Quality Innovation, Cost Innovation, Export, and Firm Productivity Evolution: Evidence from the Chinese Electronics Industry

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July 2022

Quality Innovation, Cost Innovation, Exporting, and Firm Productivity Evolution: Evidence from the Chinese Electronics Industry *

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May 29, 2022

Abstract

This paper classifies innovation as quality-improving or cost-reducing and estimates a dynamic model incorporating firm export, quality innovation, and cost innovation decisions. Estimation results show that export, quality innovation, and cost innovation increase next-period firm productivity by 1.39%, 1.23%, and 1.27%, respectively. Additionally, quality innovation raises next-period export demand by 47%. Counterfactual analyses suggest that (1) foreign market growth has a larger impact on firm export and innovation decisions than domestic market growth, but neither market significantly affects firm productivity; (2) subsidizing continuing quality innovators generates the highest financial return, and subsidizing continuing cost innovators brings the most productivity gain.

Keywords: export, quality innovation, cost innovation, firm productivity, dynamic estimation, neural network, machine learning, trade liberalization, innovation policy.
JEL Classification: F14; L10; L25; C45.

*We thank Jie Bai, Loren Brandt, John McLaren, Peter Morrow, Eric Verhoogen, and seminar participants at the Rensselaer Polytechnic Institute, the Canadian Economic Association 2021 Annual Meeting, Lehigh University, the Southern Economic Association 2021 Conference, and Fudan University. We are grateful toward Professor Xiaoji Xu at Lehigh University for his research assistance. All remaining errors are ours.

1 Introduction

A large literature examines the nexus between exporting, innovation, and firm productivity. Most papers in this literature treat innovation as a firm's investment to improve its productivity. Few have looked into the nature of innovation. Is innovation a simple act that enhances firm efficiency, or a collection of strategies that the firm chooses from, e.g., some affect the production process and others affect consumer demand?

In this paper, we distinguish between two types of innovation: (1) quality innovation - innovation that introduces a new function/product or improves the quality of an existing function/product, and (2) cost innovation - innovation that improves production efficiency or reduces production cost. The former affects product demand, and the latter affects the production process.

To explore whether quality and cost innovation have different influences on firm productivity and export decisions, we develop a dynamic model of firm export, innovation, and productivity evolution based on Aw et al. (2011, henceforth ARX). Our model differs from ARX in important ways. Instead of a homogeneous R&D investment, we allow firms to choose from two types of innovation: cost innovation and quality innovation. Both types of innovation affect the next-period firm productivity, but quality innovation also affects the next-period foreign demand. This setup allows us to examine, for the first time to the best of our knowledge, the firm's joint decisions on exporting and two distinct types of innovation. The distinction between quality and cost innovation is conceptually meaningful because cost and demand shifters are not necessarily isomorphic, especially when firms can serve markets that reward quality innovation differently. The two types of innovation interact dynamically with the firm's exporting decision through self-selection by productivity into different activities, which then re-enhance firm productivity.

We estimate the model using data from the Chinese electronics industry between 2000 and 2007. Our dataset combines firms' production and export information with their patent applications, where patents are classified as either quality-improving or cost-reducing using a neural network model.[1] Using patent application instead of R&D expenditure to measure firm innovation allows us to look into the content of firm innovation and classify it.[2]

Our empirical results generate several insights. First, we find that quality innovation, cost innovation, and exporting all improve next-period firm productivity. Their respective margins are 1.23%, 1.27%, and 1.39%. Second, in addition to its direct impact on firm productivity, quality innovation increases next-period foreign demand by as much as 47%, suggesting the foreign market strongly rewards quality innovation. Third, quality innovation is more costly than cost innovation and exporting. The fixed cost of quality innovation, at ¥3,190,000, is more than twice the fixed cost

[1] Section 2.2 explains how we create the dataset by merging four databases - the Chinese customs data, the Annual Survey of Industrial Enterprises data, and patent data from the Chinese Patent Office and PATSTAT. Appendix A explains how we use a training sample to create a neural network model (an MLP model) that reads patent titles and abstracts and classifies the patents as either quality-improving or cost-reducing.

[2] Section 2.3 discusses the nuance of patent application as a measure of firm innovation.

of cost innovation and more than 20 times the fixed cost of exporting. Its sunk cost, at ¥9,700,000, is more than 1.5 times the sunk cost of cost innovation and more than 16 times the sunk cost of exporting. Compared to similar estimates for electronic firms in Germany (Peters et al., 2018) and Taiwan (Aw et al., 2011), electronic firms in mainland China face lower costs and returns to export and innovation.[3]

We use our estimates to conduct two counterfactual analyses. First, we quantify the effect of domestic and foreign market growth and find that they both encourage export and innovation, but foreign market growth has a much stronger influence. An annual 20% foreign market expansion increases the percent of exporters, cost innovators, and quality innovators by 19%, 22%, and 16% after ten years. The corresponding impacts of an annual 20% domestic market expansion are 0.8%, 0.6%, and 0.2%. We also find that market growth has a limited impact on firm productivity. An annual 20% foreign (domestic) market expansion increases sector-level productivity by 1.17% (0.04%) after 10 years.

Second, we examine the effect of various subsidies on the costs of export and innovation, where a subsidy is modeled as a permanent reduction in the fixed or sunk cost of a firm activity. We find that fixed cost subsidies have a stronger influence on export and innovation participation than sunk cost subsidies, suggesting that compared to subsidizing inexperienced firms, subsidizing continuing exporters/innovators generates a larger repercussion on industry dynamics. However, neither fixed nor sunk cost subsidies strongly impact firm productivity. In fact, subsidies on the sunk cost of export or cost innovation even lower sector-level productivity relative to the baseline, because they disincentivize continuing exporters/innovators by reducing the opportunity cost for discontinuation. Further, we calculate returns to the subsidy programs. Our calculation reveals that subsidizing continuing quality innovators generates the highest financial return - each yuan spent on subsidy costs generates 43 yuan in profit gains. Subsidizing continuing cost innovators has the largest impact on sector-level productivity - it raises productivity by 3% after 15 years.

The remainder of this introduction provides a non-comprehensive review of relevant literature and highlights our contributions. Section 2 provides background information on the Chinese electronics industry and explains how we construct the dataset. It also provides descriptive statistics that justify modeling assumptions. Section 3 introduces the dynamic model. Section 4 outlines our estimation procedure and reports estimation results. Section 5 discusses our counterfactual analyses. Section 6 concludes.

Literature Review

Our paper closely relates to the literature on the dynamic interactions between export, innovation, and firm productivity. Aw et al. (2011) study the Taiwanese electronics industry and find that R&D and export both improve firm productivity, which in turn incentivizes firms to self-select

[3]Section 4.3 compares our estimates with Aw et al. (2011) and Peters et al. (2018).

into both activities. Peters et al. (2018) find that R&D among the German high-tech firms leads to more product and process innovation, which improves firm productivity. They separately estimate the mechanism for export and domestic markets and find the effect stronger in the export market. Maican et al. (2020) compare R&D returns for exporting and non-exporting Swedish manufacturers. They find that R&D spending has a larger impact on firm productivity in the export market than in the domestic market. Our paper's quality and cost innovation resemble the product and process innovation in Peters et al. (2018). However, we focus on their interaction with export and productivity rather than their linkage to R&D investment. Our paper contributes to the literature by separately identifying the roles of quality and cost innovation in firm export decisions and productivity evolution.

More broadly, our paper contributes to research on export and firm dynamics in developing countries.[4] While some papers find export to improve firm productivity (De Loecker, 2007; Van Biesebroeck, 2005; Alvarez and López, 2005; Blalock and Gertler, 2004; Park et al., 2010), others fail to establish such a link (Aw et al., 2000; Luong, 2013; Iacovone, 2012). In particular, the influential paper by Verhoogen (2008) spurs a series of research that establishes a positive causal relationship between trade liberalization and firm quality upgrading. Our definition of quality innovation incorporates quality upgrading. We find that export improves firm productivity. Meanwhile, if showing up as quality innovation, quality upgrading shifts up export demand, which then promotes quality upgrading by encouraging firms to engage in quality innovation.

Our paper also complements existing research on the impact of trade liberalization on Chinese firms, where most attention has been on the import channel.[5] Researchers find trade liberalization improves firm productivity (Brandt et al., 2017) and induces quality upgrading (Fan et al., 2018). The research on firm innovation, however, generates mixed results. While some find trade liberalization to reduce innovation incentives (Liu et al., 2021; Liu and Qiu, 2016), others find it to increase R&D expenditure (Chen et al., 2017; Liu and Ma, 2020).[6] We contribute to the literature by examining the export channel.[7] Our structural model allows us to disentangle the dynamic relationship between innovation and other firm decisions.

Last but not least, our research speaks to the smaller literature on the effect of patenting on Chinese firms' productivity. Hu et al. (2017) and Fang et al. (2020) both show that patenting improves firm productivity in China, with the former obtaining small estimates for 2007-2011 and the latter large estimates for 1998-2007. The data we explore overlaps with Fang et al. (2020).

[4]See Verhoogen (2021) for a comprehensive review.

[5]The literature focuses on the import channel because China's entry into WTO in 2001 was mainly associated with opening domestic markets, which provides useful variation for studying the consequence of import penetration and increasing access to imported inputs.

[6]Multiple factors could contribute to the mixed findings. First, the cited papers focus on different channels - Liu et al. (2021) on import competition, Fan et al. (2018) and Liu and Qiu (2016) on input tariff cuts, Chen et al. (2017) on import and export participation, and Liu and Ma (2020) on trade policy uncertainty. Second, the cited papers conduct multi-industry analysis and impose a constant cost structure when it is likely industry-specific. Third, the cited papers adopt reduced-form methods, which do not fully account for the rich interaction between firm decisions.

[7]Section 2.1 explains why export participation is important for the Chinese electronics industry.

Instead of a two-stage analysis, we incorporate patenting into firm productivity evolution to better capture its autocorrelation nature and find the impact of patenting small. Perhaps the most related to our paper is Chen et al. (2021), who use a structural model to quantify the impact of innovation policy. One crucial difference is that they leave out firms' export decisions, and we allow dynamic interactions between firms' exporting and patenting decisions.

2 Data and Descriptive Statistics

2.1 The Chinese Electronics Industry

This paper focuses on the Chinese electronics industry from 2000 to 2007 for two reasons.[8]

First, the industry is a stellar example of free trade. It had been through substantial trade liberalization even before China's entry into WTO. On the one hand, tariffs on electronic products in major importing countries were substantially removed in the 1990s, especially through the Information Technology Agreement (ITA).[9] According to Feenstra and Kee (2011), U.S. tariffs on the imports of electronics from China dropped from 5.1 percent in 1990 to 1.2 percent in 2001. On the other hand, China's openness to imports in the electronics industry started as early as 1979 with the processing trade regime. The regime allowed Chinese exporters to import raw materials, parts, and components duty-free. In this process, Chinese producers integrated rapidly into the global value chain (GVC). The integration received a strong momentum from China's entry into WTO.[10] During our sample period of 2000-2007, 9,239 of the 18,407 firms have exported through ordinary trade. Export revenue grew at an average annual rate of 22%.[11]

Second, the industry is innovation-intensive. The substantial removal of trade barriers and the fragmentation of the value chain across borders have gone hand in hand with increasing codifiability and modularity of the production process. For involved firms, the connectedness of the production network provides on the demand side not only a ready and rapidly growing market but also strong incentives for continuous upgrading and innovation; on the supply side, the

[8] The industry includes Communication Equipment Manufacturing (CIC401), Electronic Computer Manufacturing (CIC404), Electric Device Manufacturing (CIC405), Electronic Parts Manufacturing (CIC406), Broadcasting and Television Equipment Manufacturing (CIC403), and Home Audio-visual Equipment Manufacturing (CIC407). We exclude Radar and Accompanying Devices Manufacturing (CIC4020) due to its lack of market forces and Other Electronic Equipment Manufacturing (CIC4090) due to the ambiguity in its definition. The largest companies in our sample include Foxconn, Motorola, and Huawei.

[9] ITA was signed in 1996 by 29 WTO member countries and went into effect in 1997. Its purpose was to reduce tariffs on IT products, including computers, software, telecommunications, semiconductors, semiconductor manufacturing equipment, scientific and measuring equipment, and related parts. China became an ITA member in 2003.

[10] GVC originated between some Asian economies and North America, and now offers opportunities for newcomers in China. See Kawakami and Sturgeon (2011) for a history of GVC in the electronics industry.

[11] We define exporters as firms that report positive, direct export revenues between 2000 and 2007. Processing firms and trading companies are excluded from this sample, but indirect exporters (i.e, firms that export through intermediaries) are included. We exclude processing firms even though they account for a substantial proportion of total exports because they have limited influence over important decisions such as pricing, marketing, and most importantly, patenting.

necessity of information sharing across production stages provides new participants with access to technological know-how and facilitates the learning process. In addition, the Chinese governments (central and local) have been seeking policies to promote the development of China's high-tech sectors, with the electronics industry being one of them.[12] These push-and-pull forces are reflected in the number of patent applications. Between 2000 and 2007, the industry filed 70,456 patent applications, more than 25% of all patent applications filed by Chinese companies.

The industry's innovation-intensive nature, combined with its active export participation, provides an ideal playground for studying the interaction between export and innovation decisions.

2.2 Data Construction

Our data come from four sources. (i) The ASIE (Annual Survey of Industrial Enterprises) database contains Chinese manufacturing firms' production and export information. (ii) The customs database contains information on all transactions that go through the Chinese Customs. (iii) The CNIPA database, in Chinese, contains all patent application records at the Chinese National Intellectual Property Administration. (iv) The PATSTAT database, in English, contains comprehensive patent application records from 194 patenting authorities worldwide.

The ASIE and customs data both contain information on firm export decisions, the former reported by firms and the latter by the Chinese Customs. We match the two databases using the method in Yu (2015). The discrepancy between export records from the two databases helps us identify exporter types. Firms with positive export revenue in ASIE and zero export revenue in the customs data are considered indirect exporters and are included in our sample, because they do not pay the same export costs as the ordinary exporters. Firms with zero export revenue in ASIE and positive export revenue in the customs data are considered export intermediaries and are excluded from our sample, because they do not produce electronics. Firms with positive export revenue in both databases are considered ordinary exporters and kept in our sample. We use ASIE variables (e.g., capital stock, total revenue, employment, and export revenue) for productivity estimation.

The PATSTAT and CNIPA databases both contain the universe of Chinese patent applications. The former, in English, allows us to classify patents into quality-improving ones and cost-reducing ones using machine learning algorithms (explained later in this section). The latter, in Chinese, allows us to match the ASIE firms with their patent records based on their Chinese names. We first merge the PATSTAT and CNIPA data using patent application numbers, then match patent data with the ASIE production data using concordance by He et al. (2017), who using string matching algorithms to match Chinese firms with their patent data based on their Chinese names.

The merged dataset contains information on the Chinese electronic firms' production and export decisions and the universe of patents they filed between 2000 and 2007. Importantly, each

[12] Among the various policies are establishing industry clusters, various forms of tax incentives, and innovation subsidies. For a thorough review of China's Science and Technology policy, see Fu (2015).

patent is classified as quality-improving or cost-reducing using a neural network model called multilayer perceptron (MLP).[13] A quality-improving patent is a patent that "improves the quality of an existing function/product" or "introduces a new function/product." A cost-reducing patent is a patent that "reduces production cost" or "improves production efficiency."[14] In short, a quality-improving patent affects a firm's demand side, and a cost-reducing patent affects a firm's production side.[15] For the remainder of this paper, we refer to quality-improving patents as quality patents and cost-reducing patents as cost patents for succinctness.

2.3 Innovation and Patenting

We use patent applications to measure innovation, a novel activity that affects the firm's sales or production. There are two complications. First, innovation and patent application may not be synchronous. R&D expenditure is considered a contemporary measure of innovation, and patent application is the output of (successful) R&D. If this is true, there could be a lag between R&D expenditure and the ensuing patent applications. The literature, however, has found that R&D expenditure is the most strongly correlated with concurrent patent applications. Table C.1 in the appendix replicates the exercise by Hall et al. (1986) and reveals that controlling for sales, industry fixed effects, and year fixed effects, a firm's number of patent applications is the most strongly correlated with its same-year R&D expenditure. Based on this finding, we consider patenting and innovation to be largely concurrent.

Second, not all innovations that affect firm productivity are captured by patent applications, and not all patent applications affect firm productivity. For example, a firm may adopt a previously patented technology. This new technology improves the focal firm's productivity but does not show up as the focal firm's patent application. On the other hand, strategic patenting, the act of pharmaceutical companies filing patents to secure their future competitive space, does not reflect the focal firm's innovation or productivity improvement (Blind et al., 2009). The first bias (innovation not captured by patent application) works against our results and does not negate any significant findings on innovation. The second bias (patent applications that do not translate to productivity improvements) should result in a weak correlation between R&D expenditure and patent applications, which contradicts the strong correlation in Table C.1.

We use patent, innovation, and patent applications interchangeably for the rest of this paper.

[13]The classification process is elaborated in Appendix A. In short, two research assistants are hired to hand-code a training sample of patents, where they label each patent as either quality-improving or cost-reducing. The training sample is used to train a multi-layer perception (MLP) model. The trained model then classifies the rest of the patents.

[14]Section 3 of Liu and Trefler (2020) discusses the empirical sensibility of this classification, where quality-improving patents are referred to as "ideas-oriented", and cost-reducing patents are "cost-oriented."

[15]Quality-improving and cost-reducing patents are close in definition to product and process innovation. We use different names because this paper is not closely related to the literature on product and process innovation.

2.4 Descriptive Statistics

This section highlights several empirical observations that help us set up the model.

2.4.1 Firm Characteristics

Table 1: Firm Characteristics by Export Mode

	Firms		Mean domestic revenue		Median domestic revenue	
Year	Non-exporters	Exporters	Non-exporters	Exporters	Non-exporters	Exporters
2000	1,193	659	78,796	174,247	13,896	7,399
2001	1,720	973	70,855	164,486	12,785	7,051
2002	1,917	1,076	54,619	171,323	13,546	8,700
2003	1,879	1,205	76,539	214,929	16,213	10,389
2004	2,823	2,077	58,355	162,382	15,957	7,891
2005	3,357	2,297	103,000	171,051	18,975	10,895
2006	3,654	2,363	72,229	210,378	22,146	14,590
2007	3,132	1,990	85,310	215,714	28,048	18,494
Total	19,675	12,640	76,545	187,878	18,605	10,952

Notes: Revenues are in thousands of Chinese yuan.

Table 1 summarizes firm characteristics by export status. The first two columns report the numbers of non-exporters and exporters by year. With 35-43% exporters each year, the electronics industry is extremely export-intensive. The next two columns show that, on average, an exporter is 50% larger than a domestic firm. The last two columns show that the median exporter is 60% the size of the median non-exporter. The four columns combined suggest that compared to non-exporters, exporters' domestic revenue features a right-skewed distribution with a fatter right tail. If domestic revenue is proportional to firm productivity, the observation also applies to productivity distribution.

Table 2: Correlation between Domestic and Foreign Revenues by Innovation Mode

Firm innovation decisions:	Neither	Cost only	Quality only	Both
All firm-year observations	0.464	0.552	0.158	0.131
Firm-year obs. with positive export revenue	0.497	0.550	0.176	0.171
Average total revenue	63,825	159,674	138,885	727,489

Notes: Revenues are in thousands of Chinese yuan.

Table 2 reports the correlation between domestic and foreign revenues by innovation mode. *Neither* refers to firms that did not file any patent applications between 2000 and 2007; *Cost only* refers to firms that filed only cost patents between 2000 and 2007; *Quality only* refers to firms that filed only quality patents between 2000 and 2007; *Both* refers to firms that filed both cost and quality patents between 2000 and 2007.[16]

Correlation is much stronger for the *cost only* firms than the *quality only* firms. The contrast is consistent with our definitions of quality and cost patents in Section 2.2. Recall that we defined quality patents as affecting a firm's demand side and cost patents as affecting its production side. The high correlation among cost innovators is consistent with the fact that cost innovation improves productivity and hence, introduces a comovement between domestic and foreign revenues, strengthening their correlation. On the other hand, domestic and foreign consumers may value quality innovation differently. As a result, quality patent introduces a wedge between domestic and foreign revenues, weakening their correlation.[17]

2.4.2 Dynamic Innovation and Export Decisions

The transition of innovation and export decisions provides insight into the fixed and sunk costs of firm activities.

Table 3: Annual Transition Rates for Innovation and Exporting

	Status year t+1			
Status year t	neither	only innovate	only export	both
neither	89.89	3.22	6.51	0.38
only innovate	48.92	41.26	4.03	5.78
only export	10.29	0.28	85.23	4.20
both	4.58	3.10	35.45	56.87

Table 3 describes the transition of innovation and export decisions.[18] First, there is strong persistence in status over time. (41.26% + 5.78% =) 47.07% of the innovators continue to innovate in the next year. (85.23% + 4.20% =) 89.43% of the exporters continue to export in the next year. 89.89% of the firms that engage in neither activities remain dormant in the next year. Only 4.58% of the firms that both innovate and export completely abandon both activities in the next year. The persistence in status suggests that both innovation and export are associated with high startup costs and relatively low fixed costs.

Second, firms that undertake one activity are also more likely to undertake the other activity. Of the firms that innovate in the year t, 9.81% will export in year $t+1$. The same rate for firms that do neither activity is 6.89%. Of firms that export in year t, 4.48% will innovate in year $t+1$. The same rate for firms that do neither is 3.60%.

[16] Table C.2 groups firms based on their annual innovation decisions. The patterns are similar to Table 2.

[17] We refrain from comparing correlations in the *cost only* and *quality only* groups with the *neither* and *both* groups. This is because the *neither* firms are much smaller and the *both* firms are much bigger, as shown in the last row of Table 2. The size difference suggests that productivity, rather than innovation-decision, is likely the dominant factor driving correlations.

[18] Innovation incorporates both quality and cost innovations.

Third, firms that conduct both activities are less likely to abandon either of them than firms that conduct only one activity. Firms that both innovate and export in year t have a 40.03% probability to stop innovating and a 7.68% probability to stop exporting in year $t+1$. Firms that only innovate or only export have stopping probabilities of 52.95% and 10.57%, respectively.

The last two observations suggest the importance of modeling innovation and export in a unified framework.

Table 4: Annual Transition Rates for Innovation Decisions

	Status year t+1			
Status year t	neither	cost only	quality only	both
neither	96.06	1.40	1.41	1.13
cost only	57.39	18.23	9.85	14.53
quality only	58.96	5.18	16.85	19.01
both	28.80	7.43	13.59	50.18

Table 4 describes the transition of firm innovation decisions. First, there is low persistence in *quality only* and *cost only* statuses and high persistence in *both* and *neither* statuses. 32.76% of the cost innovators continue the activity in year $t+1$. 24.19% of the quality innovators continue the activity in year $t+1$. 96.06% of the firms that engage in neither innovation remain dormant in year $t+1$. 71.2% of the firms that engage in both types of innovation continue to innovate in year $t+1$.

Second, firms that engage in one type of innovation in year t are more likely to engage in the other type of innovation in year $t+1$. 24.38% of the cost innovators engage in quality innovation in year $t+1$. 24.19% of the quality innovators engage in cost innovation in year $t+1$. The same rates for firms that do not innovate are 2.54% and 2.53%.

Third, firms that conduct both quality and cost innovation are less likely to abandon either innovation than firms that conduct only one type of innovation. For firms that engage in both types of innovation in year t, 36.23% abandon quality innovation, and 42.39% abandon cost innovation in year $t+1$. The same rates for firms that engage in quality or cost innovation are 64.14% and 67.24%, respectively.

3 A Structural Model of Innovation and Export Decisions

Our model builds on ARX with two deviations. First, innovation in ARX is a homogeneous measure proxied by R&D expenditure. Innovation in our model is a dichotomous variable proxied by quality and cost patents. In doing so, we hope to recover the different natures of quality and cost innovation. Second, the export demand shifter in ARX is modeled as a first-order Markov process. We introduce quality innovation as an exogenous shock to this process. This setup is consistent with our definition of quality innovation as a demand shifter, and it explains the empirical pattern observed in the data.

Like ARX, firms in our model differ in productivity levels and face different export demand curves. They make static decisions (price and quantity) to maximize their short-run profits and dynamic decisions (export and innovation) to maximize their expected long-run profits.

3.1 Static Decisions

Firm i's short-run marginal cost function is

$$\ln c_{it} = \ln c(k_{it}, w_t) - \omega_{it} = \beta_0 + \beta_k \ln k_{it} + \beta_{\mathbf{w}} \ln \mathbf{w_t} - \omega_{it}, \tag{1}$$

where k_{it} is the firm's capital stock. $\mathbf{w_t}$ is a vector of variable input prices common to all firms. ω_{it} is firm productivity.

The domestic demand function is

$$q_{it}^D = \Phi_t^D (p_{it}^D)^{\eta_D}, \tag{2}$$

where Φ_t^D represents the domestic market aggregates. p_{it}^D is firm i's domestic price. η_D is the domestic demand elasticity.

The export demand function is

$$q_{it}^X = \Phi_t^X (p_{it}^X)^{\eta_X} \exp(\upsilon_{it}), \tag{3}$$

where Φ_t^X represents the export market aggregates. p_{it}^X is firm i's export price. η^X is the foreign demand elasticity. υ_{it} is a firm-specific export demand shifter that can be affected by the firm's previous-period quality-innovation decision (elaborated in the next section). υ_{it} is observed by the firm before its export decision but not observed in the data.

Solving the firm's profit maximization problem gives the following domestic and foreign revenue functions:

$$\ln r_{it}^D = (\eta_D + 1) \ln \left(\frac{\eta_D}{\eta_D + 1} \right) + \ln \Phi_t^D + (\eta_D + 1)(\beta_0 + \beta_k \ln k_{it} + \beta_w \ln w_t - \omega_{it}); \tag{4}$$

$$\ln r_{it}^X = (\eta_X + 1) \ln \left(\frac{\eta_X}{\eta_X + 1} \right) + \ln \Phi_t^X + (\eta_X + 1)(\beta_0 + \beta_k \ln k_{it} + \beta_w \ln w_t - \omega_{it}) + \upsilon_{it}. \tag{5}$$

The related domestic and foreign profit functions are:

$$\pi_{it}^D = -\left(\frac{1}{\eta_D} \right) r_{it}^D (\Phi_t^D, k_{it}, \omega_{it}); \tag{6}$$

$$\pi_{it}^X = -\left(\frac{1}{\eta_X} \right) r_{it}^X (\Phi_t^X, k_{it}, \omega_{it}, \upsilon_{it}). \tag{7}$$

3.2 Transition of State Variables

Productivity evolves over time as a Markov process that depends on the firm's innovation decisions, its export market participation, and a random shock:

$$\begin{aligned}\omega_{it} &= g(\omega_{it-1}, d_{it-1}, e_{it-1}) + \xi_{it} \\ &= \alpha_0 + \sum_{k=1}^{3} \alpha_k (\omega_{it-1})^k + \alpha_4 d^Q_{it-1} + \alpha_5 d^C_{it-1} + \alpha_6 e_{it-1} + \alpha_7 d^Q_{it-1} e_{it-1} + \alpha_8 d^C_{it-1} e_{it-1} + \xi_{it}, \quad (8)\end{aligned}$$

where d^Q_{it-1}, d^C_{it-1} and e_{it-1} denote the firm's previous-period quality innovation, cost innovation, and export decisions. ξ_{it} is an i.i.d. shock with zero mean and variance σ^2_ξ. α_4 and α_5 capture the effects of quality and cost innovation on firm productivity. α_6 captures the effect of export market participation on firm productivity. We allow the firm's innovation decisions to interact with its export decision. These interaction effects are captured by α_7 and α_8.[19]

The export demand shifter (v_{it}) defined in equation (3) evolves according to the following process:

$$v_{it} = \rho_d d^Q_{it-1} + z_{it}, \quad (9)$$

where ρ_d captures the effect of the firm's previous-period quality innovation on its export demand shifter. z_{it} follows a Markov process:

$$z_{it} = \rho_z z_{it-1} + \mu_{it}, \quad \mu_{it} \sim N(0, \sigma^2_\mu).$$

A generalized expression of v_{it} is $v_{it} = \sum_{j=1}^{k} \rho^j_d d^Q_{it-j} + z_{it}$, where $k > 1$ allows one to capture the effects of multiple previous-period quality innovations.[20] We experimented with $k > 1$ and found that innovations from earlier periods have little impact on the export demand shifter.

3.3 Dynamic Decisions

The state variable of firm i in year t is $s_{it} = (\omega_{it}, v_{it}, k_{it}, \Phi_t, e_{it-1}, d^C_{it-1}, d^Q_{it-1})$.[21] Observing s_{it}, the firm draws its fixed or sunk cost of exporting, γ^{Ef}_{it} and γ^{Es}_{it}, and decides whether or not to export. Following this, it draws its fixed or sunk cost of innovation, γ^{Cf}_{it} and γ^{Cs}_{it}, and decides whether or not to engage in cost innovation. After this, the firm draws its fixed and sunk cost of quality innovation, γ^{Qf}_{it} and γ^{Qs}_{it}, and decides whether or not to engage in quality innovation.[22] We assume that γ^{Ef}_{it} and γ^{Es}_{it} are i.i.d. draws from joint distribution G^E, γ^{Qf}_{it} and γ^{Qs}_{it} are i.i.d. draws from joint

[19] Including the interaction between quality and cost innovation does not affect our estimation results.

[20] v_{it} is essentially an auto-regressive variable with exogenous shocks $(d_{it-1}, ..., d_{it-j})$. The process can be equivalently expressed as $\left(v_{it} - \sum_{j=1}^{k} \rho^j_d d^Q_{it-j}\right) - \rho_z \left(v_{it-1} - \sum_{j=2}^{k+1} \rho^j_d d^Q_{it-j}\right) = \mu_{it}$. This means z_{it} is a Markov process with white noise μ_{it} and variance $\sigma^2_\mu/(1 - \rho^2_z)$. It can be estimated using the method developed by Das et al. (2007).

[21] Like ARX, we replace k_{it} with $k_i \equiv (\sum_{t=1}^{T} k_{it})/T$ in our empirical estimation to reduce the computation burden.

[22] The order of these decisions does not matter for our estimation results.

distribution G^Q, and γ_{it}^{Cf} and γ_{it}^{Cs} are i.i.d. draws from joint distribution G^C.[23]

The firm's value function before observing its fixed and sunk costs is

$$V_{it}(s_{it}) = \pi_{it}^D + \int \max_{e_{it}} \{\pi_{it}^X - e_{it-1}\gamma^{Ef} - (1 - e_{it-1})\gamma^{Es} + V_{it}^E(s_{it}), V_{it}^D(s_{it})\} dG^E, \tag{10}$$

where e_{it} and e_{it-1} are $0/1$ indicators of the firm's export statuses in t and $t-1$, respectively. The firm's export cost in t depends on its export status in $t-1$. Specifically, the firm pays a fixed cost γ^{Ef} to export if it exported in $t-1$ ($e_{it-1} = 1$); otherwise, the firm pays γ^{Es} to participate. If the firm chooses to export ($e_{it} = 1$), it receives export profit π_{it}^X net of its export costs, plus its expected future payoff (V^E); if the firm chooses not to export ($e_{it} = 0$), it receives zero plus its expected future payoff (V^D). V_{it}^E and V_{it}^D are value functions of an exporting firm and a non-exporting firm integrating over different cost states for cost innovation under optimal decisions:

$$V_{it}^E(s_{it}) = \int \max_{d_{it}^C} \{V_{it}^C(s_{it}, e_{it} = 1) - d_{it-1}^C \gamma_{it}^{Cf} - (1 - d_{it-1}^C)\gamma_{it}^{Cs}, V_{it}^{NC}(s_{it}, e_{it} = 1)\} dG^C; \tag{11}$$

$$V_{it}^D(s_{it}) = \int \max_{d_{it}^C} \{V_{it}^C(s_{it}, e_{it} = 0) - d_{it-1}^C \gamma_{it}^{Cf} - (1 - d_{it-1}^C)\gamma_{it}^{Cs}, V_{it}^{NC}(s_{it}, e_{it} = 0)\} dG^C. \tag{12}$$

d_{it}^C and d_{it-1}^C are $0/1$ indicators of the firm's cost innovation decisions in t and $t-1$, respectively.[24] The firm pays fixed cost γ^{Cf} to engage in cost innovation if it filed a cost patent in $t-1$; otherwise, it pays γ^{Cs} to participate. The firm chooses d_{it}^C to maximize its expected future payoff. V_{it}^C and V_{it}^{NC} are value functions of a cost-innovating firm and a non-cost-innovating firm integrating over different cost states for quality innovation under optimal decisions:

$$V_{it}^C(s_{it}, e_{it}) = \int \max_{d_{it}^Q} \{\delta E_t V_{it+1}(s_{it+1}|s_{it}, e_{it}, d_{it}^C = 1, d_{it}^Q = 1) - d_{it-1}^Q \gamma_{it}^{Qf} - (1 - d_{it-1}^Q)\gamma_{it}^{Qs}, \tag{13}$$

$$\delta E_t V_{it+1}(s_{it+1}|s_{it}, e_{it}, d_{it}^C = 1, d_{it}^Q = 0)\} dG^Q, \tag{14}$$

$$V_{it}^{NC}(s_{it}, e_{it}) = \int \max_{d_{it}^Q} \{\delta E_t V_{it+1}(s_{it+1}|s_{it}, e_{it}, d_{it}^C = 0, d_{it}^Q = 1) - d_{it-1}^Q \gamma_{it}^{Qf} - (1 - d_{it-1}^Q)\gamma_{it}^{Qs}, \tag{15}$$

$$\delta E_t V_{it+1}(s_{it+1}|s_{it}, e_{it}, d_{it}^C = 0, d_{it}^Q = 0)\} dG^Q, \tag{16}$$

where $E_t V_{it+1}$ is the firm's expected future value conditional on its current period export and

[23]Since we do not model the probability of innovation success, the risky nature of innovation is subsumed in the costs. The lower the probability of success, the higher the cost. For example, if a firm pays cost c to innovate and succeeds with a probability of p. The expected cost associated with a successful innovation is c/p, which is the cost that our model captures.

[24]There is a slight abuse of notations in that we use the same d^C and d^Q in the value functions and in productivity evolution in equation (8). In the value functions, d^C and d^Q are $0/1$ indicators. In equation (8), they are measures of cost and quality innovation, where they could be either $0/1$ indicators or continuous measures of innovation intensity.

innovation decisions:

$$E_t V_{it+1}(s_{it+1}|e_{it}, d^C_{it}, d^Q_{it}) = \int_{z'} \int_{\omega'} V_{it+1}(s') dF(\omega'|\omega_{it}, e_{it}, d^C_{it}, d^Q_{it}) dT(v'|v_{it}, d^Q_{it}). \tag{17}$$

The evolution of productivity $dF(\omega'|\omega_{it}, e_{it}, d^C_{it}, d^Q_{it})$ is conditional on e_{it}, d^Q_{it} and d^C_{it} because of equation (8). The evolution of export demand shifter $dT(v'|v_{it}, d^Q_{it})$ is conditional on d^Q_{it} because of equation (9).

4 Estimation Strategy and Empirical Results

We divide our estimation into two stages. In the first stage, we recover the demand function parameters (Φ^D, Φ^X, η^D, and η^X), the marginal cost function parameters (β_0, β_k, and β_w), and parameters governing the productivity evolution process ($\alpha_0, \alpha_1, ..., \alpha_8$). In the second stage, we recover the remaining parameters, including parameters governing the evolution of the exporter demand shifter v_{it} (ρ_d, ρ_z, and σ_μ) and the fixed and sunk costs of export (γ^{Ef} and γ^{Es}), cost innovation (γ^{Cf} and γ^{Cs}), and quality innovation (γ^{Qf} and γ^{Qs}).

4.1 Demand and Cost Parameters

The first-order conditions in the firm's profit maximization problem imply the following relationship between its total variable cost and its domestic and foreign revenues:

$$tvc_{it} = r^D_{it}\left(1 + \frac{1}{\eta_D}\right) + r^X_{it}\left(1 + \frac{1}{\eta_X}\right) + \varepsilon_{it}, \tag{18}$$

where the error term ε_{it} reflects measurement error in total variable cost.[25] The regression results are reported in Table 5. The implied elasticities are $\eta_D = -4.59$ and $\eta_X = -5.56$.[26]

Table 5: Demand Elasticities

Parameter	Coefficient	Standard Error
$1 + 1/\eta_D$	0.782***	(0.002)
$1 + 1/\eta_X$	0.820***	(0.003)
Observations	35,401	
R squared	0.892	

Notes: Numbers in parentheses report standard errors.

The domestic revenue function in equation (4) is appended with an i.i.d. error term u^D_{it} that

[25] Total variable cost is the sum of the firm's material costs and its wage bill. Domestic revenue is the difference between total revenue and export revenue. All variables are drawn from the ASIE database.

[26] The demand elasticities in ARX are $\eta_D = -6.38$ and $\eta_X = -6.10$.

captures measurement errors and re-written as follows:

$$\begin{aligned}\ln r_{it}^D &= \lambda_0^D + \sum_{t=1}^{T} \lambda_t^D D_t + (\eta_D + 1)(\beta_k \ln k_{it} - \omega_{it}) + u_{it}^D \\ &= \lambda_0^D + \sum_{t=1}^{T} \lambda_t^D D_t + h(k_{it}, m_{it}, l_{it}) + \zeta_{it}^D, \end{aligned} \tag{19}$$

where D_t is a series of time dummies that absorb all non-firm-specific factors, such as aggregate demand and factor prices. $h(\cdot)$ a cubic function of capital and variable inputs. The fitted value of $h(k_{it}, m_{it}, l_{it})$, denoted by $\hat{\phi}_{it}$, is an approximation of $(\eta_D + 1)(\beta_k \ln k_{it} - \omega_{it})$. Substituting $\omega_{it} = -(1/(\eta_D + 1))\hat{\phi}_{it} + \beta_k \ln k_{it}$ into equation (8) gives:

$$\begin{aligned}\hat{\phi}_{it} = \;& \beta_k^* \ln k_{it} - \alpha_0^* + \alpha_1(\hat{\phi}_{it-1} - \beta_k^* \ln k_{it}) - \tfrac{\alpha_2}{\eta_D+1}(\hat{\phi}_{it-1} - \beta_k^* \ln k_{it})^2 + \tfrac{\alpha_3}{(\eta_D+1)^2}(\hat{\phi}_{it-1} - \beta_k^* \ln k_{it})^3 \\ & -\alpha_4^* d_{it-1}^Q - \alpha_5^* d_{it-1}^C - \alpha_6^* e_{it-1} - \alpha_7^* d_{it-1}^Q e_{it-1} - \alpha_8^* d_{it-1}^C e_{it-1},\end{aligned}$$

where coefficients with asterisks are multiplied by $(\eta_D + 1)$. This equation can be estimated by NLS, and the underlying α and β_k parameters can be retrieved given $\hat{\eta}_D$.

Table 6: Demand, Cost, and Productivity Evolution Estimates

Parameter	patent dummy	patent counts	weighted patent counts
	(1)	(2)	(3)
β_k ($\ln k_{it-1}$)	-0.0701***	-0.0648***	-0.0649***
	(0.002)	(0.002)	(0.002)
α_0 (ω_{it-1}, nonparametric)	0.0386***	0.0478***	0.0477***
	(0.003)	(0.004)	(0.004)
α_1 (ω_{it-1}, nonparametric)	0.830***	0.842***	0.841***
	(0.007)	(0.008)	(0.008)
α_2 (ω_{it-1}, nonparametric)	0.123***	0.126***	0.126***
	(0.008)	(0.009)	(0.009)
α_3 (ω_{it-1}, nonparametric)	-0.0595***	-0.0666***	-0.0662***
	(0.006)	(0.006)	(0.006)
α_4 (d_{it-1}^Q)	0.0123*	0.0176**	0.0101**
	(0.007)	(0.008)	(0.005)
α_5 (d_{it-1}^C)	0.0127*	0.00913	0.00731
	(0.008)	(0.010)	(0.005)
α_6 (e_{it-1})	0.0139***	0.0138***	0.0137***
	(0.002)	(0.002)	(0.002)
α_7 ($d_{it-1}^Q \cdot e_{it-1}$)	0.00326	-0.00210	-0.00103
	(0.011)	(0.011)	(0.007)
α_8 ($d_{it-1}^C \cdot e_{it-1}$)	0.00522	-0.00459	-0.00119
	(0.012)	(0.013)	(0.007)
Observations	22,909	22,909	22,909
R^2	0.804	0.796	0.796

Notes: Numbers in parentheses report standard errors.

Table 6 reports estimation results using three measures of d_{it}^Q and d_{it}^C: (1) a dummy that equals one if firm i files one or more patent applications in year t and zero otherwise, (2) firm i's number of patent applications in year t, and (3) firm i's weighted number of patent applications in year t, where each patent is weighted by one plus its number of citations. Table 6 shows all three measures render very similar results. We use results from the first column for dynamic estimation.

β_k is the coefficient on capital stock in the marginal cost function in equation (1). It is negative and significant, indicating that firms with high capital stocks enjoy low marginal costs. The estimates of α_0-α_3 indicate a strong nonlinear relationship between ω_{it-1} and ω_{it}, as described in equation (8). α_4-α_6 measure the direct effects of quality innovation, cost innovation, and export on firm productivity. α_6 measures the direct effect of export on firm productivity. It suggests that a firm that engaged in export and no innovation in $t-1$ is 1.39 percent more productive in t than a firm that engaged in neither export nor innovation. This number is very similar to the finding of 1.96 percent in ARX. ARX finds that lagged R&D expenditure improves the productivity of a non-exporting firm by 4.79 percent. This effect is jointly captured by our estimates of α_4 and α_5, which suggest that lagged innovation improves firm productivity by 2.5 percent. In addition, our results suggest that quality innovation has a stronger effect on firm productivity than cost innovation because the impact of quality innovation, captured by α_4, is more robust across specifications. Lastly, like ARX, coefficients of the interactions between innovation and export (α_7 and α_8) are insignificant. We conclude that there is unlikely any spillover between innovation and exporting through the productivity channel.

Given estimates of $\hat{\eta}_D$, $\hat{\phi}_{it}$ and $\hat{\beta}_k$, we construct productivity estimate as

$$\hat{\omega}_{it} = -\frac{1}{\hat{\eta}_D + 1}\hat{\phi}_{it} + \hat{\beta}_k \ln k_{it}.$$

We confirm that our productivity estimate has strong correlations with export participation, cost and quality innovation, and domestic and foreign revenues by replicating Table 4 in ARX. The results are reported in Table C.4 in the appendix.

4.2 Dynamic Parameters

We now solve parameters in the export demand shifter's evolution process (ρ_d, ρ_z, and σ_μ) and the fixed and sunk costs of export and innovation decisions (γ^{Ef}, γ^{Es}, γ^{Qf}, γ^{Qs}, γ^{Cf}, and γ^{Cs}).

The dynamic estimation is based on the likelihood function for firm i's export pattern $e_i \equiv (e_{i0}, ...e_{iT})$, export revenues $r_i^X \equiv (r_{i0}^X, ...r_{iT}^X)$, quality innovation decisions $d_i^Q \equiv (d_{i0}^Q, ...d_{iT}^Q)$, and cost innovation decisions $d_i^C \equiv (d_{i0}^C, ...d_{iT}^C)$. Firm i's contribution to the likelihood function is:

$$P(e_i, d_i^Q, d_i^C, r_i^X | \omega_i, k_i) = P(e_i, d_i^Q, d_i^C | \omega_i, k_i, z_i^+) h(z_i^+), \tag{20}$$

where $\omega_i \equiv (\omega_{i0}, ...\omega_{iT})$ is the sequence of firm i's productivity estimates from static estimation.

$k_i \equiv (k_{i0}, ...k_{iT})$ is the sequence of firm i's capital stock. z_i^+ is the *uncensored* sequence of export demand shocks defined in equation (9). We construct z_i^+ and $h(z_i^+)$ using the method developed by Das et al. (2007).[27]

Given that we assumed the fixed and sunk costs for each activity are i.i.d. draws from the same joint distribution, the joint probability $P(e_i, d_i^Q, d_i^C | \omega_i, k_i, z_i^+)$ in equation (20) can be written as the product of the following conditional probabilities over time:

$$P(e_{it} = 1 | s_{it}) = P(e_{it-1}\gamma_{it}^{Ef} + (1 - e_{it-1})\gamma_{it}^{Es} \le \pi_{it}^X + V_{it}^E(s_{it}) - V_{it}^D(s_{it})), \tag{21}$$

$$P(d_{it}^C = 1 | s_{it}, e_{it}) = P(d_{it-1}^C \gamma_{it}^{Cf} + (1 - d_{it-1}^C)\gamma_{it}^{Cs} \le V_{it}^C(d_{it}^C = 1 | s_{it}, e_{it}) - V_{it}^C(d_{it}^C = 0 | s_{it}, e_{it})), \tag{22}$$

$$\begin{aligned} P(d_{it}^Q = 1 | s_{it}, e_{it}, d_{it}^C) = P(d_{it-1}^Q \gamma_{it}^{Qf} + (1 - d_{it-1}^Q)\gamma^{Qs} \le & \delta E_t V_{it+1}(s_{it+1} | s_{it}, e_{it}, d_{it}^C, d_{it}^Q = 1) \\ & - \delta E_t V_{it+1}(s_{it+1} | s_{it}, e_{it}, d_{it}^C, d_{it}^Q = 0)), \end{aligned} \tag{23}$$

where $s_{it} = (\omega_{it}, z_{it}, k_i, e_{it-1}, d_{it-1}^C, d_{it-1}^Q)$ is the state vector. The inequalities in the probability functions reflect the firm's tradeoff when making export and innovation decisions. Firms choose to engage in an activity if and only if its benefit exceeds the cost.

The above equations imply that the conditional probabilities depend on the firm's value functions EV_{it+1}, V_{it}^E, V_{it}^D, V_{it}^C, and V_{it}^{NC}. For a given set of parameters, we compute the value functions by solving for the firm's dynamic programming problem defined in Section 3.3. Our algorithm is elaborated in Appendix B. We then use the value functions to compute the corresponding likelihood, which is an assessment of the fitness of the set of parameters. Like ARX, we use the MCMC estimator to find the optimal parameter values, which are reported in Table 7.

First, the fixed cost is always lower than the sunk cost for each activity (export, quality innovation, and cost innovation). This is unsurprising and consistent with theoretical and empirical findings in the mainstream literature. Second, innovation is much more expensive than exporting. The fixed cost of quality innovation is more than 20 times that of exporting, and the sunk cost is more than 16 times that of exporting. Third, quality innovation is more expensive than cost innovation. The fixed cost of quality innovation is 2.17 times that of cost innovation, and the sunk cost is 1.54 times that of cost innovation. Lastly, quality innovation improves next-period export demand by as much as 47%. This implies that quality innovation could improve an exporter's next-period productivity by as much as 1.88 percent.

We examine the performance of these parameters by using them to simulate firm decisions.

[27]Recall from footnote 20 that $z_{it} = v_{it} - \rho_z d_{it-1}^Q$ follows a Markov process. It is not observed for the years firm i does not export. Constructing z_i^+ requires z_i, the sequence of export shocks for the years firm i exports. To get z_i, we first obtain v_i, the sequence of firm i's export demand shifter for the years it exports. We do so by deducting firm i's non-zero export revenue r_{it}^X by the industry's market-share-weighted average r_t^X. This purges industry-level time trends from the export revenues and gives us an estimate of v_{it}, which is used to construct v_i. We then deduct v_i by ρ_z times the firm's lagged quality innovation decisions to obtain z_i, which is used to construct z_i^+ and $h(z_i^+)$ using the method in Das et al. (2007).

Table 7: Dynamic Parameter Estimates

Parameter	Description	Range	Value
γ^{Ef}	export fixed cost	[0, 100]	0.015
γ^{Es}	export sunk cost	[0, 500]	0.059
γ^{Qf}	quality innovation fixed cost	[0, 100]	0.319
γ^{Qs}	quality innovation sunk cost	[0, 500]	0.970
γ^{Cf}	cost innovation fixed cost	[0, 100]	0.147
γ^{Cs}	cost innovation sunk cost	[0, 500]	0.631
ρ_z	export demand shifter AR process	[0, 1]	0.669
ρ_d	coefficient on quality innovation	[0, 1]	0.470
$\log \sigma_\mu$	export demand shifter std. dev.	[0, 1]	0.344

Notes: The fixed and sunk costs are in tens of millions of Chinese yuan. We constrain ρ_d to be positive to reduce computation time. Relaxing the range to incorporate negative values does not change the estimation result.

Using data from the year 2000 as the starting point, we use our parameters to draw firm-specific shocks, let these shocks determine firm decisions, and use these firm decisions to simulate the next-period firm behavior. Our simulation results, reported in Tables C.5 and C.6 in the appendix, closely match firm decisions and productivity evolution in the data.

4.3 Estimates Comparison

This section compares our estimates with two papers that adopt similar empirical strategies. In doing so, we hope to understand better the incentive structure faced by the Chinese electronic firms. Specifically, we compare our estimates on export participation with ARX's study on Taiwanese electronic firms, and our estimates on quality and cost innovation with the effect of product and process innovation on German electronic firms in Peters et al. (2017).[28]

First, export and innovation in our sample have a comparable but smaller influence on firm productivity than in the other two papers. Export participation increases firm productivity by 0.014 in our sample and 0.020 in ARX. Quality and cost innovation increase firm productivity by 0.012 and 0.013 in our sample. Their effects are 0.036 and 0.029 in Peters et al. (2017). Aw et al. (2011) estimate R&D expenditure to increase productivity by 0.048. This effect is also larger than our two types of innovation combined.

Second, the fixed and especially sunk costs of firm activities (relative to firm size) are low in

[28] Peters et al. (2017) study the nexus between R&D, product and process innovation, and firm productivity evolution. Their definition of product and process innovation follows the Oslo Manual, where product innovation is a new or significantly improved product or service, and process innovation refers to new or significant changes in the way products are produced, delivered, or supplied. The definitions are very close to our definition of quality and cost innovation in Section 2.2. The only difference is that their innovation data is reported by the firm, while our innovation data is recovered from the patent database.

our sample. The fixed and sunk cost of exporting are respectively 0.15 and 0.59 million Chinese yuan, which are fairly small percentages of the median domestic revenues of 12 to 28 million for non-exporters and 7 to 18 million for exporters (Table 1, this paper). In Aw et al. (2011), the fixed and sunk cost of exporting are respectively 11 and 51 million new Taiwan dollars, while the median domestic sales are 17 to 22 million for non-exporters and 36 to 53 million for exporters (Tables 1 and 5, Aw et al. (2011)). In our sample, the fixed costs of quality and cost innovation are 3 and 1.5 million Chinese yuan, and the sunk costs of quality and cost innovation are 9.7 and 6.3 million Chinese yuan. These are small percentages of the aforementioned median domestic revenues. In Peters et al. (2017), the fixed (maintenance) and sunk (startup) costs of innovation are 0.6 and 8.7 million euros, and the median revenues for R&D active and inactive firms are 13 and 3 million euros (Tables 7, Peters et al. (2017)).

Third, the ratio between sunk and fixed costs in our sample is comparable to Aw et al. (2011), but our ratio for innovation is significantly lower than Peters et al. (2017). In our paper, the sunk-cost-to-fixed-cost ratios for export, quality innovation, and cost innovation are respectively 4, 3, and 4.3. In Aw et al. (2011), the sunk-cost-to-fixed cost ratio is 4.6 for exporting and 5 for R&D investment (Table 5).6 In Peters et al. (2017), the sunk-cost-to-fixed-cost ratio for innovation is 13.5 (Table 7, Model B, electronics industry).

To summarize, compared to German and Taiwanese electronic firms, exporting and innovation are low-cost, low-return activities for the electronic firms in mainland China. The low-cost property is demonstrated by the fact that costs are low relative to firm revenues, and the low-return property by their small effects on firm productivity.[29] Lastly, we expect low sunk-cost-to-fixed-cost ratios to generate lower persistence in firm activities. The similar ratios in our paper and Aw et al. (2011) are consistent with the similar numbers in our transition matrices (Table 3 in our paper and Table 2 in Aw et al. (2011)). Given the large ratio in Peters et al. (2017), we expect German firms' innovation activity to be much more persistent than Chinese firms.

5 Counterfactuals

5.1 Market Expansion

This section explores the effect of domestic and foreign market expansions on firm decisions and firm productivity evolution. The domestic market expansion simulates any policy intervention that increases the domestic demand, e.g., government procurement, domestic protection, and domestic market growth. The foreign market expansion simulates positive shocks on foreign demand driven

[29] It is worth pointing out, however, that the low effect of innovation on productivity can be driven by two mechanisms. First, Chinese firms' innovation may be less valuable than German firms' innovation due to their late entry into the electronics industry. Second, innovation in our paper is inferred from patent applications. In Peters et al. (2017), it is reported by firms. Due to reasons elaborated in Section 2.3, our patent measures may not capture all firm innovations and hence, understate their effect on firm productivity.

by income growth or trade liberalization. We introduce market expansion as an annual expansion of 20% in domestic or foreign demand, modeled as a percentage increase in Φ_D or Φ_X in equations (2) and (3), and simulate its effect in 10 years.[30] Productivity distribution and state variables for year 0 are obtained from the data.

Table 8: Effects of 20% Market Expansions in 10 Years

(a) Percent of Exporters

	Exporters (%)		
Expansion type:	Domestic	Foreign	None
Productivity quantile	(1)	(2)	(3)
<25%	30.54%	50.38%	29.85%
25%-50%	33.80%	50.60%	33.06%
50%-75%	40.54%	58.83%	39.74%
>75%	60.21%	77.49%	59.23%
Total	41.27%	59.33%	40.47%

(b) Percent of Cost Innovators

	Cost innovators (%)		
Expansion type:	Domestic	Foreign	None
Productivity quantile	(1)	(2)	(3)
<25%	2.34%	23.27%	2.05%
25%-50%	2.51%	18.27%	2.22%
50%-75%	5.03%	26.25%	4.51%
>75%	19.82%	49.27%	18.45%
Total	7.43%	29.27%	6.81%

(c) Percent of Quality Innovators

	Quality innovators (%)		
Expansion type:	Domestic	Foreign	None
Productivity quantile	(1)	(2)	(3)
<25%	5.11%	18.14%	4.96%
25%-50%	5.75%	18.19%	5.62%
50%-75%	8.75%	24.78%	8.54%
>75%	22.20%	45.63%	21.71%
Total	10.45%	26.68%	10.21%

(d) Productivity

	Productivity (simple avg.)		
Expansion type:	Domestic	Foreign	None
Productivity quantile	(1)	(2)	(3)
<25%	0.157	0.165	0.157
25%-50%	0.247	0.255	0.247
50%-75%	0.329	0.340	0.328
>75%	0.520	0.537	0.519
Total	0.313	0.324	0.313

Table 8 reports the effect of 20% domestic and foreign market expansions after 10 years. Each panel focuses on one target variable, and firms are put into four categories based on the quartile position of their productivity in the sample distribution of 2000.

Three insights emerge from Table 8. First, both domestic and foreign market expansions encourage firms to export and innovate, with the latter having a much larger impact than the former. A 20% foreign market expansion increases the percent of exporters, cost innovators, and quality innovators by 19%, 22%, and 16%. In contrast, a 20% domestic market expansion's corresponding effects are merely 0.8%, 0.6% and 0.2%. The contrast between domestic and foreign market expansions is caused by the different channels through which domestic and foreign profits drive firm decisions.[31] As equations (21), (22), and (23) show, the firm's decision is driven by the cost of undertaking an activity versus its marginal benefit. While domestic profit does not enter any marginal benefit, foreign profit directly enters the marginal benefit of exporting in equation

[30]We experiment with expansion percentages from 10% to 50% in 10% intervals and simulate their effects in 2, 5, 10, and 15 years. The patterns are similar to what we report in the main text.

[31]With constant markups, a percentage expansion in firm demand translates to the same percentage expansion in firm profit, as equations (6) and (7) show.

(21). This implies that an increase in domestic profit augments all expected values – those from undertaking an activity and those from *not* undertaking an activity. In contrast, an increase in foreign profit immediately raises the benefit of export, thereby increasing the firm's likelihood to export. Since the marginal benefit of innovation is bigger for exporters than for non-exporters, export also increases the firm's likelihood of engaging in innovation.[32]

Second, Table 8d shows that domestic and foreign market expansions both improve firm productivity. Domestic market expansion increases the average firm productivity (relative to the baseline) by 0.04%; foreign market expansion by 1.17%. The magnitudes are small but not out of line. For example, ARX simulate a 37% foreign market expansion and find its 10-year effect on average firm productivity to be 3.7%. Market expansion indirectly improves firm productivity by encouraging firms to export and innovate. Although foreign market expansion increases the number of exporters and innovators, as shown in panels (a)-(c), given that export and innovation have small influences on productivity (reported in Table 7 and discussed in Section 4.3), it is unsurprising to see little change in firm productivity.

Third, the higher a firm's productivity, the more it benefits (in terms of productivity) from market expansions. Take foreign market expansion for example. Productivity in the fourth quartile increases by 1.85%, which is more than twice the increment for the firms in the first quartile (0.84%). This result is intuitive. Foreign market expansion disproportionately increases high productivity firms' marginal benefit of exporting. Since the marginal benefit of innovation is larger for exporters, high productivity firms also have higher incentives to innovate. The combined incentives to export and innovate means high productivity firms also see the largest improvement in their productivity.

5.2 Export and Innovation Subsidies

Our estimates in Table 7 showed that export and innovation have limited impacts on firm productivity. These estimates are partial in that they do not account for the dynamic interaction between export and innovation over time. This section explores their interactions by simulating the effect of export and innovation subsidies over 15 years. A subsidy is modeled as a percentage reduction in the firm's export or innovation cost.[33] We have three firm activities (export, quality innovation, and cost innovation) and two costs for each activity (fixed cost and sunk cost), so there are six subsidies to consider. Section 5.2.1 focuses on the effect of subsidies on firm activities. Section 5.2.2 focuses on the effect of subsidies on productivity evolution.

[32]The proof for the fact that the marginal benefit of innovation/exporting increases in exporting/innovation activity is straightforward and resembles Section C in ARX.

[33]Cost reduction can be driven by a number of factors, including tax rebates to exporters or innovators, the removal of hurdles to exporting and innovation, and the agglomeration of export and innovation activities.

5.2.1 Effect on firm decisions

This section explores the effect of subsidies on firms' export and innovation decisions. Figure 1 focuses on fixed cost subsidies; figure 2 on sunk cost subsidies. In each figure, the three columns correspond to activities as the targets of subsidies (export subsidy, cost-innovation subsidy, and quality-innovation subsidy), and the three rows correspond to activities as outcomes (export, cost innovation, and quality innovation).[34] For each subsidy-activity combination, we report outcomes for three groups of firms: all firms that participate in the activity, incumbent firms (firms that participated in $t-1$ and continue to participate in t), and entrants (firms that did not participate in $t-1$ but start participating in t). The marked lines report participation *with* the subsidy, and the dashed lines report participation *without* the subsidy (the baseline case).

When discussing each figure, we refer to a subsidy by the activity it subsidizes for succinctness. Specifically, we refer to subsidies on the fixed (Figure 1) or sunk (Figure 2) costs of exporting, quality innovation, and cost innovation as export subsidy, quality-innovation subsidy, and cost-innovation subsidy, respectively.

A few patterns are noteworthy in Figure 1. First, the diagonal panels suggest that participation in subsidized activities is responsive to fixed cost subsidies. The upper-left panel shows that both incumbents and new exporters respond positively to export subsidies in the first year. While the percent of incumbents stays above the baseline level in subsequent years, the percent of new firms drops back to the baseline level. This indicates firms that enter the export market become continuing exporters in subsequent years. The middle panel shows that a large number of firms begin cost innovation in response to the cost subsidy. These firms become incumbent innovators in subsequent years, driving the percent of incumbent firms above the baseline level. The lower-right panel resembles what we observe in the middle panel but with weaker magnitudes.

Second, the off-diagonal panels show that the three subsidies have varying cross effects.[35] Export subsidy has little impact on innovation decisions. Cost-innovation subsidy encourages export and quality-innovation participation, mostly by incentivizing the incumbents to stay. Quality-innovation subsidy works similarly in keeping cost-innovators continue but has a slightly negative impact on export participation. To understand these patterns, note that equations (21), (22), and (23) suggest that while subsidies directly enter the tradeoff in the subsidized activity, they do not directly affect the tradeoff in unsubsidized activity. Therefore, the cross effects depend on changes in the marginal benefits of unsubsidized activities in response to firm participation in other activities. Our observations in the off-diagonal panels suggest that while export and cost-innovation subsidy have small or positive impacts on the marginal benefits of unsubsidized activities, quality-innovation subsidy increases the marginal benefit of cost innovation but decreases the marginal

[34] This layout allows us to observe the effect of a subsidy on both subsidized and unsubsidized activities. For example, the three panels in the first column of Figure 1 respectively report the effect of export subsidy on exporting, cost innovation, and quality innovation.

[35] Cross effect is the effect of a subsidy on unsubsidized activities. For example, the cross effect of export subsidy refers to its impact on quality and cost innovation activities.

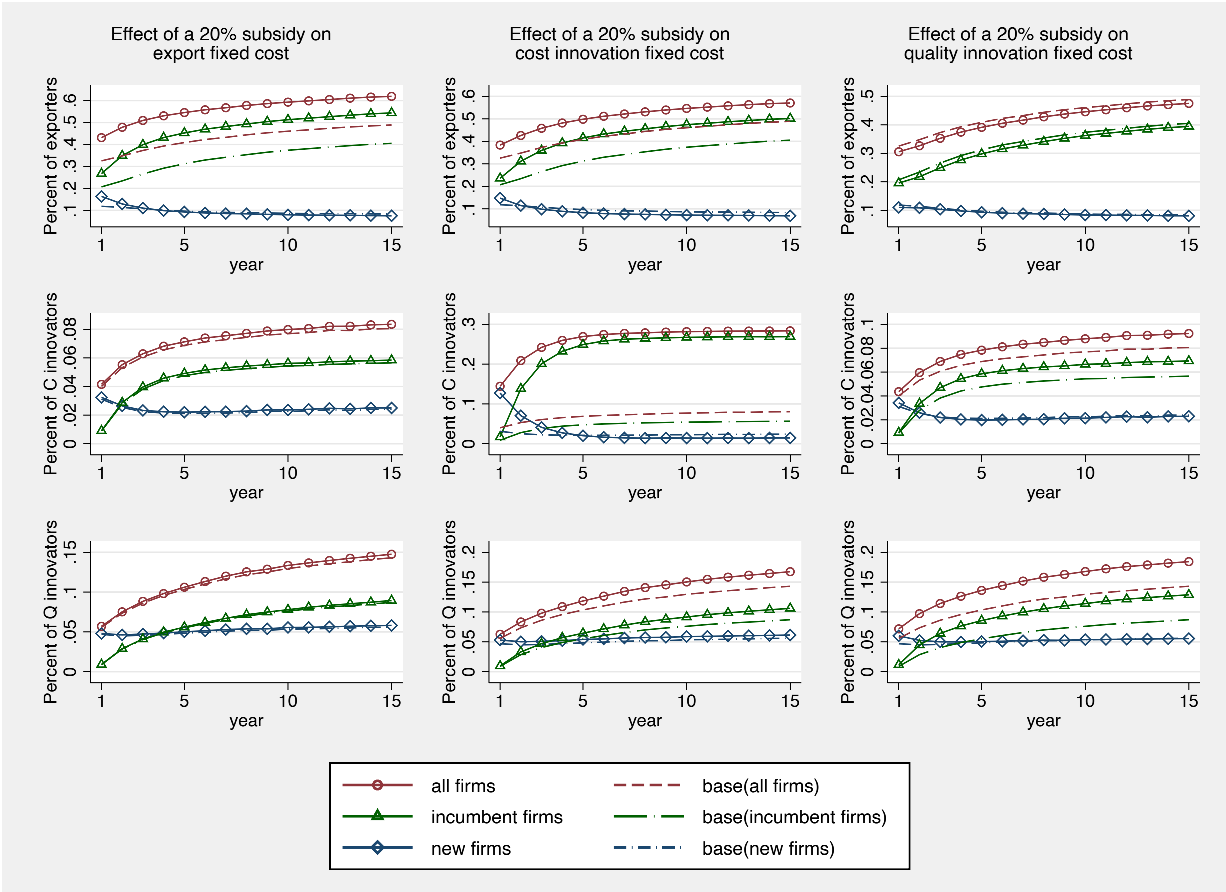

Figure 1: Effect of 20% Fixed Cost Subsidies

benefit of exporting.

Figure 2 presents the impact of sunk cost subsidies. Firstly note that a sunk cost subsidy does not necessarily raise participation in the subsidized activity. In our case, export and cost-innovation subsidies even lower the total participation rate in each activity. This relates to the dynamic nature of sunk costs. While lower sunk costs provide positive incentives for nonparticipants to enter, they also lower incumbents' incentives to remain active. The relative magnitudes of these two opposing forces determine a subsidy's impact on the total participation rate. For export and cost-innovation subsidies, the discouraging effects on incumbents dominate, lowering total participation rates. For quality-innovation subsidy, the incumbent firms are not significantly discouraged, so new entrants drive up the total participation rate. In addition, we find positive cross effects for quality-innovation subsidy and little cross effects for export and cost-innovation subsidies. The results suggest that quality-innovation subsidy has the largest impact on the marginal benefits of exporting and cost innovation.

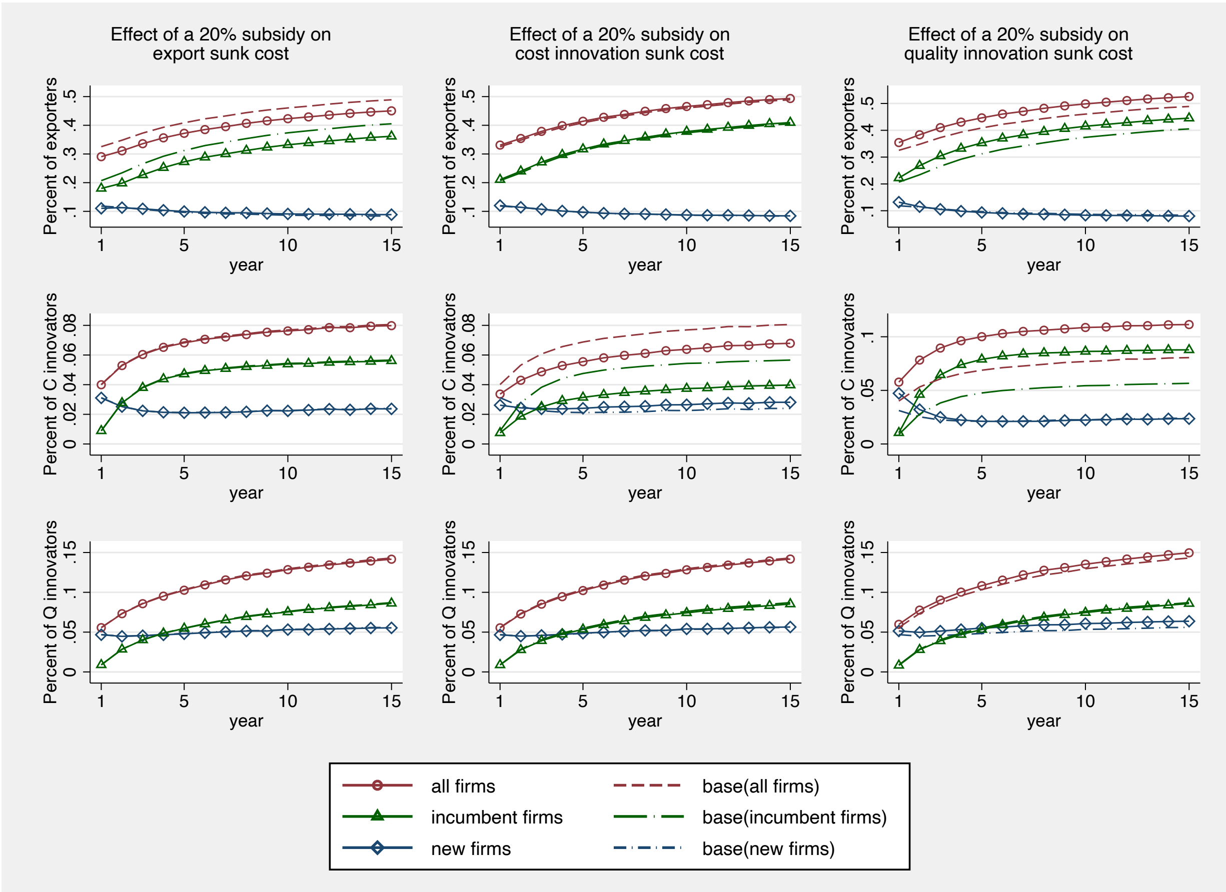

Figure 2: Effect of 20% Sunk Cost Subsidies

5.2.2 Effect on profit and productivity

This section provides a comprehensive evaluation of the subsidies by examining their cumulative profits and costs, as well as their effect on sector-level productivity.[36]

Table 9 presents results for 20% subsidies in 15 years. Column 1 reports differences from the baseline productivity of 1.78. First, all six subsidies have small impacts on firm productivity. Out of the three fixed cost subsidies, the one on cost innovation has the largest impact on productivity, with a magnitude of 3.1% over 15 years. The lack of impact on productivity is consistent with our estimation results in Table 7 and discussion in Section 4.3. Second, sunk cost subsidies on export and cost innovation slightly *lower* productivity. This is consistent with our observation in Figure 2 that subsidy to the sunk cost of export and cost innovation discourages continuing participation more than it encourages new starters.

Columns 2 and 3 report the present values of the cumulative cost and profit gain. A subsidy's profit gain equals the difference between sector-level profits with and without the subsidy. Unsurprisingly, we find subsidies lowering sector-level productivity also lead to lower profits. Overall,

[36]Cumulative profits and costs are present values of future flows with a discount rate of 0.9.

Table 9: Effect of 20% Subsidies on Productivity and Profit in 15 Years

Subsidy type	ΔProductivity (10^{-3})	Subsidy cost *(billions CNY)*	ΔProfit *(billions CNY)*	$\frac{\Delta\text{Profit}}{\text{Subsidy cost}}$
	(1)	(2)	(3)	(4)
Fixed cost subsidies				
Export	12.26	0.65	8.34	12.8
Cost innovation	30.64	2.97	97.39	32.8
Quality innovation	3.64	2.14	91.35	42.8
Sunk cost subsidies				
Export	-3.60	0.21	-2.50	-11.8
Cost innovation	-1.16	0.19	-19.39	-103.2
Quality innovation	7.03	0.93	9.17	9.8

Notes: The baseline productivity is 1.78. The baseline profit is 700 billion Chinese yuan.

fixed cost subsidies, although less expensive on a per-firm basis, generate much larger profit gains than sunk cost subsidies.

Column 4 divides Column (3) by Column (2) to measure the financial returns of different subsidy programs. It suggests that subsidy on the fixed cost of quality innovation, i.e., encouraging incumbent quality innovators to continue their innovation activity, is the most "profitable" - each yuan spent on subsidizing incumbent innovators generates a financial return of ¥43.

To summarize, these subsidy programs have a limited long-run impact on sector-level productivity. Some subsidies pay off financially in that each yuan spent on subsidy costs generates more than one yuan in profits. Given the small change in productivity, the profit gains will mostly come from selling more to the oversea markets via either the extensive or the intensive margin.

6 Conclusion

This paper estimates a dynamic structural model that captures the interaction between export, cost innovation, and quality innovation decisions by embedding these decisions into firm productivity and export demand trajectories.

We find that all three activities positively improve firm productivity, and quality innovation differs from cost innovation in two dimensions. Conceptually, quality innovation affects product demand, and cost innovation affects production. Empirically, they have a similar effect on firm productivity, but quality innovation significantly raises demand from the export market.

Our counterfactual analyses shed important light on the effect of market growth and export and innovation policies. While market growth, especially foreign market growth, significantly raises export and innovation participation rate, it has little impact on firm productivity. The same can be said about export and innovation policies. Despite their little impact on firm productivity, however, export/innovation policies that target continuing exporters/innovators have the potential to generate great profit gains. In the case of the Chinese electronics industry, policies targeting continuing quality innovators seem to be the most promising.

In conclusion, our paper suggests that it is important to look into the nature of innovation and identify the different channels through which innovation affects firm and industry dynamics.

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Appendix

A Patent Classification

This section describes the classification of all patents in the PATSTAT database, not just those matched to the Chinese firms. The general procedure is as follows:

1. Two research assistants manually classify 6,000 randomly drawn patents as either quality-improving or cost-reducing. Patents for which the two assistants give the same classification are more informational.
2. The classified patents' abstracts and titles are processed and coded into a sparse matrix, referred to as a training set, is produced.
3. The multilayer perceptron (MLP) model is fitted to the training set. The hyperparameters of the model are tuned so as to provide the best accuracy rates.
4. The MLP model is applied to the rest of the patent database that has undergone the cleaning process described in step 2.

The text below describes the training process in more detail. More details on the training process can be found in the online appendix to Liu and Trefler (2020).

To create a training sample, we hire two research assistants, RA1 and RA2, to manually classify 6,000 randomly selected patents by reading their titles and abstracts. RA1 has a science background and RA2 has an economics background. The patents are classified into two categories: quality-improving and cost-reducing, shortened as quality and cost. Quality patents are patents that improve the quality of an existing function, create a new function of an existing product, or create a new product. Cost patents are patents that improve production efficiency or reduce production costs. The research assistants' classification results are listed in the table below:

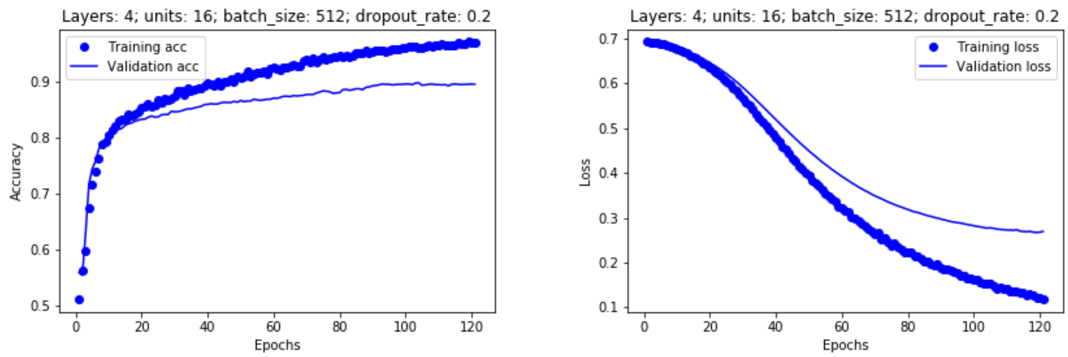
Table A.1: Patent Classification: 6000 Samples

		RA2's Classification		
		Cost	Quality	Total
RA1's Classification	Cost	920	351	1,271
	Quality	2,932	1,797	4,729
	Total	3,852	2,148	6,000

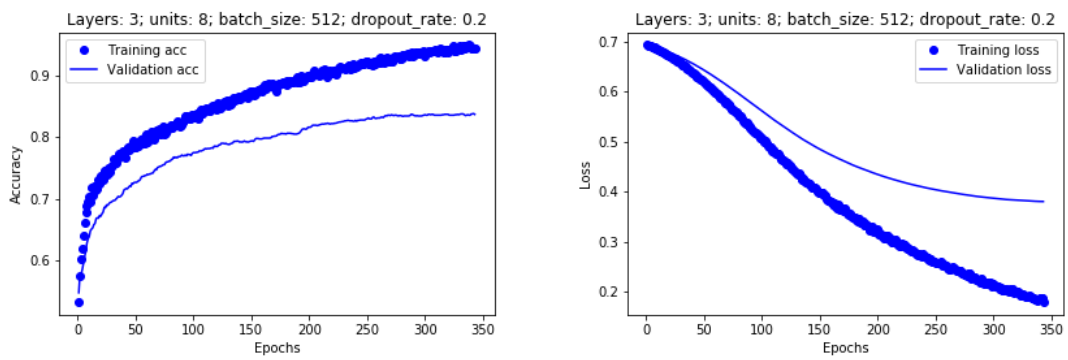
The two RAs' classifications are not quite consistent and we trust RA1's classifications over RA2's classifications for two reasons. First, we hired two additional research assistants with an economics background to classify 1000 of the 6000 sample patents. The additional classifications highly overlap with RA1's classifications. Second, as shown later in this section, RA1's classifications achieve higher accuracy rates than RA2's classifications. The benefit of this discrepancy is that it generates a highly credible sample: the common classifications between RA1 and RA2. These patents contain information that clearly identifies the nature of a patent.

The two RAs' classifications generate three training samples: RA1's classifications, RA2's classifications, and the common classifications. For each training sample, we use Google's Tensorflow to train an MLP model with a set of hyperparameters, including number of layers, units per layer, and dropout rate. The first two hyperparameters control the complexity of the MLP model, and the dropout rate controls the fraction of observations that are randomly thrown out of the training sample before each training session (epoch) so as to avoid the overfitting problem. We handpick the best combination of hyperparameters.

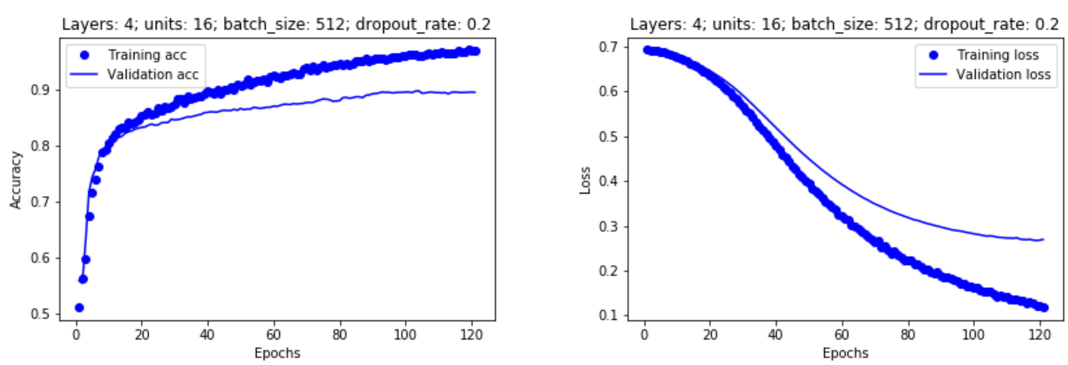
An MLP model is assessed by its accuracy and loss rates in the training set (5900 classified patents) and in the validation set (100 classified samples). Figures A.1 illustrates the training process using patent abstracts. Each panel corresponds to a training sample with the left figure reporting the training and validation accuracies and the right figure reporting the training and validation losses. The numbers above each figure report the set of hyperparameters that renders the best performance. In each panel, we observe how training and validation accuracies improve over the training sessions (epochs), and how the training and validation losses decline over the training sessions (epochs). Figure A.2 reports similar information but the models are trained using patent titles instead. Based on the model performances, we pick the MLP model with 4 layers, 16 neurons per layer, and a dropout rate of 0.2, and train this model on the common classifications sample of patent abstracts to classify the 29,666,609 matched patents.



(a) Training Accuracy and Loss for RA1's Classification

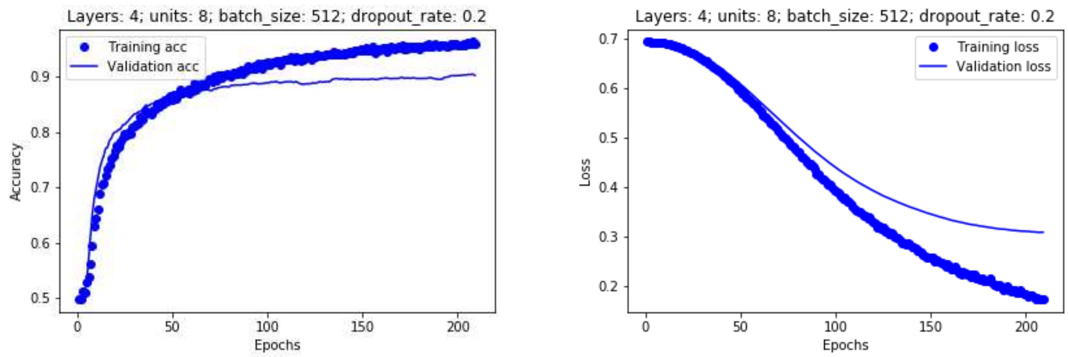


(b) Training Accuracy and Loss for RA2's Classification

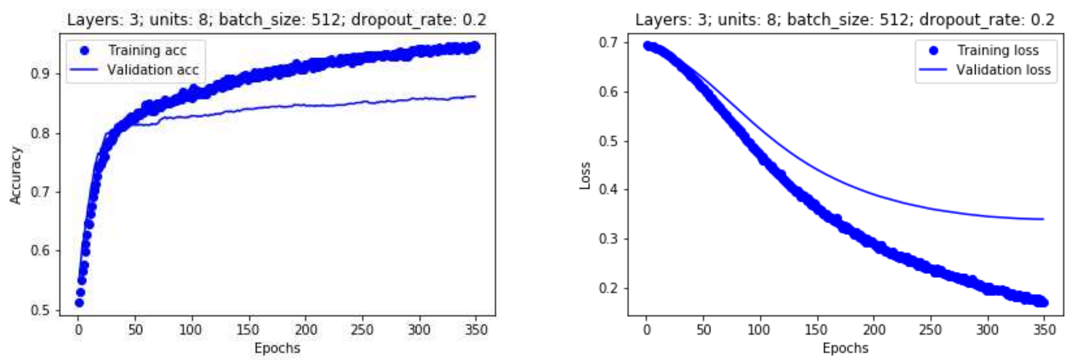


(c) Training Accuracy and Loss for Common Classification

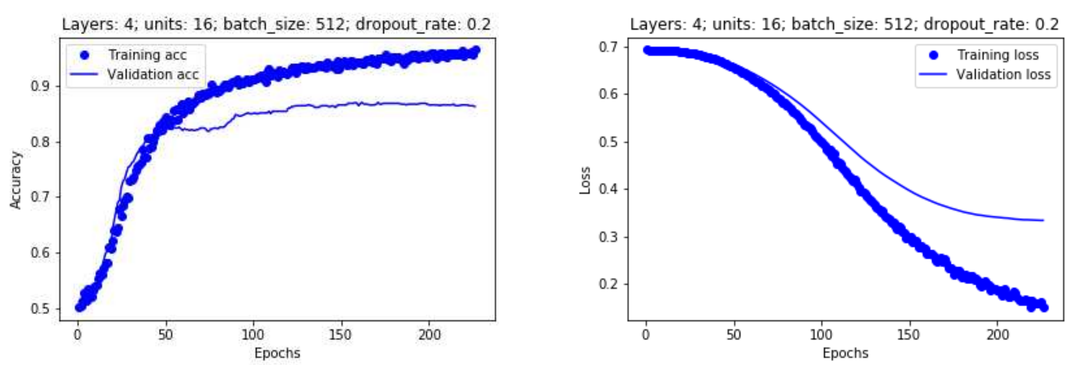
Figure A.1: Training Results Using Patent Abstracts



(a) Training Accuracy and Loss for RA1's Classification



(b) Training Accuracy and Loss for RA2's Classification



(c) Training Accuracy and Loss for Common Classification

Figure A.2: Training Results Using Patent Titles

B Algorithm

We use the following algorithm to calculate the value functions defined in equations (10), (11) and (13).

1. Begin with an initial guess of the value function $V^0(s)$.

2. Calculate $EV^0(e, d^C, d^Q) = \int_{z'} \int_{\omega'} V^0(z', \omega', e, d^Q, d^C, k, \Phi) dF(\omega'|\omega, e, d^Q, d^C) dT(z'|z)$, where $F(\omega'|\omega, e, d^Q, d^C)$ is calculated using equation (8) and $T(z'|z, d^Q)$ is from (9). Notice that EV^0 depends on e and d for three reasons: (1) both e and d affect future productivity, (2) entry into either activity involves a sunk cost, (3) d^Q affects future export demand shifter.

3. Calculate V^{C0} and V_t^{NC0} using equations (13) and (15):

$$\begin{aligned} V^{C0}(e, d_{-1}^Q) &= \Pr[d_{-1}^Q \gamma^{Qf} + (1 - d_{-1}^Q)\gamma^{Qs} < \delta EV^0(e,1,1) - \delta EV^0(e,1,0)] \cdot (\delta EV^0(e,1,1) - d_{-1}^Q E(\gamma^{Qf}|\cdot) - (1 - d_{-1}^Q) E(\gamma^{Qs}|\cdot)) \\ &+ \Pr[d_{-1}^Q \gamma^{Qf} + (1 - d_{-1}^Q)\gamma^{Qs} \geq \delta EV^0(e,1,1) - \delta EV^0(e,1,0)] \delta EV^0(e,1,0), \end{aligned}$$

and

$$\begin{aligned} V^{NC0}(e, d_{-1}^Q) &= \Pr[\delta EV^0(e,0,1) - \delta EV^0(e,0,0) > d_{-1}^Q \gamma^{Qf} + (1 - d_{-1}^Q)\gamma^{Qs}] \cdot (\delta EV^0(e,0,1) - d_{-1}^Q E(\gamma^{Qf}|\cdot) - (1 - d_{-1}^Q) E(\gamma^{Qs}|\cdot)) \\ &+ \Pr[\delta EV^0(e,0,1) - \delta EV^0(e,0,0) \leq d_{-1}^Q \gamma^{Qf} + (1 - d_{-1}^Q)\gamma^{Qs}] \delta EV^0(e,0,0). \end{aligned}$$

4. Calculate V^{E0} and V^{D0} using equations (11) and (12):

$$\begin{aligned} V^{E0}(d_{-1}^C, d_{-1}^Q) &= \Pr[d_{-1}^C \gamma^{Cf} + (1 - d_{-1}^C)\gamma^{Cs} < V^{C0}(e=1, d_{-1}^Q) - V^{NC0}(e=1, d_{-1}^Q)] \cdot V^{C0}(e=1, d_{-1}^Q) \\ &+ \Pr[d_{-1}^C \gamma^{Cf} + (1 - d_{-1}^C)\gamma^{Cs} \geq V^{C0}(e=1, d_{-1}^Q) - V^{NC0}(e=1, d_{-1}^Q)] \cdot V^{NC0}(e=1, d_{-1}^Q), \end{aligned}$$

and

$$\begin{aligned} V^{D0}(d_{-1}^C, d_{-1}^Q) &= \Pr[d_{-1}^C \gamma^{Cf} + (1 - d_{-1}^C)\gamma^{Cs} < V^{C0}(e=0, d_{-1}^Q) - V^{NC0}(e=0, d_{-1}^Q)] \cdot V^{C0}(e=0, d_{-1}^Q) \\ &+ \Pr[d_{-1}^C \gamma^{Cf} + (1 - d_{-1}^C)\gamma^{Cs} \geq V^{C0}(e=0, d_{-1}^Q) - V^{NC0}(e=0, d_{-1}^Q)] \cdot V^{NC0}(e=0, d_{-1}^Q). \end{aligned}$$

5. Calculate the value function $V^1(s)$ using equation (10) by:

$$
\begin{aligned}
V^1(s) &= \pi^D \\
&+ \Pr(e_{-1}\gamma^{Ef} + (1-e_{-1})\gamma^{Es} < \pi^X + V^{E0}(d^Q_{-1}, d^C_{-1}) - V^{D0}(d^Q_{-1}, d^C_{-1})) \cdot (\pi^X + V^{E0}(d^Q_{-1}, d^C_{-1}) - e_{-1}E(\gamma^{Ef}|\cdot) - (1-e_{-1})E(\gamma^{Es}|\cdot)) \\
&+ \Pr(\pi^X + V^{E0}(d^Q_{-1}, d^C_{-1}) - V^{D0}(d^Q_{-1}, d^C_{-1}) \leq e_{-1}\gamma^{Ef} + (1-e_{-1})\gamma^{Es}) \cdot V^{D0}(d^Q_{-1}, d^C_{-1}).
\end{aligned}
$$

6. Iterate across steps 2-4 until $\left|V^{j+1} - V^j\right| < \varepsilon$.

We adopt John Rust's (1997) method to discretize the state space. We choose $N = 100$ low-discrepancy points for (ω, z). Denote the random grid points as $(\omega_1, z_1), ...(\omega_n, z_n), ...(\omega_N, z_N)$. The grid values for k are fixed with 10 categories. The firm's dynamic problem and value function $\hat{V}$ can be solved exactly on each grid point by the value function iteration method described in the previous section. For the data points that are not on the grid points, we can calculate EV using the discrete Markov operator given by:

$$
\begin{aligned}
EV &= \int_{z'}\int_{\omega'} V^0(z', \omega', e, d^Q, d^C, k, \Phi) dF(\omega'|\omega, e, d) dT(z'|z) \\
&= \frac{1}{N}\sum_{n=1}^{N} \hat{V}(z_n, \omega_n, e, d^Q, d^C, k, \Phi) p^N(z_n, \omega_n | z, \omega, e, d).
\end{aligned}
$$

where $p^N(z_n, \omega_n|z, \omega, e, d) = \frac{p(z_n|z)p(\omega_n|\omega,e,d)}{\sum_{n=1}^{N} p(z_n|z)p(\omega_n|\omega,e,d)}$. Then the calculations of V^E and V^D follow from steps 2-4 as above.

C Supplementary Tables and Figures

Table C.1: R&D and Patenting

	linear		poisson		negative binomial	
	(1)	(2)	(3)	(4)	(5)	(6)
	$\log(patent_{it}+1)$	$\log(patent_{it}+1)$	$patent_{it}$	$patent_{it}$	$patent_{it}$	$patent_{it}$
$\log(R_{it})$	0.033***	0.034***	0.114	0.275***	0.175***	0.175***
	(0.004)	(0.007)	(0.061)	(0.045)	(0.019)	(0.030)
$\log(R_{it-1})$	0.021***	0.011	-0.032	-0.095**	0.086***	0.058
	(0.004)	(0.007)	(0.018)	(0.033)	(0.019)	(0.030)
$\log(R_{it-2})$		0.022***		0.051		0.075
		(0.006)		(0.035)		(0.041)
$\log(Sales_{i2005})$	0.061***	0.063***	0.989***	0.770***	0.669***	0.587***
	(0.007)	(0.010)	(0.126)	(0.106)	(0.051)	(0.082)
Year fixed effects	Y	Y	Y	Y	Y	Y
Industry fixed effects	Y	Y	Y	Y	Y	Y
Observations	10,902	5,089	10,902	5,089	10,902	5,089

Table C.2: Correlation between Domestic and Foreign Revenues by Innovation Mode

Firm innovation decisions:	Neither	Cost only	Quality only	Both
All firm-year observations	0.220	0.398	0.331	0.191
Firm-year obs. with positive export revenue	0.359	0.400	0.325	0.180
Average total revenue	83,059	198,258	319,348	1,289,465

Notes: Revenues are in thousands of Chinese yuan.

Table C.3: Export and Innovation Decisions of Entrants and Exiters

	Percent of Exporters			Percent of C Innovators			Percent of Q Innovators		
Year	All	Entrants	Exiters	All	Entrants	Exiters	All	Entrants	Exiters
2001	37.07	35.43	33.96	3.17	2.02	2.96	3.71	2.97	3.23
2002	37.04	37.72	29.69	4.51	2.92	2.54	4.92	3.32	2.93
2003	40.38	40.93	35.38	4.81	4.34	2.84	5.64	4.19	2.96
2004	42.53	42.36	45.39	5.05	2.95	3.19	5.38	3.42	3.19
2005	39.19	39.96	47.11	4.67	2.58	3.21	4.83	2.47	4.07
2006	38.90	36.42	44.69	5.45	4.43	3.24	5.53	3.68	3.69
Total	38.80	39.62	40.20	5.10	3.35	3.43	4.91	3.16	3.02

Notes: Entrants are the firms that exist in the data in year t and do not exist in year $t-1$, with $t > 2000$. Exiters are firms that exist in year t and exit the data in year $t+1$, with $t < 2007$.

Table C.4: Export and Patenting Participation and Export Revenue Functions

	Coeff on ω_{it}	Coeff on $\ln k_{it}$	Coeff on e_{it-1}	Coeff on d_{it-1}	ρ
Bivariate probit on export and Innovation					
Exporting	0.445***	0.102***	2.612***	0.0403	0.0926***
	(0.045)	(0.008)	(0.024)	(0.050)	(0.025)
Innovation	0.582***	0.105***	-0.0297	1.630***	
	(0.049)	(0.008)	(0.030)	(0.036)	
Export revenue					
$\ln r_{it}^X$	1.595***	1.200***			
	(0.148)	(0.038)			
Export revenue with fixed effect					
$\ln r_{it}^X$	0.793***	0.518***			
	(0.146)	(0.081)			

Notes: Numbers in parentheses report standard errors.

Table C.5: Export, Innovation Rates, and Productivity Evolution

	2000	2001	2002	2003	2004	2005	2006	2007
Export market participation rate								
Data	0.307	0.312	0.312	0.343	0.367	0.374	0.350	0.357
Simulation	0.307	0.337	0.358	0.385	0.388	0.389	0.373	0.397
Quality innovation rate								
Data	0.028	0.037	0.045	0.050	0.047	0.046	0.054	0.066
Simulation	0.028	0.048	0.058	0.064	0.057	0.056	0.063	0.070
Cost innovation rate								
Data	0.028	0.028	0.039	0.046	0.042	0.043	0.053	0.065
Simulation	0.028	0.024	0.028	0.033	0.033	0.026	0.030	0.025
Average productivity								
Data	0.183	0.185	0.207	0.238	0.240	0.254	0.271	0.305
Simulation	0.183	0.207	0.230	0.254	0.249	0.260	0.266	0.285

Table C.6: Actual and Predicted Transition Rates

(a) Export and Innovation Transition

Status year t		Status year t+1			
		neither	only innovate	only export	both
Neither	Data	0.901	0.034	0.060	0.004
	Simulation	0.813	0.014	0.161	0.012
Only innovate	Data	0.488	0.411	0.040	0.061
	Simulation	0.570	0.082	0.223	0.126
Only export	Data	0.115	0.004	0.831	0.050
	Simulation	0.291	0.005	0.613	0.091
Both	Data	0.047	0.032	0.349	0.572
	Simulation	0.060	0.007	0.328	0.605

(b) Quality and Cost Innovation Transition

Status year t		Status year t+1			
		neither	only innovate	only export	both
Neither	Data	0.956	0.016	0.015	0.013
	Simulation	0.950	0.039	0.008	0.003
Only quality	Data	0.595	0.167	0.058	0.180
	Simulation	0.544	0.380	0.018	0.058
Only cost	Data	0.562	0.100	0.181	0.156
	Simulation	0.612	0.060	0.221	0.107
Both	Data	0.287	0.137	0.082	0.495
	Simulation	0.288	0.137	0.102	0.473

Table C.7: Counterfactual with no subsidies

	Year			
	2	5	10	15
Percent of exporters	36.7	42.9	48.0	50.8
Percent of quality innovators	6.4	9.3	11.9	13.2
Percent of cost innovators	4.2	5.5	6.2	6.4
Average productivity	0.256	0.321	0.397	0.439

Table C.8: Effect of Subsidies on Firm Productivity

	Productivity Difference from Baseline (10^{-3})						Baseline productivity
Subsidy type:	Ef	Cf	Qf	Es	Cs	Qs	
Productivity quartiles							
<25%	3.1	32.7	2.9	-0.2	-1.2	6.6	1.663
25%-50%	1.0	17.1	8.9	1.1	1.3	2.8	1.717
50%-75%	-0.7	10.6	-2.4	-0.4	-3.9	2.7	1.746
>75%	-0.4	10.4	-3.7	-0.3	-1.9	6.8	1.785
Total	0.7	17.7	1.4	0.1	-1.4	4.7	1.728