is also noticed by Lu and Ng (2013) and Autor et al. (2013). They infer that one of the main reasons is that OLS estimates may suffer from attenuation bias led by measurement errors in disaggregated trade data. Although the U.S. Manufacturing Exports and Imports dataset is comprehensive and carefully constructed, it is unlikely for the data to be free of measurement errors, especially given the fact that "the aggregation of import value at the ten-digit HS product level to the industry level is fundamentally tricky" (Lu and Ng, 2013, p. 1409). In addition, the previously mentioned omitted variable and reversed causality issues can also lead to downward bias in OLS estimates of β. For example, if both firm innovation and imports from China are positively correlated with unobserved shocks to the U.S. market, the OLS estimate of how rising Chinese import penetration affect innovation of U.S. manufacturing firms may understate the true impact. Thus, the increase in the estimated magnitude of positive effect meets the prediction of econometric theory and is in line with previous studies.

Based on the "rule of thumb" indicated in Staiger and Stock (1997) and Baum et al. (2007), weak identification should not be considered a problem in the IV specifications, when the F statistics of first-stage regressions are larger than 10. The weak identification test statistics for all specifications in Table 3.3 are larger than 10. Based on the detailed first-stage estimation results presented in Table C.1, the correlation between import penetration ratios of China in the U.S. and the UK markets are significant and positive. In general, we can tell that Chinese import penetration to the UK is not a weak instrument in our analysis.

3.4.4 Heterogeneous Effects of Chinese Import Competition

We have so far shown a positive and significant impact of Chinese import penetration on firm innovation, when patents are weighted by citations received. In this subsection, we investigate if the effect varies across industries and firms. We start with comparing firm responses to import competition from China in sectors differing in technology intensity and the scope of quality differentiation. The we proceed to discuss if firm characteristics, such as capital intensity and labour productivity, can change how innovation responds to Chinese import competition.

3.4.4.1 Industries Characteristics and Effects of Chinese Import Competition

Given the low technology intensity of products in labour-intensive industries industries, goods produced by domestic firms can be easily substituted by those shipped from low-wage countries. Therefore, when imports from low-wage producers increase, firms operating in these low-tech, labour-intensive industries experience more intensive competition than those in high-tech sectors, even if the computed import penetration ratios are similar across sectors. Besides technology intensity, manufacturing industries also differ in other

Table 3.3: Endogeneity Results: Chinese Import Penetration in the UK as an IV

	Unweighted		Citation-weighted	
	(1) Narrow Sample	(2) Main Sample	(3) Narrow Sample	(4) Main Sample
Independent Variables				
Import Penetration	4.495	4.039	7.675*	6.713*
	(3.509)	(3.157)	(4.075)	(3.705)
R&D Intensity	0.785***	0.769***	0.747**	0.645**
	(0.289)	(0.279)	(0.336)	(0.292)
Patent Stock	0.160***	0.163***	0.131**	0.134**
	(0.061)	(0.061)	(0.056)	(0.055)
Log(*No. of Employees*)	0.150***	0.142***	0.156***	0.140***
	(0.052)	(0.049)	(0.055)	(0.050)
Log(*Capital Intensity*)	0.138***	0.125***	0.148***	0.134***
	(0.049)	(0.045)	(0.053)	(0.049)
Log(*Net Operating Income*)	0.060***	0.058***	0.067***	0.063***
	(0.019)	(0.017)	(0.019)	(0.017)
Endogeneity C Statistic	1.077	1.204	2.066	2.187
p-value	0.299	0.273	0.151	0.139
K-P Weak ID F Statistic	20.40	16.58	19.83	16.55
Number of Firms	1,136	1,228	1,104	1,228
Observations	7,435	7,844	7,248	7,844

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. All regressions include firm and year fixed effects. Standard errors are clustered by industry and year.

dimensions that can affect how firms respond to import competition from low-wage countries, One important characteristic proposed by Khandelwal (2010) is the scope of quality differentiation, or their "quality ladders" (p. 3). In industries with short quality ladders, firms are more vulnerable to competition from low-wage countries, since their current products cannot differentiate from their competitors with lower wage cost. Therefore, firms in low-tech, less-differentiated industries are more likely to innovate, and upgrade their product quality to insulate themselves from import competition.[8]

To check if firms in low-tech industries innovate more when Chinese import competition rises, we classify all the 4-digit U.S. SIC87 industries into low- and high-tech sectors, and estimate our baseline model on firms in each sector separately. Following the industry classification method proposed by Chandler (1994) and Hall and Vopel (1997), we partition the U.S. manufacturing sector into the low- and high-tech sectors, and link each of them to a group of 4-digit U.S. SIC87 industries. The high-tech sector in our study includes the same list of industries as in Hall and Vopel (1997), whereas the low-tech sector contains both low- and stable-tech sectors, in which average R&D intensities of firms are substantially lower than in the high-tech sector. Then we are able to divide our data into two sub-samples, one with firms in the low-tech sector and the other with firms in the high-tech sector.

Estimation results for Equation (3.1) for the two sub-samples are given in Table 3.4. We can confirm that firms in low-tech industries were more motivated to innovate, since the coefficients for Chinese import competition are positive and significant at 5% level, when innovation is proxied by citation-weighted patent applications. On the other hand, none of the corresponding coefficients for firms in high-tech industries is significant even at 10% level. This fact implies that innovation of firms in high-tech industries seems to be unaffected by the surge in imports from China, while firms in low-tech industries are stimulated to perform better in innovation.

To examine if Chinese import competition triggers more innovation of firms in less-differentiated industries, we classify all the 4-digit U.S. SIC87 industries into two sectors based on quality ladder measures calculated by Khandelwal (2010). We attribute industries with quality ladder measures lower than the median into the short-ladder sector, in which their products are unlikely to differentiate from goods produced by low-wage exporters in terms of quality. Industries with quality ladder measures higher than the median are attributed into the long-ladder sector. Hence, we again divide our dataset into two sub-samples based on industry characteristics: one sub-sample contains firms in the short-ladder sector, while the other contains firms in the long-ladder sector.

We report estimation results for Equation (3.1) for the two sub-samples in Table 3.5. The results indicate that firm innovation in the short-ladder sector were stimulated under Chinese import competition, since three

[8] Another way to escape from competition is to alter their product mix and switch to less-affected industries. These patterns are studied in Bernard et al. (2006) and Bernard et al. (2011).

Table 3.4: Heterogeneous Effects of Chinese Import Penetration across Low- and High-tech Industries

	Unweighted		Citation-weighted	
	(1)	(2)	(3)	(4)
	Narrow	Main	Narrow	Main
Independent Variables	Sample	Sample	Sample	Sample
	Panel A: firms in the low-tech sector			
Import Penetration	1.112	0.867	1.660**	1.390**
	(0.751)	(0.617)	(0.802)	(0.662)
Number of Firms	495	534	481	534
Observations	3,454	3,627	3,346	3,627
	Panel B: firms in the high-tech sector			
Import Penetration	0.288	0.341	1.160	1.151
	(1.825)	(1.773)	(1.945)	(1.849)
Number of Firms	641	694	623	694
Observations	3,981	4,217	3,902	4,217

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. All regressions include firm and year fixed effects. Standard errors are clustered by industry and year.

of the coefficients for this sub-sample are positive and significant at least at 10% level. The insignificant coefficients for the long-ladder sector suggest that firms in these more vertically differentiated industries did not innovate more to deal with competition. In general, our results suggest that the positive impact on firm innovation is more evident in industries featured either with low technology intensity or low quality differentiation, and thus facing more direct competition from low-wage countries.

3.4.4.2 Firm Characteristics and Effects of Chinese Import Competition

Besides the technology intensity of their main industries and the quality of their products, firms may differ in many other dimensions and thus vary in innovative activities spurred by import competition. For instance, if factors are "trapped" in production of old products as illustrated in Bloom et al. (2014), and the adjustment cost of within-firm reallocation is higher for labour than for capital, firms with higher capital intensity may experience less friction in shifting resources towards development and production of new products. On the other hand, firms with lower labour productivity may be hit harder by increasing imports from low-wage countries, as these less efficient producers cannot afford loss in revenues. In these cases, capital-intensive producers and less productive firms have greater incentives to innovate under import competition from low-wage countries.

To examine if capital intensity affects how firms adjust their innovative activities under Chinese import competition, we split the observations in our dataset into two sub-samples: one contains those with capital

Table 3.5: Heterogeneous Effects of Chinese Import Penetration across Short- and Long-ladder Industries

	Unweighted		Citation-weighted	
Independent Variables	(1) Narrow Sample	(2) Main Sample	(3) Narrow Sample	(4) Main Sample
	Panel A: firms in the short-ladder sector			
Import Penetration	1.170*	0.931	1.808**	1.517**
	(0.709)	(0.604)	(0.867)	(0.736)
Number of Firms	597	633	578	633
Observations	3,855	4,035	3,746	4,035
	Panel B: firms in the long-ladder sector			
Import Penetration	0.255	0.315	0.927	0.909
	(1.926)	(1.900)	(1.850)	(1.812)
Number of Firms	517	567	505	567
Observations	3,427	3,628	3,353	3,628

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. All regressions include firm and year fixed effects. Standard errors are clustered by industry and year.

intensity lower than the median of this indicator, and the other contains those with higher-than-median capital intensity. As shown in Table 3.6, the coefficients for firms with higher-than-median capital intensity are positive and significant at least at 10% level while others are insignificant, indicating that capital intensive firms are stimulated to apply for more patents when Chinese import competition increases.

Now we proceed to discuss how firm responses differ according to their productivity. We define labour productivity as the ratio of net sales to number of employees, and divide our data into two sub-samples based on the median of this variable: one contains those with lower-than-median labour productivity, and the other contains those with higher-than-median labour productivity. Our previous discussion suggests stronger and more significant impacts of Chinese import penetration for firms with lower labour productivity. Base on estimate results of Equation (3.1) for the two sub-samples in Table 3.7, we can conclude that this argument is supported when patent applications are weighted by citations receive, since coefficients in columns (3) and (4) are positive and significant at 5% level while others are insignificant.

3.4.5 Robustness Results

A concern with our baseline results is that the positive effects on firm innovation may not be achieved by import competition from low-wage countries as a whole. Another concern is that import competition from developed countries can also motivate firms to innovate. From Figure 3.1 we can tell that along with a sharp rise in imports from China, the share of imports in the U.S. from non-Chinese low-wage countries

Table 3.6: Heterogeneous Effects across Firms with Low- and High-Capital Intensity

	Unweighted		Citation-weighted	
Independent Variables	(1) Narrow Sample	(2) Main Sample	(3) Narrow Sample	(4) Main Sample
	Panel A: firms with capital intensity lower than median			
Import Penetration	0.875	0.613	1.186	0.921
	(0.847)	(0.690)	(0.836)	(0.676)
Number of Firms	642	697	625	697
Observations	3,384	3,608	3,294	3,608
	Panel B: firms with capital intensity lower than median			
Import Penetration	2.407*	2.488**	3.429**	3.378**
	(1.283)	(1.265)	(1.471)	(1.407)
Number of Firms	658	697	640	697
Observations	3,920	4,094	3,826	4,094

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. All regressions include firm and year fixed effects. Standard errors are clustered by industry and year.

Table 3.7: Heterogeneous Effects across Firms with Differences in Labour Productivity

	Unweighted		Citation-weighted	
Independent Variables	(1) Narrow Sample	(2) Main Sample	(3) Narrow Sample	(4) Main Sample
	Panel A: firms with productivity lower than median			
Import Penetration	1.187	0.833	1.746**	1.301**
	(0.790)	(0.634)	(0.753)	(0.643)
Number of Firms	645	696	626	696
Observations	3,503	3,704	3,401	3,704
	Panel B: firms with productivity higher than median			
Import Penetration	0.810	0.783	1.426	1.402
	(0.945)	(0.868)	(1.212)	(1.115)
Number of Firms	696	743	681	743
Observations	3,723	3,916	3,648	3,916

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. All regressions include firm and year fixed effects. Standard errors are clustered by industry and year.

has only slightly increased from 1990 to 2001. Table C.2 compares the estimate results of Equation (3.1) by employing import penetration of China, all low-wage countries and OECD members (those joined before 1990) respectively.[9]

All of the coefficients for the import penetration ratio of all low-wage countries are positive and significant at 5% level, when patent counts are weighted by citations received to proxy firm innovation. Therefore, we infer that import competition from low-wage countries can be represented by import penetration of China in the U.S. market. On the other hand, coefficients for import competition from OECD members are negative and significant at least at 10% level. This fact indicates that import competition from low-wage countries enhances firm innovation in U.S. manufacturing industries, while competition from OECD members weakens firm innovation performance in the U.S.

We also check the robustness to our baseline results by re-estimating a negative binomial fixed effects model with similar RHS variables. Results presented in Table C.4 show that all coefficients on Chinese import penetration ratios are positive and significant at 1% level. Coefficients in column (4) indicate that a 1 percentage point increase in import penetration from China stimulates a representative firm to apply for 2.5 more citation-weighted patents. This measured effect is even larger than that implied in the IV results.

We also experiment various lag lengths for import penetration ratios of China and other firm characteristics, and present the results in Table C.5 The signs and significance of coefficients in Table C.5 show the same pattern as in Table 3.2: the coefficients for Chinese import penetration ratios are positive and significant at 10% level in columns (3) and (4), while those in columns (1) and (2) are insignificant. Consistent with the baseline results, these results suggest that innovation increases with Chinese import competition, when it is measured by citation-weighted patent applications.

To further check whether the impact of import competition from China on innovation varies across different measures of innovation, we use R&D expenditure as an alternative dependent variable and re-estimate the main equations with the same RHS variables except $R\&D\ intensity_{i,t-1}$. Columns (1) and (2) contain the fixed effects results for the narrow and main samples respectively, while IV results for the two samples are included in columns (3) and (4). All of the coefficients on import penetration ratios of China are positive and significant at 5% level. In addition, import penetration ratios of China in the UK are not weak instruments in the IV estimations, as suggested by the F statistics in columns (3) and (4). To summarize, results from these sensitivity tests indicate that our main findings are robust against changes in model specifications.

[9] We also experiment adding import penetration ratios of OECD members as an additional control variable. The results are presented in Table C.3 and are consistent with those in Table C.2.

3.5 Conclusion

Our results provide evidence of a positive impact of import competition from low-wage countries, such as China, on U.S. manufacturing firms' innovative activities. In particular, the positive impact of Chinese import competition on innovation is stronger for firms in low-tech or less-differentiated industries, which are characterized by comparatively high substitutability between goods produced by domestic firms and Chinese competitors. We also find the effect to be stronger for firms with high capital intensity or low labour productivity, since these firms are either more likely to adjust sufficiently quickly , or experiencing greater disadvantages when facing increased import competition from low-wage exporters.

This paper contributes to the literature on import competition and innovation in the following ways. First, we confirm that import competition from low-wage countries encourages patent applications of U.S. manufacturing firms, while other studies either use non-U.S. or industry-level U.S. data, or adopt less direct measures of innovation performance. Due to U.S. firms' significant influence in technological changes around the world, our finding based on firm-level U.S. data should be of particular interest.

Second, we find that the positive impact of import competition is significant when patents are weighted by citations received, but insignificant for simple count of patent applications. This finding is different from previous studies including Bloom et al. (2016), indicating that firms are incentivized to invest for innovation with greater returns and thus usually associated with higher risks. One possible explanation is in line with the agency-cost-reduction rationale reviewed in Section 3.2: managers of firms experiencing great profit loss due to intensive competition from low-wage producers, likely those in low-tech or less-differentiated industries, may be tempted to take higher risks in return of possible quality upgrade in the future.

Finally, results in this paper show that impacts of import competition from low-wage countries vary across industries and firms with different characteristics. The key motivation for this paper is that trade openness and innovation are both important for growth and welfare. Hence, finding firms' innovation performance improves in relative terms with increased import competition from low-wage countries is suggestive. Despite the generally positive effect of import competition, policy makers may need to contemplate the unequal impacts on different firms and industries in considering the outcomes of free trade policies. Consequently, in order to attain optimal levels of innovation in various sectors, domestic innovation policy in the developed economies may need to be considered together with trade policy.

Concluding Remarks

The three main chapters of my thesis perform microeconomic theoretical and empirical analyses to study firms' innovation performance, when they are facing environmental regulation and rising import competition from low-wage countries. I start with providing theoretical evidence for the Porter Hypothesis, which suggests that strict environmental poicies can promote, instead of hindering, firm innovation. Then I show empirically that environmental regulation can lead to growth of innovation in developing countries, using firm-level regulation and innovation data from China. Finally, I examine the impact of import competition from China on innovation of U.S. manufacturing companies, and find a positive relationship between them.

Through showing that environmental regulation can motivate firms to innovate and enhance their profitability, Chapter 1 supports both the weak and the strong versions of the Porter Hypothesis. Among studies using inter-firm spillover effect to generate results consistent with the hypothesis, this paper is the first to show that an environmental policy aiming to cut down pollution can enhance social welfare through simultaneously raising profits and consumer surplus. Nevertheless, the results presented in this paper should be interpreted with caution, since the Porter Hypothesis does not suggest that environmental regulation necessarily leads to innovation, let alone profit enhancement. The exact impact of environmental regulation on innovation and profits depend on various factors, such as marginal cost of innovation and the magnitude of spillover effects in this paper.

Previous studies on environmental regulation and innovation generally confirm the positive effect of regulation on environmental innovation, but show mixed results for overall innovative activities. Chapter 2 uses firm-level data in China to provide empirical evidence for the positive link between environmental stringency and overall innovation, which is advocated by the weak version of the Porter Hypothesis. This stimulative effect is found to be stronger after a multi-level regulatory system was finalized, and in regions where regulations were better enforced and supported by financial incentives. This finding makes this paper one of the few to discuss and support the narrow version of the Porter Hypothesis, which emphasizes the importance of policy implementation and flexibility. This paper also adds to the literature by confirming the positive effect of environmental policies on innovation at a more micro level in a developing economy.

Chapter 3 provides empirical evidence for the positive impact of import competition from low-wage countries, such as China, on U.S. manufacturing firms' innovative activities weighted by their influence and market value. This paper differentiates itself from previous literature through utilizing firm-level data in the U.S., while other studies are based on either non-U.S. or more aggregated data. Since the U.S. is generally considered to be one of the main technological leaders around the world, findings based on U.S. data in this paper should be of particular interest. In addition, this paper uses patent applications weighted by citations received as the main indicator of innovation, and thus offers another perspective to discuss the correlation between import competition and firm innovation. Since the impacts of import competition from low-wage countries are unequal across firms and industries, this paper suggests that domestic innovation policy may need to adjust with trade policy, in order for the optimal levels of innovation in various sectors are attained.

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Appendices

Appendix A

Appendix A.1 Proof of Lemma 1

To investigate whether lower marginal production costs boost product R&D investments at a symmetric non-cooperative equilibrium, I compute first order partial derivatives of R_1^N and R_2^N with respect to d_1 and d_2 as follow:

$$\begin{aligned}
\frac{\partial R_1^N}{\partial d_1}\Big|_{d_1=d_2=d^N} &= \frac{\partial R_2^N}{\partial d_2}\Big|_{d_1=d_2=d^N} = \frac{2\gamma^4[4-(1+\beta)\sigma][1-c+(1+\beta)d^N]^3}{(2-\sigma)^3(2+\sigma)^4},\\
\frac{\partial R_2^N}{\partial d_1}\Big|_{d_1=d_2=d^N} &= \frac{\partial R_1^N}{\partial d_2}\Big|_{d_1=d_2=d^N} = \frac{2\gamma^4[4\beta-(1+\beta)\sigma][1-c+(1+\beta)d^N]^3}{(2-\sigma)^3(2+\sigma)^4}.
\end{aligned} \tag{A.1}$$

The derivatives are clearly positive when evaluated at $d_1 = d_2 = d^N$, while $(\partial R_1^N/\partial d_1)\big|_{d_1=d_2=d^N} = (\partial R_2^N/\partial d_2)\big|_{d_1=d_2=d^N} > 0$ requires $\beta > \sigma/(4-\sigma)$.

Appendix A.2 Proof of Lemma 2

In this subsection, I set

$$\Gamma_1 = \frac{\gamma^2}{(4-\sigma^2)^2}, \quad \Delta_1 = \frac{2\gamma^4}{(\sigma-2)^3(\sigma+2)^4}, \quad \Sigma_1 = \frac{2\gamma^4}{(4-\sigma^2)^4}, \quad \Theta_1 = \frac{\gamma^4(2-\sigma)^2}{(4-\sigma^2)^4}.$$

I can show that a sufficient but not necessary condition for the second order condition to hold is

$$\begin{aligned}
\alpha > \tilde{\alpha}_1 = {} & (2-\beta\sigma)^2\Gamma_1\Theta_1^{\frac{1}{2}} + (\beta^2\sigma^3 - 6\beta^2\sigma^2 + 4\beta^2\sigma + \beta\sigma^3 - 4\beta\sigma^2 + 12\beta\sigma - 2\sigma^2 + 8\sigma - 16)\Gamma_1\Delta_1\Theta_1^{-\frac{1}{2}}\\
& - \frac{1}{4}(2-\sigma)[(\sigma^2-2)(\beta^2\sigma^2 + 4\beta\sigma^2 - 12\beta\sigma + \sigma^2 - 12\sigma + 24) + \sigma(\beta^2\sigma^2 - 12\beta^2\sigma + 24\beta^2\\
& + 4\beta\sigma^2 - 12\beta\sigma + \sigma^2)]\Gamma_1\Sigma_1\Theta_1^{-\frac{1}{2}} + \frac{1}{16}\{[2\sigma + 2\beta\sigma - \sigma(\sigma - 4\beta + \beta\sigma) - 8]^2\\
& + 3(2-\sigma)[(\sigma^2-2)(\sigma+\beta\sigma-4)^2 + \sigma(\sigma-4\beta+\beta\sigma)^2]\}\Gamma_1\Delta_1^2\Theta_1^{-\frac{3}{2}}\\
& - \frac{1}{2}(\beta^2\sigma^2 + 4\beta\sigma^2 - 12\beta\sigma + \sigma^2 - 12\sigma + 24)\Sigma_1,
\end{aligned} \tag{A.2}$$

since the second order condition is equivalent to $\alpha > \tilde{\alpha}_1[1-c+(1+\beta)d^N]^2$ and $1-c+(1+\beta)d^N \in (0,1]$.

The Routh-Hurwitz stability condition for reaction curves to cross "correctly" in a symmetric non-cooperative equilibrium translates as follows:

$$\left|\frac{\frac{\partial^2 \pi_i}{\partial d_i \partial d_j}\Big|_{d_i=d_j=d^N}}{\frac{\partial^2 \pi_i}{\partial d_i^2}\Big|_{d_i=d_j=d^N}}\right| = \left|\frac{\tilde{\alpha}_2[1-c+(1+\beta)d^N]^2}{\tilde{\alpha}_1[1-c+(1+\beta)d^N]^2-\alpha}\right| < 1, \quad i, j = 1, 2 \; and \; i \neq j, \tag{A.3}$$

where

$$\begin{aligned}
\tilde{\alpha}_2 = & (2\beta-\sigma)(2-\beta\sigma)\Gamma_1\Theta_1^{\frac{1}{2}} + \frac{1}{2}(\beta^2\sigma^3 - 4\beta^2\sigma^2 + 12\beta^2\sigma + 2\beta\sigma^3 - 16\beta\sigma^2 + 24\beta\sigma - 32\beta + \sigma^3 \\
& - 4\sigma^2 + 12\sigma)\Gamma_1\Delta_1\Theta_1^{-\frac{1}{2}} + \frac{1}{2}(\sigma-2)^2(\beta^2\sigma^2 - 3\beta^2\sigma + \beta\sigma^2 - 6\beta\sigma + 12\beta + \sigma^2 - 3\sigma)\Gamma_1\Sigma_1\Theta_1^{-\frac{1}{2}} \\
& - \frac{1}{16}\{[8\beta - 2\sigma - 2\beta\sigma + \sigma(\sigma+\beta\sigma-4)][2\sigma + 2\beta\sigma - \sigma(\sigma-4\beta+\beta\sigma) - 8] \\
& + 3(\sigma-2)^2(\sigma+\beta\sigma-4)(\sigma-4\beta+\beta\sigma)\}\Gamma_1\Delta_1^2\Theta_1^{-\frac{3}{2}} \\
& - (\beta^2\sigma^2 - 3\beta^2\sigma + \beta\sigma^2 - 6\beta\sigma + 12\beta + \sigma^2 - 3\sigma)\Sigma_1.
\end{aligned}$$

A straightforward simulation reveals that $\tilde{\alpha}_2 \geq 0$ when $\beta \geq \sigma$, $\tilde{\alpha}_2 < 0$ when $\beta < \sigma$, while $\tilde{\alpha}_1$ is always positive. Therefore a sufficient but not necessary condition for Equation (A.3) to hold is $\alpha > \max\{\tilde{\alpha}_1 + \tilde{\alpha}_2, \tilde{\alpha}_1 - \tilde{\alpha}_2\}$. Denote $\underline{\alpha}_2 = \tilde{\alpha}_1 + \tilde{\alpha}_2$ and $\underline{\alpha}_3 = \tilde{\alpha}_1 - \tilde{\alpha}_2$, the above discussion suggests that $\alpha > \max\{\underline{\alpha}_1, \underline{\alpha}_2, \underline{\alpha}_3\}$ ensures firms maximize their profits in a stable symmetric equilibrium.

Appendix A.3 Proof of Lemma 3

The values of d^N and d^C are determined by the intersections of the curves respectively illustrated in Equation (1.8) and Equation (1.10). When $\alpha > \max\{\underline{\alpha}_1, \underline{\alpha}_2, \underline{\alpha}_3, \underline{\alpha}_4, \underline{\alpha}_5\}$, the relation between the size of d^N and d^C is eventually decided by the slopes of curves $F_1(d)$ and $F_2(d)$, where

$$\begin{aligned}
F_1(d) &= \frac{2\gamma^4}{(2-\sigma)^3(2+\sigma)^4}[8 - 4(1+2\beta)\sigma + (1+3\beta)\sigma^2][1-c+(1+\beta)d]^3 \\
&= \frac{8 - 4(1+2\beta)\sigma + (1+3\beta)\sigma^2}{2-\sigma} \cdot f(d), \\
F_2(d) &= \frac{2\gamma^4(1-\sigma)(1+\beta)}{(2-\sigma)^2(2+\sigma)^4}[1-c+(1+\beta)d]^3 \\
&= (1-\sigma)(1+\beta) \cdot f(d).
\end{aligned}$$

Since $f(d)$ is a strictly increasing function in d, $F_2(d)$ would be intersecting the line αd at a higher level of d when

$$\frac{8 - 4(1+2\beta)\sigma + (1+3\beta)\sigma^2}{2-\sigma} < (1-\sigma)(1+\beta),$$

which is equivalent to $\sigma < \beta \leq 1$. In a symmetric equilibrium with cooperation in process R&D, two firms split profits in half, therefore $d^C > d^N$ leads to $\pi^C > \pi^N$ immediately. In addition, simulation results show that $\underline{\alpha}_4 > \underline{\alpha}_1$ and $\underline{\alpha}_5 > \max\{\underline{\alpha}_2, \underline{\alpha}_3\}$ when $\beta > \sigma$, thus the condition $\alpha > \max\{\underline{\alpha}_1, \underline{\alpha}_2, \underline{\alpha}_3, \underline{\alpha}_4, \underline{\alpha}_5\}$ reduces to $\alpha > \max\{\underline{\alpha}_4, \underline{\alpha}_5\}$.

Appendix A.4 Proof of Lemma 4

The optimal product R&D investment of firm i in the second stage of a symmetric game is

$$R_i^N = \frac{\gamma^4(2-\sigma^2)^2(1-c+d_i+\beta d_j)^2}{4(1-\sigma^2)^2(4-\sigma^2)^4}[(2-\sigma^2)(1-c+d_i+\beta d_j)-\sigma(1-c+\beta d_i+d_j)]^2. \tag{A.4}$$

The first order partial derivatives of R_i^N with respect to d_i, when evaluated at a symmetric equilibrium, are as below:

$$\begin{aligned}
\frac{\partial R_1^N}{\partial d_1}\Big|_{d_1=d_2=d^N} &= \frac{\partial R_2^N}{\partial d_2}\Big|_{d_1=d_2=d^N} = \frac{\gamma^4(2-\sigma^2)^2[4-(1+\beta)\sigma-2\sigma^2][1-c+(1+\beta)d^N]^3}{2(1-\sigma)(1+\sigma)^2(2-\sigma)^4(2+\sigma)^3},\\
\frac{\partial R_2^N}{\partial d_1}\Big|_{d_1=d_2=d^N} &= \frac{\partial R_1^N}{\partial d_2}\Big|_{d_1=d_2=d^N} = \frac{\gamma^4(2-\sigma^2)^2[4\beta-(1+\beta)\sigma-2\beta\sigma^2][1-c+(1+\beta)d^N]^3}{2(1-\sigma)(1+\sigma)^2(2-\sigma)^4(2+\sigma)^3}.
\end{aligned} \tag{A.5}$$

They are positive when $\beta > \sigma/(4-\sigma-2\sigma^2)$.

Appendix A.5 Proof of Lemma 5

Similar to the proof in Appendix A.2, I set

$$\Gamma_2 = \frac{\gamma^2}{(1-\sigma^2)(4-\sigma^2)^2}, \qquad \Delta_2 = \frac{\gamma^4(2-\sigma^2)^2}{2(\sigma-1)(1+\sigma)^2(2-\sigma)^4(2+\sigma)^3},$$
$$\Sigma_2 = \frac{\gamma^4(2-\sigma^2)^2}{2(1-\sigma^2)^2(4-\sigma^2)^4}, \quad \Theta_2 = \frac{\gamma^4(2-\sigma)^2}{4(1+\sigma)^2(2-\sigma)^4(2+\sigma)^2}.$$

Then a sufficient but not necessary condition for the second order condition to hold can be reorganized as

$$\begin{aligned}
\alpha > \tilde{\alpha}_3 = {} & (2-\beta\sigma-\sigma^2)^2\Gamma_2\Theta_2^{\frac{1}{2}} + (\beta^2\gamma^5+3\beta^2\gamma^4-3\beta^2\gamma^3-6\beta^2\gamma^2+4\beta^2\gamma+3\beta\gamma^5+2\beta\gamma^4-11\beta\gamma^3\\
& -4\beta\gamma^2+12\beta\gamma+2\gamma^6+2\gamma^5-11\gamma^4-8\gamma^3+22\gamma^2+8\gamma-16)\Gamma_2\Delta_2\Theta_2^{-\frac{1}{2}}\\
& -\frac{1}{4}(1-\sigma)^2(2+\sigma)^2(6\beta^2\sigma^3+\beta^2\sigma^2-12\beta^2\sigma+6\beta\sigma^3+4\beta\sigma^2-12\beta\sigma+6\sigma^4-23\sigma^2\\
& +24)\Gamma_2\Sigma_2\Theta_2^{-\frac{1}{2}} + \frac{1}{16}\{[\sigma(\sigma-4\beta+\beta\sigma+2\beta\sigma^2)+(2-\sigma^2)(4-\sigma-\beta\sigma-2\sigma^2)]^2\\
& +3(2-\sigma+\sigma^2)[(\sigma^2-2)(\sigma+\beta\sigma+2\sigma^2-4)^2+\sigma(\sigma-4\beta+\beta\sigma+2\beta\sigma^2)^2]\}\Gamma_2\Delta_2^2\Theta_2^{-\frac{3}{2}}\\
& -\frac{1}{2}(\beta^2\sigma^2+6\beta\sigma^3+4\beta\sigma^2-12\beta\sigma+6\sigma^4+6\sigma^3-23\sigma^2-12\sigma+24)\Sigma_2.
\end{aligned} \tag{A.6}$$

As for the stability condition, it can also be written as

$$\left|\frac{\frac{\partial^2\pi_i}{\partial d_i\partial d_j}\big|_{d_i=d_j=d^N}}{\frac{\partial^2\pi_i}{\partial d_i^2}\big|_{d_i=d_j=d^N}}\right| = \left|\frac{\tilde{\alpha}_4[1-c+(1+\beta)d^N]^2}{\tilde{\alpha}_3[1-c+(1+\beta)d^N]^2-\alpha}\right| < 1, \quad i,j=1,2 \; and \; i\neq j, \tag{A.7}$$

where

$$\begin{aligned}
\tilde{\alpha}_4 = &(\beta\sigma^2 + \sigma - 2\beta)(\sigma^2 + \beta\sigma - 2)\Gamma_2\Theta_2^{\frac{1}{2}} + \frac{1}{2}(3\beta^2\sigma^5 + 2\beta^2\sigma^4 - 11\beta^2\sigma^3 - 4\beta^2\sigma^2 + 12\beta^2\sigma + 4\beta\sigma^6 \\
&+ 6\beta\sigma^5 - 16\beta\sigma^4 - 22\beta\sigma^3 + 32\beta\sigma^2 + 24\beta\sigma - 32\beta + 3\sigma^5 + 2\sigma^4 - 11\sigma^3 - 4\sigma^2 + 12\sigma)\Gamma_2\Delta_2\Theta_2^{-\frac{1}{2}} \\
&+ \frac{1}{4}(1-\sigma)^2(2+\sigma)^2(3\beta^2\sigma^3 + 2\beta^2\sigma^2 - 6\beta^2\sigma + 6\beta\sigma^4 + 6\beta\sigma^3 - 22\beta\sigma^2 - 12\beta\sigma + 24\beta + 3\sigma^3 \\
&+ 2\sigma^2 - 6\sigma)\Gamma_2\Sigma_2\Theta_2^{-\frac{1}{2}} + \frac{1}{8}(5\beta^2\sigma^6 + 4\beta^2\sigma^5 - 19\beta^2\sigma^4 - 8\beta^2\sigma^3 + 20\beta^2\sigma^2 + 4\beta\sigma^8 + 16\beta\sigma^7 \\
&- 18\beta\sigma^6 - 88\beta\sigma^5 + 42\beta\sigma^4 + 176\beta\sigma^3 - 72\beta\sigma^2 - 128\beta\sigma + 64\beta + 5\sigma^6 + 4\sigma^5 - 19\sigma^4 - 8\sigma^3 \\
&+ 20\sigma^2)\Gamma_2\Delta_2^2\Theta_2^{-\frac{3}{2}} - \frac{1}{2}(3\beta^2\sigma^3 + 2\beta^2\sigma^2 - 6\beta^2\sigma + 6\beta\sigma^4 + 6\beta\sigma^3 - 22\beta\sigma^2 - 12\beta\sigma + 24\beta \\
&+ 3\sigma^3 + 2\sigma^2 - 6\sigma)\Sigma_2.
\end{aligned}$$

Simulation results suggest that $\tilde{\alpha}_3 > \tilde{\alpha}_4 > 0$ in spite of the values of $\sigma \in (0, \sqrt{3} - 1)$ and $\beta \in (\underline{\beta}, 1]$. Thus, a sufficient but not necessary condition for Equation (A.6) and Equation (A.7) to hold is $\alpha > \underline{\alpha}_8 = \tilde{\alpha}_3 + \tilde{\alpha}_4$.

Appendix B

Table B.1: Robustness Results: Using One-year Lagged Independent Variables

	All Patents		Invention and Utility	
Independent Variable	(1)	(2)	(3)	(4)
CPA	0.152**		0.150**	
	(0.077)		(0.064)	
CPA 2005–2008		0.119		0.123
		(0.097)		(0.084)
CPA 2009–2010		0.232***		0.211***
		(0.073)		(0.067)
Size	0.445***	0.444***	0.406***	0.405***
	(0.060)	(0.060)	(0.051)	(0.051)
Cash Flow	0.023	0.023	0.026	0.026
	(0.026)	(0.026)	(0.023)	(0.023)
Capital Intensity	0.103***	0.103***	0.106***	0.106***
	(0.024)	(0.024)	(0.017)	(0.017)
Prior Innovation	0.210***	0.210***	0.195***	0.195***
	(0.062)	(0.062)	(0.058)	(0.058)
No. of Firms	723	723	723	723
Observations	4,297	4,297	4,297	4,297

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Firm, industry-year and region-year fixed effects are included to generate results but omitted from reporting. Standard errors are two-way clustered by industry and year.

Table B.2: Robustness Results: Restricting Sample to Firms in the Manufacturing Sector

	All Patents		Invention and Utility	
Independent Variable	(1)	(2)	(3)	(4)
CPA	0.122*		0.159***	
	(0.073)		(0.061)	
CPA 2005–2008		0.044		0.088
		(0.068)		(0.057)
CPA 2009–2010		0.221**		0.248***
		(0.100)		(0.078)
Size	0.507***	0.506***	0.466***	0.464***
	(0.054)	(0.055)	(0.046)	(0.046)
Cash Flow	0.000	0.000	0.013	0.013
	(0.023)	(0.023)	(0.019)	(0.019)
Capital Intensity	0.160***	0.159***	0.160***	0.158***
	(0.032)	(0.031)	(0.033)	(0.032)
Prior Innovation	0.188***	0.188***	0.157***	0.157***
	(0.047)	(0.047)	(0.043)	(0.044)
No. of Firms	646	646	646	646
Observations	4,409	4,409	4,409	4,409

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Samples only include firms in the manufacturing sector. Firm, industry-year and region-year fixed effects are included to generate results but omitted from reporting. Standard errors are two-way clustered by industry and year.

Table B.3: Balancing Test: Mean Differences before and after Matching

		Mean		t-test	
Variables	Sample	Regulated	Unregulated	t	p-value
Size	Unmatched	7.935	7.368	5.38	0.00
	Matched	7.935	7.877	0.52	0.61
Cash Flow	Unmatched	2.317	2.239	1.18	0.24
	Matched	2.317	2.369	–0.71	0.48
Capital Intensity	Unmatched	5.468	5.084	3.65	0.00
	Matched	5.468	5.342	0.99	0.32
Prior Innovation	Unmatched	6.277	6.290	–0.14	0.89
	Matched	6.277	6.222	0.53	0.60
		Pseudo R^2	LR chi^2	p-value	
	Unmatched	0.063	47.130	0.00	
	Matched	0.006	2.700	0.61	

Table B.4: PSM Results: Patent Applications and Mandatory CPA Participation

	All Patents		Invention and Utility	
Independent Variable	(1)	(2)	(3)	(4)
CPA	0.159**		0.183***	
	(0.069)		(0.067)	
CPA 2005–2008		0.026		0.038
		(0.040)		(0.057)
CPA 2009–2010		0.353***		0.395***
		(0.117)		(0.072)
Size	0.607***	0.599***	0.537***	0.529***
	(0.121)	(0.123)	(0.100)	(0.103)
Cash Flow	–0.045	–0.043	–0.027	–0.025
	(0.058)	(0.056)	(0.057)	(0.055)
Capital Intensity	0.096	0.088	0.060	0.051
	(0.061)	(0.063)	(0.061)	(0.062)
Prior Innovation	0.338***	0.342***	0.301***	0.306***
	(0.091)	(0.093)	(0.079)	(0.081)
No. of Firms	272	272	272	272
Observations	2,174	2,174	2,174	2,174

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. Firm, industry-year and region-year fixed effects are included to generate results but omitted from reporting. Standard errors are two-way clustered by industry and year.

Appendix C

Table C.1: First-stage Endogeneity Results: Chinese Import Penetration in the UK as an Instrumental Variable

	Import Penetration in the U.S.			
Independent Variables	(1) Narrow Sample	(2) Main Sample	(3) Narrow Sample	(4) Main Sample
$Import\ Penetration_{UK}$	0.523***	0.579***	0.528***	0.578***
	(0.116)	(0.142)	(0.119)	(0.142)
K-P Weak ID F Statistic	20.39	16.58	19.83	16.55
Number of Firms	1,136	1,228	1,104	1,228
Observations	7,435	7,844	7,248	7,844

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. All regressions include firm and year fixed effects. Standard errors are clustered by industry and year.

Table C.2: Patent Applications and Imports from Low-wage Countries and OECD Members

	Unweighted		Citation-weighted	
Independent Variables	(1) Narrow Sample	(2) Main Sample	(3) Narrow Sample	(4) Main Sample
		China		
Import Penetration	0.912	0.755	1.563**	1.351**
	(0.711)	(0.611)	(0.774)	(0.669)
Number of Firms	1,136	1,228	1,104	1,228
Observations	7,435	7,844	7,248	7,844
		All low-wage countries		
Import Penetration	0.954	0.789	1.605**	1.385**
	(0.711)	(0.606)	(0.773)	(0.664)
Number of Firms	1,136	1,229	1,104	1,229
Observations	7,446	7,858	7,259	7,858
		OECD members		
Import Penetration	–0.637*	–0.630*	–0.729**	–0.741**
	(0.352)	(0.345)	(0.370)	(0.360)
Number of Firms	1,138	1,231	1,106	1,231
Observations	7,463	7,878	7,275	7,878

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. All regressions include firm and year fixed effects. Standard errors are clustered by industry and year.

Table C.3: Patent Applications and Imports from Low-wage Countries, with Imports from OECD Members Controlled

Independent Variables	Unweighted (1) Narrow Sample	Unweighted (2) Main Sample	Citation-weighted (3) Narrow Sample	Citation-weighted (4) Main Sample
	China			
Import Penetration	0.840	0.698	1.484*	1.286*
	(0.737)	(0.631)	(0.812)	(0.694)
Number of Firms	1,136	1,228	1,104	1,228
Observations	7,435	7,844	7,248	7,844
	All low-wage countries			
Import Penetration	0.893	0.742	1.538*	1.330*
	(0.737)	(0.625)	(0.810)	(0.689)
Number of Firms	1,136	1,229	1,104	1,229
Observations	7,446	7,858	7,259	7,858

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. All regressions include firm and year fixed effects. Standard errors are clustered by industry and year.

Table C.4: Negative Binomial Results: Patent Applications and Import Penetration

Independent Variables	Unweighted (1) Narrow Sample	Unweighted (2) Main Sample	Citation-weighted (3) Narrow Sample	Citation-weighted (4) Main Sample
Import Penetration	2.204***	2.204***	2.481***	2.481***
	(0.836)	(0.836)	(0.902)	(0.902)
R&D Intensity	–0.020	–0.020	–0.256	–0.256
	(0.699)	(0.699)	(0.725)	(0.725)
Patent Stock	0.262***	0.262***	0.239***	0.239***
	(0.046)	(0.046)	(0.050)	(0.050)
Log(*No. of Employees*)	–0.111**	–0.111**	–0.080	–0.080
	(0.050)	(0.050)	(0.050)	(0.050)
Log(*Capital Intensity*)	0.018	0.018	0.018	0.018
	(0.068)	(0.068)	(0.065)	(0.065)
Log(*Net Operating Income*)	0.062**	0.062**	0.073***	0.073***
	(0.024)	(0.024)	(0.025)	(0.025)
Number of Firms	976	976	947	947
Observations	6,704	6,704	6,556	6,556

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. All regressions include firm and year fixed effects. Standard errors are clustered by industry.

Table C.5: Various Lag Lengths: Fixed Effects (FE) and Instrumental Variable (IV) Approach

	Unweighted		Citation-weighted	
Independent Variables	(1) Narrow Sample	(2) Main Sample	(3) Narrow Sample	(4) Main Sample
	Using Contemporaneous RHS variables, FE results			
Import Penetration	1.012*	0.861*	1.447**	1.252**
	(0.576)	(0.495)	(0.643)	(0.551)
Observations	9,518	10,151	9,243	10,151
	Using Contemporaneous RHS variables, IV results			
Import Penetration	3.697	3.399	6.291*	5.529*
	(3.077)	(2.743)	(3.638)	(3.242)
K-P Weak ID F Statistic	18.05	12.27	17.40	12.24
Observations	9,518	10,151	9,243	10,151
	Using 2-year lagged RHS variables, FE results			
Import Penetration	1.165	1.005	2.063**	1.826**
	(0.828)	(0.729)	(0.957)	(0.852)
Observations	6,232	6,526	6,079	6,526
	Using 2-year lagged RHS variables, IV results			
Import Penetration	5.237	4.891	9.973**	8.934*
	(4.166)	(3.891)	(4.830)	(4.585)
K-P Weak ID F Statistic	18.74	17.44	18.18	17.40
Observations	6,232	6,526	6,079	6,526

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. All regressions include firm and year fixed effects. Standard errors are clustered by industry and year.

Table C.6: Using R&D Expenditure as the Dependent Variable

	FE Results		IV Results	
	(1) Narrow Sample	(2) Main Sample	(3) Narrow Sample	(4) Main Sample
Independent Variables				
Import Penetration	1.162**	1.070**	6.925**	6.099**
	(0.569)	(0.473)	(3.491)	(2.960)
Patent Stock	0.083***	0.084***	0.082***	0.084***
	(0.018)	(0.019)	(0.018)	(0.018)
Log(*No. of Employees*)	0.556***	0.557***	0.544***	0.546***
	(0.044)	(0.043)	(0.044)	(0.043)
Log(*Capital Intensity*)	0.195***	0.199***	0.210***	0.213***
	(0.040)	(0.039)	(0.045)	(0.043)
Log(*Net Operating Income*)	0.095***	0.093***	0.100***	0.097***
	(0.015)	(0.014)	(0.015)	(0.014)
Endogeneity C Statistic			2.893	3.019
p-value			0.089	0.082
K-P Weak ID F Statistic			19.89	15.38
Number of Firms	1,135	1,221	1,135	1,221
Observations	7,447	7,839	7,447	7,839

Notes: *** denotes 1% significance, ** denotes 5% significance, * denotes 10% significance. All regressions include firm and year fixed effects. Standard errors are clustered by industry and year.